



IEA Technology Collaboration Programme

International Energy Agency
Technology Collaboration Programme on Energy Storage
(ES TCP)

Task 37

Smart Design and Control of Energy Storage Systems

Final Report



Submitted for
the [ordinal number of the ExCo Meeting] ES TCP ExCo meeting, [date], [online meeting/location].

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KEY MESSAGES AND POLICY RECOMMENDATIONS

The goal of this Task is to design, integrate, control, and optimize energy storage systems (ESS) across various scales, from buildings to power grids. This involves developing methods, optimization, and advanced control strategies to predict, evaluate, and improve ESS performance. This comprehensive review includes six subtasks, each providing essential insights for effective ESS deployment.

Key Messages

Task 37 of the IEA Energy Storage Technology Collaboration Programme (ES TCP) was established to deliver practical methods and tools for the smart design and control of energy storage systems (ESS), ranging from buildings to grid-level integration. The ultimate goal is to enable widespread, efficient deployment of ESS that improves energy system resilience, reduces operational costs, enhances integration of renewables, and supports decarbonization objectives.

This Task has produced a coordinated body of research, frameworks, and case studies that together offer new insights and actionable strategies for both technical stakeholders and policymakers. Outputs include a suite of design methodologies, performance benchmarking tools, control strategies, and modeling approaches—many of which leverage advanced technologies such as AI, IoT, and data-driven analytics. These outputs are intended for engineers, researchers, building designers, energy system operators, and policy advisors, and will be disseminated through this final report, peer-reviewed publications, and future annexes or collaborative projects within the ES TCP network.

The key achievements and new contributions of Task 37 are summarized below:

1. Smart Data Analytics and IT Integration (Subtask 0)

What's new: Developed a classification of predictive analytics specific to ESS, and established frameworks for integrating IoT, BMS, and BIM to support smarter control and lifecycle management.

Expected benefits: Improved system efficiency, more reliable performance predictions, and extended lifetime of ESS through enhanced monitoring and control.

2. Forecasting Models for Control (Subtask A)

What's new: Introduced cost-effective Direct Multi-Step (DMS) forecasting models that match more complex alternatives and demonstrated the practical application of Transfer Learning for ESS control.

Expected benefits: Reduced data collection costs and improved forecasting accuracy for operational decisions, leading to better grid integration and energy savings.

3. Machine Learning for ESS Modeling (Subtask B)

What's new: Highlighted the untapped potential of advanced machine learning—particularly Artificial Neural Networks—in modeling complex, nonlinear ESS behavior, including underexplored technologies like sorption storage.

Expected benefits: Faster, more flexible modeling for system designers and control engineers, supporting real-time diagnostics and adaptive control strategies.

4. Smart Design Methodology (Subtask C)

What's new: Delivered a comprehensive seven-step methodology for designing thermal energy storage (TES) systems, validated through multiple international case studies.

Expected benefits: Improved alignment between system design and application needs, resulting in optimized energy use and better return on investment.

5. AI-Based Control Systems (Subtask D)

What's new: Demonstrated the effectiveness of AI-driven predictive control systems in real-world settings, enhancing system responsiveness and user comfort during power disruptions.

Expected benefits: Higher system reliability, lower carbon footprints, and improved energy resilience in buildings and districts.

6. Cooperative Control at District/Grid Scale (Subtask E)

What's new: Provided a detailed typology of ESS control architectures and identified strategies for stabilizing microgrids and enhancing real-time grid responsiveness.

Expected benefits: Better integration of distributed storage, improved grid stability, and reduced vulnerability to outages or supply-demand imbalances.

Policy Recommendations

In light of the findings from Task 37, several policy directions are recommended to support the effective deployment of smart energy storage systems across buildings, districts, and power grids. These recommendations aim to inform policymakers on enabling frameworks that can foster innovation, improve resilience, and advance energy sustainability.

To begin with, the integration of digital technologies—such as the Internet of Things (IoT), Artificial Intelligence (AI), and Building Information Modeling (BIM)—into energy storage systems should be a key focus of energy policy. Public investment and regulatory support can help accelerate the deployment of these technologies, ensuring better management, monitoring, and control of energy systems.

Furthermore, policymakers are encouraged to support data-sharing initiatives and the development of standardized frameworks that facilitate interoperability among energy systems. Such efforts will enhance forecasting and operational control, particularly when existing data and models can be reused through techniques like Transfer Learning. Reducing barriers to data access will enable broader use of forecasting tools that can optimize energy storage performance while minimizing implementation costs.

In the area of system design, policy should promote adaptive approaches that consider the diversity of buildings and energy infrastructures. Incentives for customized, application-specific design—especially in retrofitting existing buildings—can lead to more efficient and resilient energy systems. Supporting pilot projects and demonstration cases of advanced thermal energy storage (TES) design methods can serve as valuable benchmarks for wider adoption.

To optimize the operation of energy storage, investment in AI-based control systems should be encouraged. These systems are critical in increasing energy resilience, especially in the face of

growing disruptions linked to climate change and energy demand fluctuations. Policymakers can play a crucial role by supporting research, establishing guidelines, and creating market incentives for resilient energy infrastructure that integrates smart storage solutions.

Lastly, as power grids evolve into more dynamic and decentralized systems, real-time control, protection mechanisms, and cybersecurity become essential. Policymakers should prioritize the development and deployment of quick protection devices and smart grid technologies, which are instrumental for ensuring stability and preventing system vulnerabilities. Cross-sector collaboration—between government, academia, and industry—will be key to realizing these advancements.

By adopting these policy directions, governments can help unlock the full potential of energy storage technologies, advancing climate goals, energy equity, and long-term system reliability.

General Recommendations for Deployment

1. Invest in Advanced Technologies:

Prioritize IoT, AI, and ML integration in ESS for enhanced performance.

2. Customize Solutions:

Tailor methodologies and models to specific applications and buildings.

3. Enhance Resilience and Stability:

Focus on predictive and real-time control systems for improved resilience.

4. Collaborate and Share Data:

Use Transfer Learning and collaborative approaches to minimize costs and leverage existing knowledge.

By implementing these recommendations, stakeholders can effectively design, optimize, and control energy storage systems, leading to more sustainable and efficient energy management across various scales.

MAIN RESULTS IN A NUTSHELL

The general objective of this task is to address the design, integration, control, and optimization of energy storage systems (ESS) within buildings, districts, power grids, and local utilities. The focus is on developing advanced design methods, optimization techniques, and control strategies to effectively predict, evaluate, and improve the performance of buildings and districts when energy storage is available. This task consists of six subtasks, each providing critical insights for the deployment of energy storage solutions. Here are the main results and conclusions for each subtask.

1. Data Analytics and Information Technologies for Smart Energy Storage

- **Critical Role of ESS:** ESS are crucial for efficient energy management, involving complex variables that require accurate state and trend estimation for optimal operation and control.
- **Integration with IoT:** IoT technologies play a key role in integrating distributed energy storage (DES) systems, helping balance renewable energy supply and demand through effective design and operation.
- **Importance of BMS and BIM:** Building Management Systems (BMS) and Building Information Modeling (BIM) are essential for smart design and control features in ESS, enhancing efficiency and performance.

2. Forecasting for Control of Smart Energy Storage Systems

- **Efficiency of DMS Models:** Simple neural Direct Multi-Step (DMS) models perform similarly to complex Machine Learning (ML) models but with lower computational costs.
- **Transfer Learning Benefits:** Data collection requirements for new control systems can be minimized by reusing measurement data and trained models from existing buildings.
- **Forecasting Challenges:** Forecasting grid electricity price and carbon intensity is generally easier than predicting building electrical load, which varies in difficulty across different buildings.
- **Data vs. Accuracy Trade-off:** There is a trade-off between using less data (reducing costs) and achieving better prediction accuracy (reducing operational costs). Finding the optimal balance is crucial.

3. Data-driven Modelling of Energy Storage Devices using Machine Learning

- **Underutilization of ML Potential:** Current energy storage modeling often underutilizes the potential of modern ML.
- **Focus on Sorption Technologies:** Few studies focus on physical and chemical sorption, which requires precise control and has significant potential.
- **Advantages of ANN:** Artificial Neural Networks (ANN) handle highly non-linear problems better than traditional white-box approaches, which often lead to stiff differential equations.
- **Applications Beyond Predictive Modeling:** ML can be used for real-time learning, anomaly detection, and data mining, expanding its applications beyond predictive modeling.

4. Smart Design/Integration Methodology for Energy Storage Systems

- **Seven-Step Design Methodology:** A proposed seven-step design methodology can guide the process from describing the thermal process to defining TES geometry based on thermal application requirements and constraints.
- **Discrepancies in Design Parameters:** There is a discrepancy between design cases regarding input parameters to the proposed design methodology.
- **Application Type Consideration:** Including the type of application (retrofit or new construction) as a decisive factor in the design methodology is recommended for better alignment with specific needs.
- **Need for More Applications:** Additional applications are needed to validate and refine the design methodology.

5. Advanced Storage Control Applied to Optimize Operation of Energy Storage Systems

- **Predictive Capabilities of AI:** AI-based control systems can predict important factors like energy storage performance, weather conditions, and demand, optimizing energy storage for environmental and economic benefits while maintaining system stability.
- **Enhanced Resilience:** AI-based control improves building and district resilience during disruptions, adjusting energy use to maintain comfort and minimize the impact of power outages.
- **Transformative Potential:** Energy storage technology, combined with AI-based control, offers a transformative approach to sustainable energy management, significantly enhancing efficiency and reliability.

6. Cooperative Control of Building/District/Grid

- **Challenges with Renewable Energy:** Renewable energy sources are unpredictable, and energy demand varies, necessitating a consideration of costs and constraints for optimization.
- **Microgrid Stability:** Developing quick protection devices for stable microgrid operation during isolated events is a significant challenge that needs addressing.
- **Real-time Control Needs:** As power grids evolve into smarter systems, real-time control, mitigation, and protection become crucial.
- **Vulnerability Prevention:** Detecting and preventing vulnerabilities is essential to avoid financial and proprietary losses, ensuring the security and stability of energy systems.

Summary Recommendations

- **Invest in IoT and AI Technologies:** Enhance the integration and control of ESS by leveraging IoT and AI technologies.
- **Tailor Solutions:** Customize design methodologies and forecasting models to specific building characteristics and application types.
- **Enhance Resilience:** Focus on predictive and real-time control systems to improve system resilience and stability.
- **Utilize Transfer Learning:** Apply Transfer Learning to reduce setup costs and leverage existing data and models.

By implementing these strategies, stakeholders can optimize the design, control, and performance of energy storage systems, contributing to more sustainable and efficient energy management across various scales.

EXECUTIVE SUMMARY

1 Short Description of Task 37

1.1 Objectives and Scope

The general objective of this Task is to address the design/integration, control, and optimization of energy storage systems within buildings, districts, power grids, and/or local utilities. The focus will be on the development of design methods, optimization, and advanced control strategies for effectively predicting, evaluating, and improving the performance of Buildings and districts when energy storage is available. The Task shall deal with the fundamental of smart technology and its application to energy storage systems in buildings, districts, and grids.

1.2 Organisational Structure

Project group managed by the Task Leader Ryoza Ooka.

Participating countries: Japan, Canada, UK, France, Denmark, Italy, Korea, China, Sweden, US, Norway, Turkey, Israel and Ireland.

The Task Leader reports to the ExCo of the TCP on a regular basis.

1.3 Beginning and End of Task

Start: May 2020. End of Task: June 2024.

1.4 Experts Meetings

City	Country	Date	# Participants
Online	-	12 June 2020	39
Online		10 July 2020	44
Online		14 August 2020	35
Online		25 September 2020	35
Online		26 October 2020	30
Online		27 May 2021	35
Online		22 October 2021	32
Online		6 May 2022	25
London	UK	18 October 2022	21
Tokyo	Japan	18 May 2023	23
Turin	Italy	27 October 2023	21
Lyon	France	1 June 2024	12

2 Summary of Subtasks

2.1 Subtask 0

This sub-task is mandated to investigate the state-of-the-art smart tools and technologies to support integration, optimization, control and coordination of energy storage systems at/with various integration scales (building, district, and community), various operational & control scenarios (real-time vs predictive), various technologies (batteries, thermal storage, CAES, etc.), and various objectives (cost efficiency, resilience & self-reliance, renewables penetration, etc.).

This report provides a state-of-the-art review on emerging applications of smart tools such as data analytics and smart technologies such as Internet-of-things (IoT) in case of design, management and control of energy storage systems. In particular, we have established a classification of the types and targets of various predictive analytics for estimation of load, energy prices, renewable energy inputs, state of the charge, fault diagnosis, etc. In addition, the applications of information technologies, in particular, use of cloud, IoT systems, building management systems (BMS) and building information modeling (BIM) and their contributions to management of energy storage systems will be reviewed in detail. The paper concludes by highlighting the emerging issues in smart energy storage systems and providing directions for future research.

2.2 Subtask A

The prediction of energy demand in buildings and districts is a constraint that must be satisfied in control. Especially, the energy demand of buildings and districts varies significantly depending on the usage, composition of the energy system, change of weather, occupant behavior, and so on. There are many demand prediction models are previously proposed including IEA's achievement. This particular Annex will focus on prediction models that support smart control and operation of energy storage technologies.

This sub-task investigates the role of data in enabling high accuracy forecasting for smart energy storage systems by studying the performance of various prediction models in providing forecasts for a Linear MPC controller that operates batteries within a multi-building energy system simulation. Specifically, it examines the capability of different Machine Learning models to forecast electricity demand, grid electricity cost, and carbon emissions, considering how different aspects of the supporting data impact prediction performance and the implications for the joint design of forecasting models and data collection strategies.

2.3 Subtask B

The objective of subtask B is to analyze the numerical models developed at the component scale for optimization, design and control of energy storage systems integrated in buildings and districts. In order to carry out such analysis, a comprehensive and up-to-date set of information is mandatory. It was therefore decided to build a database gathering as much information as possible on recent or ongoing research works on energy storage systems, including (at least some) modeling attempts.

Research on the optimal use of energy storage systems includes approaches like Rule-based Control (RBC), Model Predictive Control (MPC), and Adaptive Control (AC), all of which rely on accurate and fast system models. Creating equation-based (white-box) models can be time-consuming and require engineering services, particularly when systems change. Grey-box modelling, which uses simple

mathematical equations calibrated with data, and black-box modelling, which relies purely on data-driven methods, offer alternatives. With the rise of data availability, computing power, and machine learning algorithms, black-box modelling has gained significance. In this report, this sub-task is reviewing the existing literature on data-driven modelling of energy storage devices for buildings in Subtask B.

2.4 Subtask C

Recent research studies have focused on the optimal design of Thermal Energy Storage (TES) systems for different plants and processes, utilizing advanced optimization techniques. There are a wide range of TES technologies that can be integrated into a variety of thermal applications. Each TES technology has its own technical and economic characteristics that make it essentially suitable for a specific application. Identifying important factors and then matching an application with the most appropriate TES system is still a challenging issue. Subtask C discusses the challenges in identifying the most appropriate Thermal Energy Storage (TES) system for a specific application due to the technical and economic characteristics of each TES technology. A seven-step design methodology is proposed that can guide the process from describing the thermal process to defining the TES geometry based on the requirements and constraints of the thermal application. The steps in the proposed methodology include specifying the thermal process, thermal demand, storage technology, integration parameters, key performance indicators, optimization method, and optimization tools. The proposed methodology is implemented in seven different case studies to demonstrate its effectiveness in identifying the most appropriate TES system for a specific application. Although the case studies involve various types of applications with both sensible and latent thermal energy storage systems, the proposed design procedure is applicable. The design steps proposed in this subtask can serve as a foundation for developing a systematic approach for designing TES systems in future works.

2.5 Subtask D

Subtask D is intended to provide the latest findings on the smart control and operation strategies of energy storages into buildings and districts. Within the complex multi-source multi-energy systems that are exploited to ensure a full decarbonization of the building sector, the strategies used to control such storages may not be straightforward, as they should be set considering a large number of variables and uncertain inputs so that a multiple number of interrelated outputs are optimized.

In this subtask, the identification and review of recent studies concerning the control of energy storage integrated in systems for buildings, or group of buildings is performed. In particular, the report concentrates on papers that are not only purely theoretical or numerical studies, but where some experimental activities were carried out or where analysis are conducted based on real case-studies. This is particularly important in order to evaluate the effectiveness of the control strategies against real measurements. Thus, a systematic review process was implemented aimed at identifying the latest advancements in energy storage control, the emerging trends and the role of AI in shaping such trends, and future perspectives.

2.6 Subtask E

The main objective of this subtask is to represent all system components (in terms of their electrical or energetic inputs and outputs, efficiencies, technical constraints, static and dynamic behavior, costs,

emissions) and propose optimal control and operation methods in power grid systems.

This subtask presents a comprehensive review of the existing studies regarding ESS in power distribution networks. The contributions of this work can be summarized as follows:

- This subtask discusses various issues related to the power quality of distribution networks and their mitigation scopes with ESSs. In detail, we present a systematic review of ESS studies published in journals or conference proceedings providing a comprehensive review of ESS integration in power distribution networks.
- We approach the review of relevant ESS papers through multiple angles, including technological, design, and optimization aspects. Additionally, we provide a detailed classification of the papers based on various criteria, such as the type of ESS used, the control strategy employed, and the application area. Our review categorizes the control architectures for ESSs and explains the advantages and challenges of developing practical operational strategies and solution techniques for different ESS applications.
- Differently from most of the recalled reviews, we show all the possible applications of ESS in power distribution grids such as frequency regulation, grid stability, voltage regulation, and ancillary services. Through the review, we identify the existing gaps in the literature and provide promising research directions to fill these gaps. We also highlight the correlation between articles considering all the possible ESS applications, recent advancements in storage technologies, and relevant control approaches available in the literature.

3 Interrelationships between Subtasks and their Contribution to the Overall Task

Each subtask of Task 37 is interconnected, collectively building a comprehensive framework for the smart design and control of energy storage systems. Figure 1 shows the interrelationship between subtasks. Subtask 0 establishes the foundation by exploring smart tools and data analytics technologies essential for predictive management. Building on this, Subtask A focuses on forecasting energy demand and supply—critical for enabling real-time control strategies envisioned in Subtask 0. Subtask B then leverages these forecasts by applying machine learning to develop component-level models that inform design and operational decisions. These models support Subtask C, which proposes a structured methodology to optimally design energy storage systems for specific building and district contexts. The design outputs feed directly into Subtask D, where advanced control strategies — especially AI-based systems—are developed to manage energy systems under real-world uncertainties. Finally, Subtask E scales these concepts to the grid level, addressing coordination across buildings, districts, and power grids. Together, these subtasks form a layered and interdependent approach that enables holistic optimization and integration of energy storage across all levels of the energy system.

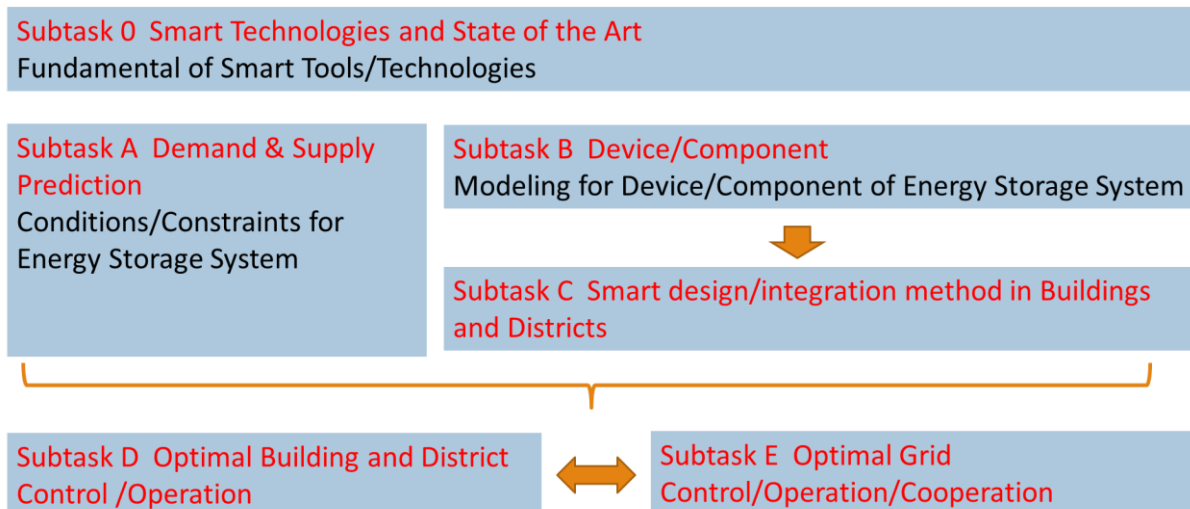


Figure 1 Interrelationship between subtasks

4 Comprehensive Results and Recommendations for Deployment

The primary goal of this Task is to address the design, integration, control, and optimization of energy storage systems within various scales, from buildings to power grids. The focus is on developing methods, optimization, and advanced control strategies to predict, evaluate, and improve the performance of energy storage systems in these contexts. This comprehensive review consists of six subtasks, each providing insights and conclusions essential for deploying effective energy storage solutions. Below is a summary of findings and recommendations for each subtask.

1. Data Analytics and Information Technologies for Smart Energy Storage

Main Conclusions:

- Energy Storage Systems (ESS) are critical for efficient energy management, requiring accurate state and trend estimation for optimal operation and control.
- IoT technologies are vital for integrating distributed energy storage (DES) systems, balancing renewable energy supply and demand.
- Building Management Systems (BMS) and Building Information Modeling (BIM) are essential for the smart design and control of ESS.

Recommendations:

- Invest in IoT technologies to enhance DES integration and operation.
- Implement BMS and BIM in the design and control phases of ESS to maximize efficiency and performance.

2. Forecasting for Control of Smart Energy Storage Systems

Main Conclusions:

- Simple neural Direct Multi-Step (DMS) models perform comparably to complex ML models with lower computational costs and better data efficiency.
- Transfer Learning minimizes data collection requirements by reusing data and trained models from existing buildings.
- Forecasting grid electricity price and carbon intensity is generally easier than predicting building electrical load, though the difficulty varies by building.

Recommendations:

- Use DMS models for efficient forecasting in ESS control systems.
- Apply Transfer Learning to leverage existing data and models, reducing setup costs.
- Tailor forecasting models to specific building characteristics for improved accuracy.

3. Data-driven Modelling of Energy Storage Devices using Machine Learning

Main Conclusions:

- Current energy storage modeling underutilizes modern ML potential.
- Few studies focus on physical and chemical sorption, despite its promise and need for precise control.
- ANN can handle highly non-linear problems, offering advantages over traditional white-box approaches.

Recommendations:

- Expand research on physical and chemical sorption technologies.
- Utilize ANN for modeling complex, non-linear energy storage systems.
- Match ML algorithms to specific system characteristics for better modeling accuracy.

4. Smart Design/Integration Methodology for Energy Storage Systems

Main Conclusions:

- The seven-step design methodology applies to various TES systems across different buildings.
- Input parameters vary significantly between design cases.
- The type of application (retrofit or new construction) should be a decisive factor in the design process.

Recommendations:

- Adopt the seven-step methodology for designing TES systems.
- Customize input parameters based on specific project requirements.
- Consider application type in the design phase to ensure optimal integration and performance.

5. Advanced Storage Control Applied to Optimize Operation of Energy Storage Systems

Main Conclusions:

- AI-based control systems can predict and optimize energy storage performance, weather conditions, and demand.
- These systems enhance resilience during disruptions, maintaining comfort and minimizing outage impacts.
- AI-based control and energy storage technology offer significant benefits for sustainable energy management.

Recommendations:

- Implement AI-based control systems to optimize energy storage operations.
- Focus on resilience improvements through predictive control strategies.
- Leverage AI to enhance both environmental and economic outcomes.

6. Cooperative Control of Building/District/Grid

Main Conclusions:

- Renewable energy sources are unpredictable, and energy demand varies, requiring cost and constraint consideration for optimization.
- Quick protection devices for stable microgrid operation during isolated events are necessary.
- Real-time control, mitigation, and protection are crucial as power grids evolve.
- Preventing vulnerabilities is essential to avoid financial and proprietary losses.

Recommendations:

- Develop and deploy quick protection devices for microgrid stability.
- Invest in real-time control and protection systems for smart grids.
- Enhance vulnerability detection and prevention mechanisms to safeguard energy systems.

General Recommendations for Deployment

- Invest in Advanced Technologies: Prioritize the integration of IoT, AI, and ML in ESS to enhance performance and control.
- Customize Solutions: Tailor methodologies and models to specific applications and building characteristics for optimal results.
- Enhance Resilience and Stability: Focus on predictive and real-time control systems to improve system resilience and stability.
- Collaborate and Share Data: Utilize Transfer Learning and collaborative approaches to minimize costs and leverage existing knowledge.

By implementing these recommendations, stakeholders can effectively design, optimize, and control energy storage systems, contributing to more sustainable and efficient energy management across various scales.

FINAL REPORT

1 Objectives, Structure, and Approach of Task

1.1 Objectives

The final objective of this Annex is to address the design/integration, control, and optimization of energy storage systems with buildings, districts, and/or local utilities. In order to realize optimal control, the constraints must be properly predicted, and the system must first be optimally designed. For designing the system more optimally, it is necessary to properly understand the performance of the components. Therefore, the focus here is to model components, develop design methods and advanced control strategies for effectively predicting, evaluating, and improving the performance of Buildings and districts when energy storage is available.

■ Establishment of prediction method

In order to properly design and control the system, it is necessary to predict various conditions. For example, the prediction of renewable energy production and the prediction of electricity price change are boundary conditions for appropriate control. The prediction of energy demand in buildings and districts is a constraint that must be satisfied in control. Especially, the energy demand of buildings and districts varies significantly depending on the usage, composition of the energy system, change of weather, occupant behavior, and so on. There are many demand prediction models are previously proposed including IEA's achievement. In this Annex, we will summarize those findings and examine the establishment of prediction methods that contribute to smart design and control.

■ Establishment of modeling method of component and system

To optimally design and control different energy systems depending on the building, it is necessary to construct a prediction model that reproduces system behavior. Specifically, performance prediction models of the system and its components such as heat pumps, pumps, and energy storage devices are required. Various components and systems have already been modeled in the previous IEA Annexes. However, in order to use it for actual real-time control, it is necessary to predict fast and accurately. In addition, it is necessary to reproduce the deterioration over time the change in performance of the component. The recent development of artificial intelligence enables them to be realized.

■ Establishment of optimization method for design and control

Optimization technologies are very useful to both design and control. The design act is to determine a specification that maximizes the functionality to achieve a certain purpose under limitation of resources. In addition, when there are multiple objectives and they are in a trade-off relationship with each other, finding a compromise between them is also a design act. In order to minimize costs or fossil energy consumption or maximize human comfort, how to arrange various devices including heat storage devices is a major design issue. On the other hand, control/operation is to decide which devices, when and how we should activate for a certain purpose. These are both optimization problems.

Previously, the system was simple, so these problems could be handled by human designers and operators. Today, however, the system has become more and more sophisticated and complex, it is almost impossible to handle these problems with human abilities. Again here, artificial intelligence is a very useful tool. Conventionally, many optimization methods based on mathematical programming such as linear programming have been proposed. Recently, optimization methods based on metaheuristics and deep-Q learning have attracted attention as highly generic methods. Therefore, investigation of an optimization method that can efficiently solve such difficult optimization problem is important from the viewpoint of realization of optimum design and control. This Annex deals with the following subjects.

- Classification of optimization methods (mathematical programming, metaheuristics, deep-Q learning)
- Strong and weak points of different optimization methods: in terms of search efficiency and stability
- Setting of objective function for optimal control problems

1.2 Scope

Smart Design and Control of Energy Storage Systems are essential for energy efficiency in buildings and district. They pose several challenges. . These challenges arise from the complex nature of energy storage technologies, diverse applications, and the evolving energy landscape. Here are some key challenges in developing smart design and control for energy storage systems:

1. Diversity of Energy Storage Technologies:

There are various energy storage technologies, such as Thermal Energy System, Chemical Energy System, Electrical Energy System, Mechanical Energy System, and more. Each technology has unique characteristics, performance metrics, and operational requirements. Developing a universal smart design and control system that accommodates this diversity is challenging.

2. Optimal Sizing and Integration:

Determining the optimal size of an energy storage system for a specific application is crucial. The system needs to be sized to meet the energy demand while considering factors like cost, available space, and technology limitations. Integrating the energy storage system seamlessly into existing energy infrastructure is also a challenge.

3. Dynamic Nature of Energy Systems:

Energy systems are dynamic and influenced by various factors, including weather conditions, energy demand fluctuations, and the intermittent nature of renewable energy sources. Designing control systems that can adapt to these dynamic conditions and optimize energy storage usage accordingly is a significant challenge.

4. Lifecycle Management and Aging Effects:

Energy storage systems undergo degradation over time due to factors like charge-discharge cycles, temperature variations, and other environmental conditions. Developing control systems that can monitor and manage the lifecycle of energy storage systems, including predictive maintenance strategies, is essential to ensure long-term reliability.

5. Grid Integration and Regulatory Challenges:

Integrating energy storage systems into existing power grids involves addressing regulatory hurdles and compliance issues. Different regions may have varying standards and regulations governing the deployment and operation of energy storage systems, making it challenging to develop universally applicable control systems.

6. Economic Viability and Cost Considerations:

Developing smart design and control systems that balance the economic viability of energy storage installations is crucial. This includes considering the initial costs, operation and maintenance expenses, and the potential revenue streams from services provided by the energy storage system.

7. Interoperability:

Ensuring interoperability between different components, technologies, and systems is a challenge. Standardization in communication protocols and control interfaces is essential for seamless integration into larger energy management systems.

8. Technological Advancements and Innovation:

The field of energy storage is rapidly evolving, with ongoing advancements in materials, designs, and technologies. Developing smart design and control systems that can adapt to and leverage these innovations is crucial for staying at the forefront of energy storage capabilities.

Addressing these challenges requires collaboration among researchers, engineers, policymakers, and industry stakeholders to create effective and adaptive smart design and control systems for energy storage.

1.3 Structure and Approach

This task is composed of six sub-tasks, (i) Subtask 0: Smart Technologies and State of the Art, (ii) Subtask A: Demand & Supply Prediction, (iii) Subtask B: Device/Component, (iv) Subtask C: Building and District Design, (v) Subtask D: Optimal Building and District Control /Operation, (vi) Subtask E: Optimal Grid Control/Operation/Cooperation. In addition to expert meetings attended by all members, each subtask carried out its activities independently.

1.4 Meetings and Participating Countries/TCPs

The official start of the Annex/Task was 12 June. Table 1.1 gives an overview of the expert meetings in this Task 37.

Table 1.1: Details about the date and location of each expert meeting.

City	Country	Date	# Participants
Online	-	12 June 2020	39
Online	-	10 July 2020	44
Online	-	14 August 2020	35
Online	-	25 September 2020	35
Online	-	26 October 2020	30
Online	-	27 May 2021	35
Online	-	22 October 2021	32
Online	-	6 May 2022	25
London	UK	18 October 2022	21
Tokyo	Japan	18 May 2023	23
Turin	Italy	27 October 2023	21
Lyon	France	TBA	TBA

2 Subtask 0 Data Analytics and Information Technologies for Smart Energy Storage

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2.1 Introduction

Demand for reliable electricity with constant voltage and frequency is increasing worldwide due to the economic growth, population rise, and considerable changes in quality of life. Demand could have significant variation at different times due to unexpected behavior of the users, at certain times, leading to its imbalance with electricity production [7]. Therefore, to ensure maintaining the balance between demand and supply, avoid economic losses, shortages, and damages caused by such instabilities of the latter, the use of energy storage systems has emerged as a solution. The importance of energy storage systems rises further when all or part of the energy source on the supply side comes from renewable resources. This is due to the high intermittent characteristic of renewable energies such as solar or winds [118].

Although there are several ways to classify the energy storage systems, based on storage duration or response time [26, 79], the most common method in categorizing ESS technologies identifies four main classes: mechanical, thermal, chemical, and electrical [100, 152] as presented in Figure 2.1.

- Mechanical storage systems store the energy in two different forms, potential and kinetic [37]. Examples of potential energy storage are compressed energy storage (CAES) and pumped hydro, while flywheels could be also considered for storing kinetic energy.
- The thermal energy storage systems are grouped based on their temperature mode; high and low temperatures [42]. An example of a low-temperature method used for electricity generation is cryogenic energy storage [135]. On the other hand, sensible or latent heat storages are two types of high-temperature energy storage [40].
- Chemical energy storage comprises regular batteries such as lithium-ion, lead-acid, and flow batteries (such as vanadium redox and metal-air batteries). There are other forms of chemical storage that are called electrochemical storages and thermochemical storages. Fuel cells such as proton exchange membrane fuel cells (PEMFC), molten carbonate fuel cells (MCFC), and solid oxide fuel cells (SOFC) are considered as other forms of electrochemical storage while solar hydrogen and solar ammonia are two examples of thermochemical storage.
- Electrical energy storage consists of two main types of storage: electrostatic and magnetic. Capacitors and ultracapacitors are two main types of the electrostatic energy storage [38] while superconducting magnetic energy storage is an example of the magnetic method of storage [22].

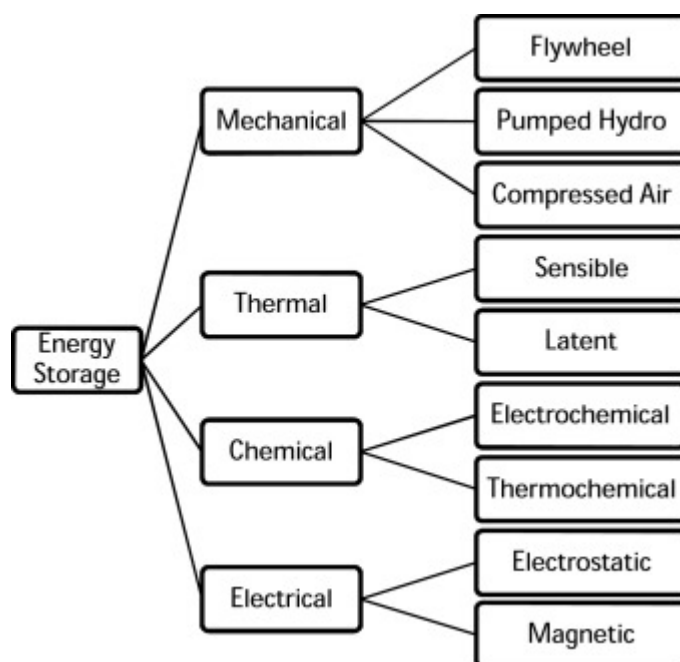


Figure 2.1 Different energy storage technologies.

Energy storage systems are to play a vital role in integration of renewable energy systems with direct impact on the cost, reliability, and resilience of energy supply. This role is even more magnified in distributed generation systems where buildings act as prosumers. Storage systems could reduce the operational cost (in comparison with energy supplied from the conventional grid), storing the low price energy during off-peak, and using it during peak, removing the indirect costs associated with power outages and saving money by participating in demand response programs. Acting as a backup in power outages situations and providing uninterrupted power can decrease the risk of power supply loss and increase the reliability of energy systems. Furthermore, adding an energy storage system could improve the system's ability to withstand the disturbances (in case of disruptions or shortages) and quickly return to a normal state [12]; therefore, it increases the system's resilience.

In the light of the above benefits, it shall be mentioned that the high intermittent nature of renewable energies, while using energy storage, could still lead to operational safety and power quality issues [172]. One of the major solutions to deal with this issue is to ensure a data-driven (predictive) control of the energy storage systems by implementing artificial intelligence (AI) techniques to anticipate and incorporate the intermittency of renewable sources. AI could be implemented as a predictive tool for demand, supply, and storage stages. For example, the state of charge of the battery could be estimated using the reinforcement learning method [60], while the uncertainties related to the unexpected fluctuations of the load demand could be addressed by employing machine learning prediction techniques [118]. Moreover, AI could be used to predict wind speed and solar irradiance to diminish the supply side inaccuracies in establishing optimal control solutions [51, 131]. Furthermore, the recent development in Internet of Things (IoT), advancement of the digital twin concept, and cloud battery management have had a considerable impact on improving the storage systems' reliability, safety, and durability [68].

This chapter aims at providing a state-of-the-art review of smart energy storage concepts and its integration into energy management practices. In doing so, we will provide a review of the applications of AI and information technologies in establishing smart energy storage systems. The also articles

reviewed and cited in this chapter are to show the advantages and usefulness of adopting “smart” tools and technologies in management of energy storage systems. The remainder of the paper is classified into four main sections. Section 2 represents the data analytics and AI techniques used for storage energy management. Section 3 describes smart technologies such as IoT, building management systems (BMS), and building information modeling (BIM). Finally, a conclusion providing a summary of the article and suggestions for future research is discussed in section 4.

2.2 Smart Energy Storage Systems: Data Analytics

Energy storage systems (ESSs) are nowadays recognized as an important element that can improve the energy management of buildings, districts, and communities. Their use becomes essential when renewable energy sources (RESs) are involved due to the volatile nature of these sources. In order to design an accurate model of the system and to select effective control strategies for the ESSs deployment, accurate data analytics tools are necessary. Data analytics is the use of data and predictive techniques to estimate or predict future outcomes. Figure 2.2 shows a classification of data analytics applications in energy storage systems, which will be discussed in the following sections.

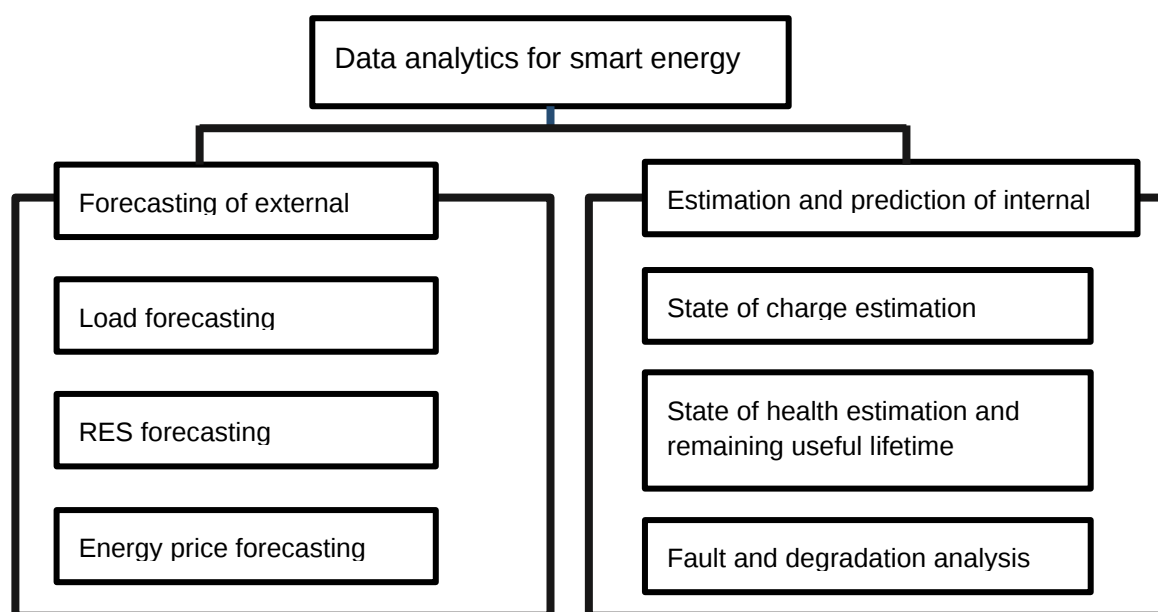


Figure 2.2: Classification of data analytics for smart energy storage.

2.2.1 Load, renewable energy, and energy price estimation

The effective deployment of ESSs is mainly based on the operational control approaches. In fact, is crucial for an efficient management system to adjust the charging and discharging operation based on the estimated needs in order to maximize the performance, i.e., maximize the profits and minimize the operational costs, and prolong the predicted device's lifetime [5]. This should be selected in accordance with the expected energy demand, RESs energy production and energy price. These three

are usually referred together as energy forecasting. There are a large number of publications in this area that cannot be fully included in this work [48], however, we can divide the related works into probabilistic, data-based, ensemble and hierarchical approaches. Due to the inherent stochastic yet recurrent or cyclic nature of loads and RESs, the simplest approach is to analyse these patterns to define probability distribution to predict future behaviours [110]. In fact, probabilistic approaches are deeply used for load [39, 141, 142] and RES prediction [29, 110, 154] due to their straightforwardness. A more advanced class of forecasting tools are the data-based approaches that can generate reliable energy forecasting from a set of input parameters. The simplest methods are linear regression, multiple linear regression and polynomial regressions [21, 149]. Various advanced machine learning techniques such as artificial neural network ANN with different setups from single-layer network [59, 138] to recurrent neural network (RNN) [64, 89, 116] deep neural network (DNN) [116, 132], reinforcement [157], and transfer learning networks. Combining forecasts has been widely recognized as one of the best practices in forecasting [90]. Hence, ensemble and hierarchical forecasting technique, which reconciles forecasts generated individually at different levels, are the most promising approaches for the energy forecasting [52, 53, 90, 127].

2.2.2 ESS state estimation

Storage devices are complex systems with several variables whose state is most of the time unknown. Hence, accurate state estimation is necessary for effective control of the device. In particular, essential tasks are monitoring and estimating the status of the device and predicting the lifespan and remaining capacity.

2.2.2.1 State of charge estimation

For the management of ESSs, it is crucial the estimation of the state of charge (SOC), which is quantified by the ratio of the releasable capacity of an ESS over its rated capacity. There is large literature on SOC estimation that can be divided into look-up table, integral, Kalman filter and data-driven approaches [130]. The look-up table approach is the simplest one since it requires only a mapping between the ESS's SOC and the characteristic parameters, such as the internal resistance [150], open-circuit voltage [33], or impedance [14, 160]. Nevertheless, these approaches can be used only for static analysis and cannot be used in real-time applications [49]. Another widely used approach is based on the integral counting approach of the current [65]. If this approach is used in an open-loop fashion it may lead to the accumulation of the prediction errors [130]. In order to define a better approach, the well-known Kalman filter can be adopted. In fact, when a model of the ESS is available the Kalman filter can be used to reconstruct its state. The literature presents a large number of contributions employing linear Kalman filters [65][134], extended Kalman filters [69, 92] and other Kalman filters [10, 20, 30, 56, 168]. A more recent and performant class of SOC estimation are the data-driven techniques. These approaches can estimate the SOC employing all the characteristics in a self-learning algorithm. The SOC estimation within the data-driven approaches is usually done with regression methods [50, 106]. Besides these approaches, ANN-based models are widely used for SOC estimation show high accuracy in the prediction [25, 126, 164]. (Deep-) Convolutional neural network and recurrent neural network RNN are used to estimate the ESS's SOC based on complex feature datasets with time-series characteristics [115, 140, 153].

2.2.2.2 State of health estimation and remaining useful lifetime prediction

In order to quickly assess the health state of ESSs, several different indicators are available in the literature. Nevertheless, to forecast the health conditions and provide a tool for the replacement of a device the state of health (SOH) and the remaining useful lifetime (RUL) are widely used. However, the SOH and the RUL are not uniquely defined in the related literature [158]. Usually, the SOH is defined as the ratio of the original capacity of the device and the actual one [51], while the RUL is typically quantified by the time or cycling number when the capacity or SOH decreases to a threshold value [70]. Accurately predicting the SOH/RUL is critical to adjust its controlling strategy to ensure the performance, safety, and lifetime. Besides, accurate estimation and prediction, the RUL is vital in guiding device reuse or recycling. The estimation methodologies for the SOH/RUL estimation can be categorized into measurement-based, Kalman filter, and data-based approaches [109]. The measurement-based approaches aim to predict the SOH/RUL directly from specific measures. These approaches are the most straightforward; however, their accuracy is low. The inputs used in the lifetime prediction are various since they range from charging voltage curve, trend surface temperature (acquired from the infrared images), electrical information (incremental current/voltage data) [136, 163] and electrochemical impedance spectroscopy. As for the SOC estimation, the model-based approaches employing the Kalman filter have in general better results [133, 148]. The latter category is based on machine learning methods applied to predict the SOH/RUL starting from a set of complex input features [123]. Regression algorithms are often used to estimate and predict SOH/RUL with their linear version [112], Gaussian processing regression [75] or with kernel-ANN regression algorithm [165]. Besides the regression approach, decision trees [168] and support vector machines (SVM) are used to predict SOH/RUL [76, 95, 162]. When handling dataset with complex time-series characteristics various ANN-based models are applied for SOH/RUL prediction [93, 126, 139], such as DNN [63, 121], RNN [153] and long short-term memory (LSTM) neural networks [81].

2.2.2.3 Fault and degradation analysis

An important issue in the management of ESSs is the detection of defects, as well as the detection of abnormal behaviours, to ensure the future availability of the device. Most of the approaches used to detect anomalies are based on machine learning techniques since faults are usually the results of a series of complex interactions between different factors. Several machine learning algorithms are applied to classify the unbalance and damage of battery cells including logistic regression ANN, kernel-SVM [33, 61]. Classical regression techniques such as the Gaussian process regression [78] and deep learning approaches are also gaining significant attention [70, 74, 151, 159]. In some applications, the input to the machine learning models is in the form of images, such as the snapshots of the battery electrode microstructure. Under this circumstance, CNN, which is highly capable of extracting the features of images, can be utilized [13, 128]. The estimation of the device's degradation is a very complex issue since the cycle-based degradation depends on the charge/discharge sequence and on natural factors that contribute to the degradation such as ambient temperature, humidity, and storage technology. The degradation analysis aims to predict the future SOH/RUL based on the predicted operating conditions. In fact, a vital aspect of energy storage operation is to accurately model the operational cost, which for many devices mainly comes from the loss of energy capacities under repeated cycling [144]. Hence, predicting the impact of different charging/discharging processes on the ESS's health state can be useful to select the best performing control inputs [161]. Several ESSs studies include degradation models either based on battery charging/discharging power or energy throughput [91]. These degradation models are convenient to be incorporated in existing optimization problems, at a cost of losing accuracy in quantifying the actual degradation cost. The capacity fading

can be properly described in terms of the fatigue process since mechanical stress plays a key role in the degradation of the device performances [144]. The similarities of the storage devices' degradation with the classical approach for the ageing of mechanical systems subject to fatigue cycle loading led many papers to select this as the most appropriate model for describing the performance deterioration [66, 117, 144]. The battery ageing process is fundamentally described by a set of partial differential and algebraic equations, however, they are in some sense too detailed and thus semi-empirical degradation models are often used. These approaches define a relation between cycle depth and battery degradation, and the loss of battery life is the accumulation of degradation from all cycles. To count these cycles several algorithms for cycle identification in material fatigue analysis as well as for battery degradation [88, 117] can be used.

2.3 Smart Energy Storage Systems: Smart Technologies

The integration of energy storage into energy systems could be facilitated through use of various smart technologies at the building, district, and communities scale. These technologies contribute to intelligent monitoring, operation and control of energy storage systems in line with supply and demand characteristics of energy systems:

2.3.1 Internet of Things (IoT) and smart energy storage

Internet of Things (IoT) addresses the needs of the energy sector to move forward towards a promoting efficient and sustainable use of natural resources. In order to achieve this, the concept of IoT proposes the development of a smart industrial platform enables to improve the efficiency and sustainability of system operations and to predictive maintenance by connecting cyber and physical systems. Therefore, IoT is the fundamental technology for realization of smart power and energy systems with energy storage. Such smart systems require bidirectional information exchange among different segments that can be provided with IoT-based technologies. IoT is not a single technology, but an interconnected network comprises of several technologies enabling communication of physical objects (Things) via the Internet in real time. The key elements of IoT technologies are, IoT devices embedded with IoT sensors and software for collecting real-time information, IoT networks and gateways for secure transmission of sensors data and an IoT management platform with several functions such as data storage management, data analytics and application enablement [94, 98]. In energy sector, the advancement of IoT technologies support a wide range of applications, along with Smart Grid concept, in power generation, transmission, distribution and consumption, including smart deployment of energy storage systems in buildings, districts and communities.

2.3.1.1 Cloud computing and fog computing technologies

The value of IoT is in the ability to process and analyse massive data streams in real time in order to make optimized informed decisions. This necessitates advanced data processing approaches, instead of storing and processing data only on local hard drives. Cloud computing and fog computing are the two well-accepted computing platforms for IoT applications [87]. Cloud computing platforms provide on-demand services including data storage, data processing and computation without owning the

hardware systems through the Internet. This allows access to heterogeneous data shared among different sectors anywhere and anytime, while reducing the costs of hardware and maintenance and enhancing the computational power and storage capacity.

However, such a centralized computing approach cannot satisfy all IoT applications, particularly latency sensitive applications with widely geo-distributed IoT devices [101]. Fog computing is a distributed computing approach, which extends cloud computing to the edge of network. That can be using any IoT devices with storage and computing capabilities for data processing instead of sending the data to the Cloud. Figure 2.3 shows the Cloud and fog computing architecture for IoT applications.

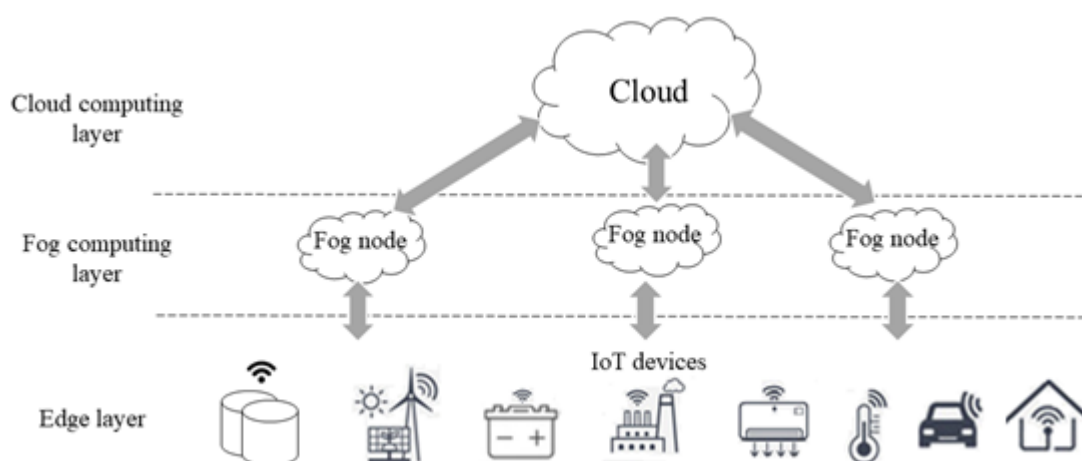


Figure 2.3: Cloud and fog computing architecture

2.3.1.2 IoT-based energy storage systems

In industrial energy sector, the use of IoT technologies enables renewable energy suppliers and utilities to efficiently design and operate their storage systems in order to tackle the intermittency of renewable resources hence, promoting the sustainability and stability of power grid. Relying on the IoT cyber-physical network technology, which provides a bank of information for optimized decision, an energy management platform comprising of two main layers; a "core cloud" and the "edge clouds" has been proposed in [41]. At edge clouds, microgrid aggregators solve optimization problems to determine the energy balance of each microgrid, whereas, at the core cloud, the distribution system operator solves an optimisation problem to meet the energy balance of the distribution grid with optimal scheduling of energy storage systems. Motivated by widespread use of lithium-ion (Li-ion) batteries as grid-level energy storage systems, a battery condition monitoring platform has been proposed in [62], which utilizes IoT devices and cloud components. The architecture consists of wireless module management systems incorporating IoT devices and a cloud battery management platform with cloud storage, analytics tools, battery algorithms, and visualization modules. Critical model parameters of the battery cells and battery conditions such as state of charge and state of health can be estimated with the proposed platform for the purpose of fault detection and predicting the remaining useful time of the battery cells.

In domestic energy sector, IoT technologies are the main driver for integration of distributed energy storage (DES) systems, e.g. battery of electric vehicles (EVs), roof top photovoltaic panels and local solar thermal storage systems in energy systems leading to a more flexible and scalable power grid [3, 17]. EVs as mobile distributed energy storage devices will become an integral part of Smart Grid and

smart buildings with vehicle-to-grid (V2G) and vehicle-to-home (V2H) technologies [8, 85]. This has led to extensive research studies focused on optimal planning for EVs charging/discharging. For instance, based on the distributed fog computing technology, three optimization algorithms have been proposed in [24], for an intelligent scheduling of EVs plugin. The system architecture consists of centralized cloud data centers and decentralized fog data centers for real-time information exchange, such as EVs requests for charging/discharging and energy prices. A new concept of DES system referring as cloud energy storage (CES) has been proposed in [75], which enables residential and small commercial consumers to rent a customized amount of energy storage from a so-called CES operator via the Internet, instead of using their own on-site energy storage systems. Different centralized energy storage technologies, such as flow batteries or compressed air energy storage can be provided as distributed energy services to the users, who aim to reduce their electricity bills considering volatile real-time energy prices by CES technology.

2.3.1.3 Challenges of IoT technologies in smart energy systems

Similar to other technologies, adoption of IoT technology presents both opportunities and challenges. There are several challenges have been discussed in the literature, for example in relation to network coverage and bandwidth, interoperability of the system components or data storage and security [58]. Particularly, with respect to the use of IoT in smart buildings and cities, there two major challenges:

- **IoT energy consumption:** IoT technology comprises of numerous IoT devices that consume power. Therefore, It is important to have plugged-in IoT devices with low power consumption and remote IoT devices with long battery lifetime in order to make IoT solution affordable and sustainable for energy system applications. This has led to the emergence of green IoT technologies. A comprehensive review of the techniques and strategies for enabling green IoT technologies has been provided in [6]. Energy harvesting techniques, that is converting ambient energy sources such as ambient light into electrical energy, has been studied in the literature e.g. in [1] as a technique for prolonging the battery life time of the IoT devices. High energy consumption of cloud-based data centers is also a topic of research studies related to the IoT energy consumption. For instance, a multiobjective optimization problem has been formulated in [44] for integrated planning the capacity of internet data centers and the battery energy storage systems in a coupled smart grid and communication system.
- **IoT privacy:** Application of IoT devices, especially in residential sector, increases the risk of privacy violations with sharing smart meters data that can be translated to behavioral patterns of smart building occupants [155]. There are several techniques have been discussed in the literature for preserving the privacy in IoT applications, such as data anonymisation which removes attribute information from the meter readings [102] or data obfuscation which distorts customer energy profile by integrating another energy source e.g. energy storage units at the customer premises [122].

2.3.2 Building Management Systems (BMS) and Smart Energy Storage

The energy consumed in the building sector has recently grown considerably and hit a new record of

100% increase compared to 2010. According to the latest reports, 40% of global energy and 25% of total electricity demand is associated with buildings [18]. More than 84% of this energy is provided by fossil fuels leading to higher CO₂ concentrations in the atmosphere and global temperature increment [171]. As a result, the need for the building management system (BMS) as a promising technique becomes necessary to address these challenges and makes a big step toward decarbonization [54]. By definition, BMS is a computer-based system providing a set of approaches to monitor and control the building's mechanical and electrical equipment. Examples of main operational subsystems monitored by the BMS are heating, ventilation, and air conditioning (HVAC) systems, energy storage units, lighting systems, power equipment, and fire systems [108]. The most important features of BMS are increased energy efficiency, less environmental effects, lower energy costs, improved standards of building functioning, and efficient use of staff (see Figure 2.4). However, higher initial, operating, and maintenance costs and the need for an expert operator are the negative characteristics of BMS [34].

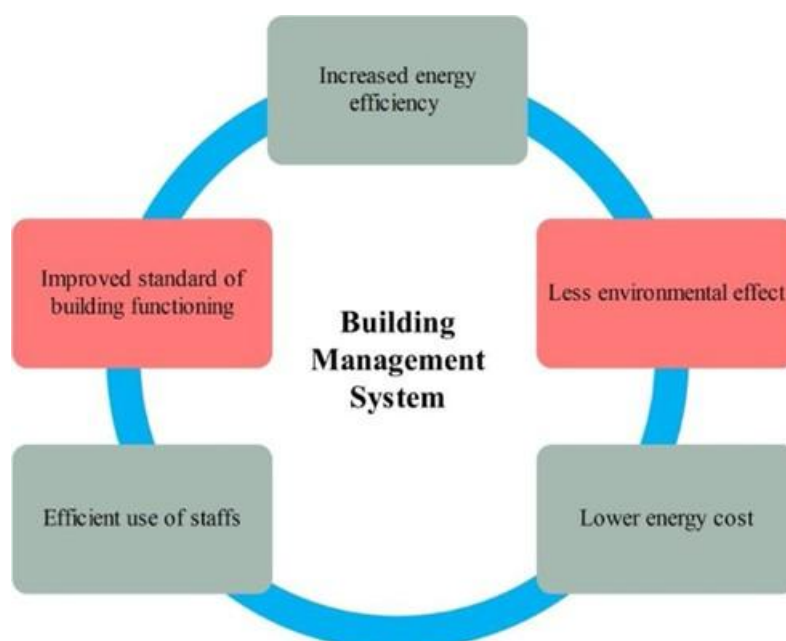


Figure 2.4: The most significant features of BMS.

With the development of technology, various BMS techniques have been accomplished to introduce innovative standards, designs, and web-based services to decrease energy costs, optimize energy use, and enhance the quality of living. Kaiwen et al. [57] proposed an intelligent BMS model based on the PHP web server monitoring the comfort level and occupant behaviors working. According to their results, BMS played a critical role as a bridge between the user and smart grid, leading to 30% higher primary energy saving in a custom building. They recommended that highly developed techniques should be demonstrated for disabled people to use as well. The performance of in-home BMS using a wireless sensor network (WSN) was assessed and compared against the optimization-based model by Kantarci and Mouftah [36], concluding that WSN results in lower energy cost, peak load, and carbon emission. In a recent study, Chaouch et al. [23] introduced a new smart BMS approach driven by fuzzy logic and machine-to-machine communication (see Figure 2.5).

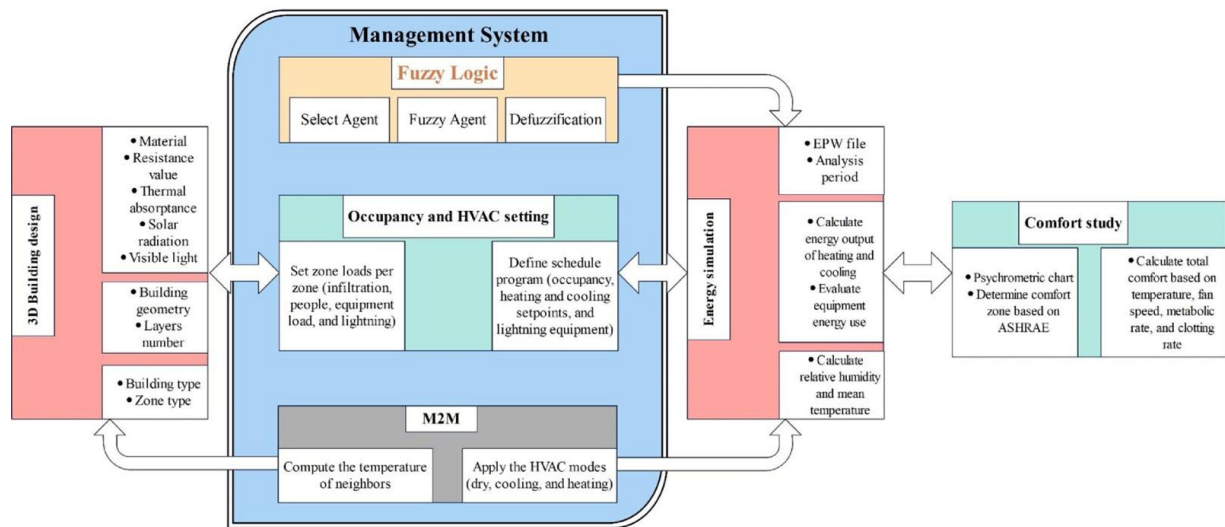


Figure 2.5: Outline of the BMS design investigated by Chaouch et al. [23].

They revealed that the yearly energy consumption is decreased by about 16% without influencing the occupant's thermal comfort. Because keeping the occupant thermally comfortable is more complex in larger buildings, they recommend applying other artificial intelligence approaches to the smaller buildings. Considering the case of Aarhus, located in Denmark, an innovative multi-model BMS supporting demand response and energy-efficient control simultaneously was proposed and validated by Griful et al. [43]. Tien et al. [124] investigated a new vision-based BMS approach monitoring and controlling both the openable windows and HVAC system, as shown in Figure 2.6.

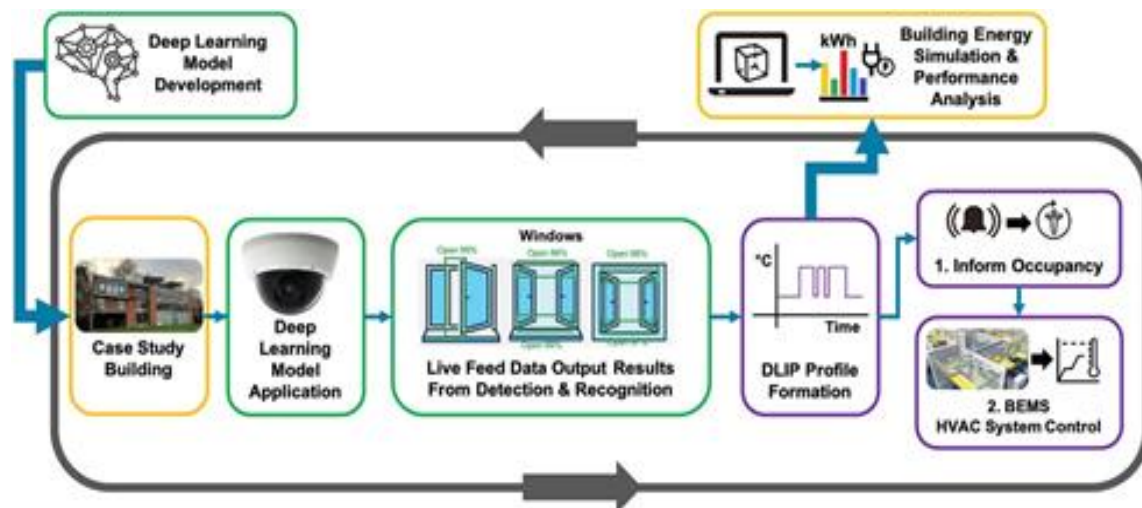


Figure 2.6: The pictorial representation of the BMS model proposed by Tien et al. [124]

They showed that a significantly lower heat loss and annual energy bill are attained because of their innovative BMS design. Lately, Salerno et al. [107] presented an innovative, adaptable BMS for a house in Montreal, Canada, with no energy transfer from the nearby unit. Their results indicated that due to BMS and smart design integration, the levelized cost of heating and cooling is reduced by about 35% and 97%, respectively. Also, they showed that the energy consumption would decrease by more than

49%, which is so considerable. They suggested that the feasibility study of the proposed smart system on a larger scale in the presence of district heating and cooling networks would be an interesting research topic for future extension of their work.

The possible mismatch between energy supply and demand and their intermittency is one of the most critical challenges of building energy systems [19]. A smart design of an energy storage system controlled by BMS must be applied to increase reliability and stability and reduce the building energy consumption and greenhouse gas emission. Hernandez et al. [82] showed that aside from generation, demand management, and control and communication, energy storage technology is the crucial component of smart houses controlled by BMS. Based on the energy type, energy storage technologies are categorized into electrical (battery and capacitor), thermal (sensible, latent, and thermochemical), mechanical (flywheel, compressed air, and pumped hydro), and magnetic, as illustrated in Figure 2.1. In BMS, selecting the appropriate storage type is important to reduce energy consumption and improve the cost-effectiveness and utilization of renewable energy (if any).

Various strategies, intelligent control techniques, and optimization approaches have been applied to energy storage technologies in BMS because they can reduce the energy cost while shaving the peak demand and improving the flexibility of time-of-use electricity prices. Sharifi and Maghouli [114] implemented a novel scheduling method based on an evolutionary genetic algorithm approach to a smart BMS integrated with an energy storage device. They demonstrated that the energy bill is reduced by managing the storage unit, and the peak-to-average ratio is improved simultaneously. Xu et al. [143] studied the performance comparison of different energy storage technologies applying smart BMS. They showed that the existing uncertainties significantly influence determining the best integration and optimal operating conditions. In recent research, Aznavi et al. [12] applied a new management strategy based on the energy price tag to smart energy storage units to neutralize the effect of unpredicted intermittency. It was concluded that the proposed framework keeps the system reliable and cost-effective due to lower energy bought from the network. In addition, they recommended that policymakers allocate more subsidies to the smart management of storage units to stimulate the building owners to adopt such systems. Yan et al. [145] studied the feasibility of three management approaches applied to a novel energy storage system in a building located in Beijing, China. According to their results, 30% and 16% higher cooling and power load factors were obtained, indicating long-term and short-term management effectiveness. They suggested that a comprehensive analysis of the system's cost-effectiveness and encouraging policies adopted by the government are required for future studies. A smart battery-photovoltaic system handled by an innovative novel optimum management strategy was proposed by Liu et al. [73], revealing that 48.6% higher performance efficiency and 34.7% lower carbon dioxide emissions was attained compared to the same system without smart configuration. In another work, Ahmad and Khan [2] introduced a new algorithm based on real-time joint optimization managing smart thermal and electrical energy storage units. They concluded that using the proposed intelligent algorithm leads to 16.37% lower operating costs while satisfying the comfort requirement.

2.3.3 Building Information Modeling (BIM) and Smart Energy Storage

These days, due to the increase in energy demand and environmental contamination, the need for sustainable, energy-efficient, clean, and cost-effective buildings becomes more crystal clear than ever. The last but not least significant smart technology to overcome these challenges and moves toward the green transition is the building information modeling (BIM) used by a growing number of

architecture, engineers, and contractors [119]. BIM is defined as a process equipped with several tools and technologies generating and managing smart data associated with physical and functional features of geometry, components, and materials [55].



Figure 2.7: The most significant advantages of BIM.

According to Figure 2.7, BIM provides numerous benefits: greater cost predictability, improved efficiency and effectiveness, fewer errors, optimized design, and a better understanding of future operating and maintenance. Lately, Yang et al. [147] studied the benefits, applications, and functions of BIM in smart buildings proposing a three-dimensional framework based on BIM and smart characteristics and project phases, as shown in Figure 2.8.

In the literature, BIM has been extensively used to assess and improve the building's performance metrics from various aspects. Many researchers have applied BIM to a smart building for safety and equipment control analysis [27, 69, 105]. Some scholars have studied the numerical and experimental evaluation of an intelligent green building using BIM to assess the environmental and sustainability indicators [11, 77, 158]. Some have investigated the cost and schedule estimation to enhance the project's economic benefits [28, 71, 83]. Others have carried out the energy and exergy performance simulations and life cycle assessment through BIM to reduce the building energy consumption and improve the quality of energy conversion [86, 103, 132].

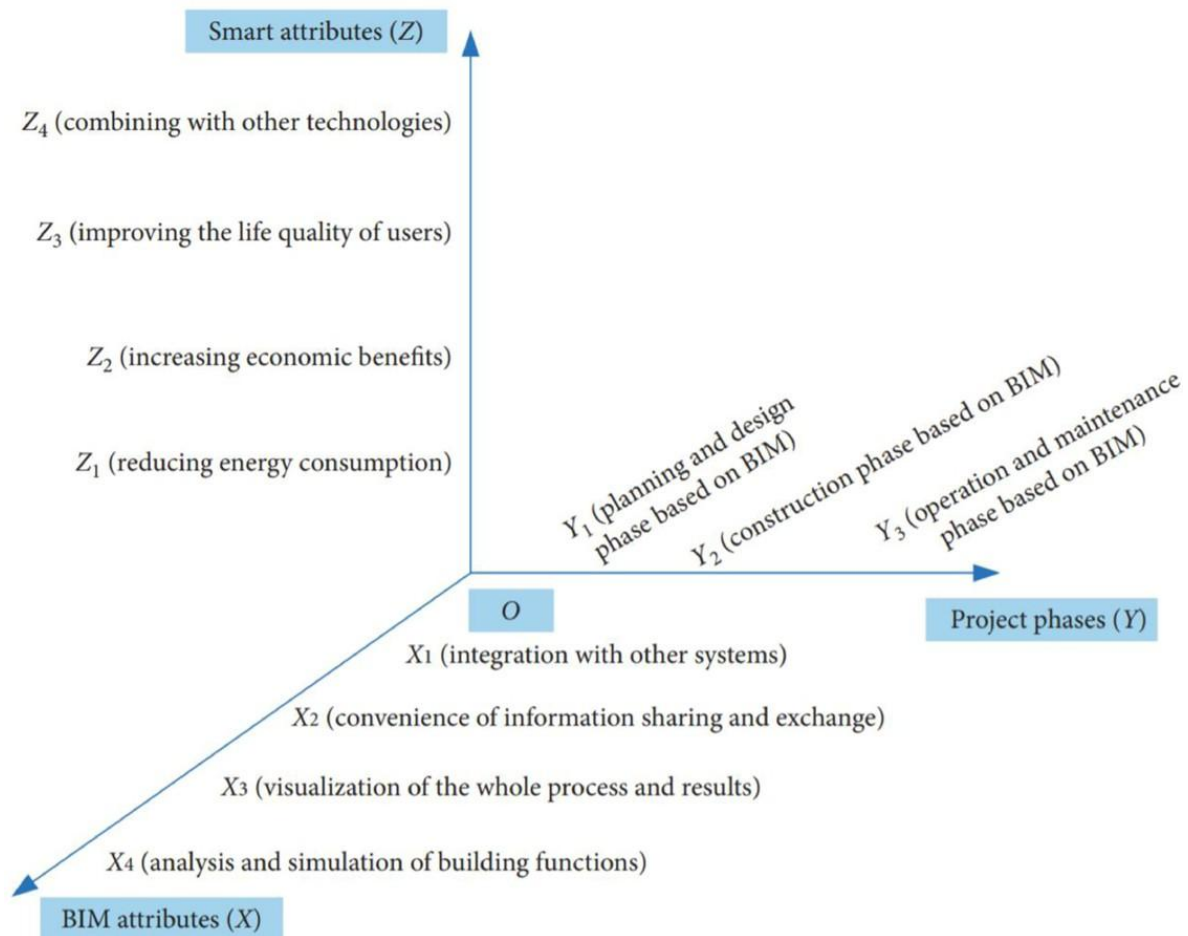


Figure 2.8: A three-dimensional representational of BIM in smart buildings [147].

Of all components of a smart building system, special attention must be paid to managing and modeling energy storage technology's physical and operational characteristics through BIM due to its importance in creating more reliability and flexibility and reducing cost and energy consumption. In a recent study, Zhuang et al. [169] proposed a BIM framework for a school building equipped with a thermal energy storage unit optimizing energy and environmental metrics simultaneously. They demonstrated that BIM application results in a higher indoor environmental quality of 11.5% and a lower life cycle cost of 36.8%. The performance assessment and maintenance management of a real case study building located in Aveiro's University, Portugal, was studied by Matos et al. [84] applying BIM. They concluded that the service life and operational interruptions of energy storage and HVAC technologies are improved significantly due to BIM use. Duarte et al. [35] applied BIM software to optimize the performance efficiency of an educational building heating and cooling system in Brazil. According to their results, modeling the building information leads to 12% higher primary energy saving and 9% lower components' energy loss in addition to indoor environmental quality improvement. In another study, Wu et al. [137] introduced an innovative BIM framework integrated with a wireless sensor network to reduce the operating cost while improving the energy efficiency of a data power center driven by electrical storage units. Schlueter and Thesseling [111] added an advanced tool to BIM software assessing energy and exergy calculations simultaneously. They obtained that BIM not only reduces the system's payback period but also enhances the quality and

reliability of thermal and electrical storage units' controls. Pishdad-Bozorgi et al. [97] investigated the use of BIM for developing facilities management of a real project and concluded that the energy storage unit is a vital component that must be tracked in the development and planning operations phases. The combination of BIM and life cycle assessment to mitigate the greenhouse gas emission for a residential building located in China was investigated by Yang et al. [148], showing that the physical appearance of components, including energy storage units, has a considerable contribution to reduce the carbon emission footprint.

2.4 Conclusions

This chapter provided several categorizations and detailed review of the applications of smart tools (with an emphasis on data analytics) and smart technologies (focusing on BMS and BIM) in design, operation, and control of smart energy storage systems (ESS). As energy storage systems are complex with several variables subject to a great extent of variation and uncertainty, the literature pointed to the importance of accurate estimation of their state and the trends in their input (supply side) and output (demand side) variables, and its necessity to support effective operation and control of ESS. The state of charge, i.e. the ratio of the releasable capacity of an ESS over its nominal capacity, was shown as a key estimation linking the supply and demand side variables affecting the operation of an energy storage system. In addition, forecasting the condition and state of health (SOH) of ESS has emerged as a means of improving their useful lifetime (RUL) through systematic detection of defects, as well as the detection of abnormal behaviours as signs of failure and availability issues.

IoT technologies were identified as the main emerging driver for integration of distributed energy storage (DES) systems. In particular, the use of IoT technologies has created the capability of bringing the renewable energy suppliers and utilities to a balancing equilibrium maintained through effective design and operation of storage systems. The main advantage reported in the literature was to tackle the intermittency of renewable resources, and thus, promoting the sustainability and stability of power grid and energy security. Relying on the IoT has provided access to large amount of operational data and demand-side information that can serve as a basis for optimization of the operation of energy storage systems using data-driven training of intelligent control algorithms. However, there are still several challenges with respect to applications of IoT applications in management of ESS including their energy intensity as well as issues with respect to privacy and accessibility of information.

Integration of building management systems (BMS) and building information modeling (BIM) have also been reported in the literature as means of incorporating smart design and control features for energy storage systems. An ESS controlled by BMS contributes to increasing reliability and stability while reducing building energy consumption and greenhouse gas emissions. Various strategies, intelligent control techniques, and optimization approaches have been also applied to energy storage technologies resulted in shaving the peak demand and improving the flexibility of time-of-use electricity prices. In this regard, the recent surge in applications of building information modeling in facilities management has emerged with widespread benefits; greater cost predictability, improved efficiency and effectiveness, fewer errors, optimized design, and a better understanding of future operating and maintenance conditions of buildings, occupants, and the impact on operation of ESS.

2.5 References

- [1] Adila, A. S., Husam, A., & Husi, G. (2018). Towards the self-powered Internet of Things(IoT) by energy harvesting: Trends and technologies for green IoT. In 2018 2nd International Symposium on Small-Scale Intelligent Manufacturing Systems, SIMS 2018,2018-January (pp. 1–5). <https://doi.org/10.1109/SIMS.2018.8355305>
- [2] Ahmad, A., & Khan, J. Y. (2020). Real-Time Load Scheduling, Energy Storage Control and Comfort Management for Grid-Connected Solar Integrated Smart Buildings. *Applied Energy*, 259(December 2019), Article 114208. <https://doi.org/10.1016/j.apenergy.2019.114208>
- [3] Ahmad, T., & Zhang, D. (2021). Using the internet of things in smart energy systems and networks. In *Sustainable Cities and Society*, 68. Elsevier Ltd. <https://doi.org/10.1016/j.scs.2021.102783>
- [4] Akbari, S., & Haghighat, F. (2021). Occupancy and occupant activity drivers of energy consumption in residential buildings. *Journal of Energy and Buildings*, 250, Article 111303.
- [5] Al-Ghandoor, A. J. J. O., Jaber, J. O., Al-Hinti, I., & Mansour, I. M. (2009). Residential past and future energy consumption: Potential savings and environmental impact. *Renewable and Sustainable Energy Reviews*, 13(6-7), 1262–1274.
- [6] Almalki, F. A., Alsamhi, S. H., Sahal, R., Hassan, J., Hawbani, A., Rajput, N. S., Saif, A., Morgan, J., & Breslin, J. (2021). Green IoT for Eco-Friendly and Sustainable Smart Cities: Future Directions and Opportunities. *Mobile Networks and Applications*. <https://doi.org/10.1007/s11036-021-01790-w>
- [7] AL Shaqsi, A. Z., Sopian, K., & Al-Hinai, A (2020). Review of energy storage services, applications, limitations, and benefits. *Energy Reports*, 6, 288–306. <https://doi.org/10.1016/j.egyr.2020.07.028>
- [8] Alsharif, A., Tan, C. W., Ayop, R., Dobi, A., & Lau, K. Y. (2021). A comprehensive review of energy management strategy in Vehicle-to-Grid technology integrated with renewable energy sources. In *Sustainable Energy Technologies and Assessments*, 47. Elsevier Ltd. <https://doi.org/10.1016/j.seta.2021.101439>
- [9] Ameli, M. T., Jalilpoor, K., Amiri, M. M., & Azad, S. (2021). Reliability analysis and role of energy storage in resiliency of energy systems. *Energy Storage in Energy Markets* (pp. 399–416). Academic Press.
- [10] Aung, H., & Low, K. S. (2015). Temperature dependent state-of-charge estimation of lithium ion battery using dual spherical unscented Kalman filter. *IET Power Electronics*, 8(10), 2026–2033.
- [11] Azhar, S., Khalfan, M., & Maqsood, T. (2012). Building information modeling (BIM): Now and beyond. *Australasian Journal of Construction Economics and Building*, 12(4), 15–28. <https://doi.org/10.5130/ajceb.v12i4.3032>
- [12] Aznavi, S., Fajri, P., Sabzehgar, R., & Asrari, A. (2020). Optimal management of residential energy storage systems in presence of intermittencies. *Journal of Building Engineering*, 29(December 2019), Article 101149. <https://doi.org/10.1016/j.job.2019.101149>
- [13] Badmos, O., Kopp, A., Bernthaler, T., & Schneider, G. (2020). Image-based defect detection in lithium-ion battery electrode using convolutional neural networks. *Journal of Intelligent Manufacturing*, 31(4), 885–897.

- [14] Bao, Y., Dong, W., & Wang, D. (2018). Online internal resistance measurement application in lithium ion battery capacity and state of charge estimation. *Energies*, 11(5), 1073.
- [15] Barz, T., Seliger, D., Marx, K., Sommer, A., Walter, S. F., Bock, H. G., & Korkel, S. (2018). State and state of charge estimation for a latent heat storage. *Control Engineering Practice*, 72, 151–166.
- [16] Bastani, A., Haghighat, F., & Kozinski, J. (2014). Designing building envelope with PCM wallboards: Design tool development. *Renewable and Sustainable Energy Reviews*, 31, 554–562.
- [17] Bedi, G., Venayagamoorthy, G. K., Singh, R., Brooks, R. R., & Wang, K. C. (2018). Review of Internet of Things (IoT) in Electric Power and Energy Systems. *IEEE Internet of Things Journal*, 5(2), 847–870. <https://doi.org/10.1109/JIOT.2018.2802704>. Institute of Electrical and Electronics Engineers Inc.
- [18] Behzadi, A., & Arabkoohsar, A. (2020a). Comparative performance assessment of a novel cogeneration solar-driven building energy system integrating with various district heating designs. *Energy Conversion and Management*, 220(June), Article 113101. <https://doi.org/10.1016/j.enconman.2020.113101>
- [19] Behzadi, A., & Arabkoohsar, A. (2020b). Feasibility study of a smart building energy system comprising solar PV/T panels and a heat storage unit. *Energy*, 118528. 10.1016/j.energy.2020.118528.
- [20] Bi, Y., & Choe, S. Y. (2020). An adaptive sigma-point Kalman filter with state equality constraints for online state-of-charge estimation of a Li (NiMnCo) O₂/Carbon battery using a reduced-order electrochemical model. *Applied Energy*, 258, Article 113925.
- [21] Bissing, D., Klein, M. T., Chinnathambi, R. A., Selvaraj, D. F., & Ranganathan, P. (2019). A hybrid regression model for day-ahead energy price forecasting. *IEEE Access*, 7, 36833–36842.
- [22] Boudia, A., Messalti, S., Harrag, A., & Boukhni, M. (2021). New hybrid photovoltaic system connected to superconducting magnetic energy storage controlled by PIDfuzzy controller. *Energy Conversion and Management*, 244(June), Article 114435. <https://doi.org/10.1016/j.enconman.2021.114435>
- [23] Chaouch, H., Çeken, C., & Arı, S. (2021). Energy management of HVAC systems in smart buildings by using fuzzy logic and M2M communication. *Journal of Building Engineering*, 44(December 2020), Article 102606. <https://doi.org/10.1016/j.job.2021.102606>
- [24] Chekired, D. A., Khoukhi, L., & Mouftah, H. T. (2020). Fog-Computing-Based Energy Storage in Smart Grid: A Cut-Off Priority Queuing Model for Plug-In Electrified Vehicle Charging. *IEEE Transactions on Industrial Informatics*, 16(5), 3470–3482. <https://doi.org/10.1109/TII.2019.2940410>
- [25] Chemali, E., Kollmeyer, P. J., Preindl, M., & Emadi, A. (2018). State-of-charge estimation of Li-ion batteries using deep neural networks: A machine learning approach. *Journal of Power Sources*, 400, 242–255.
- [26] Chen, H., Cong, T. N., Yang, W., Tan, C., Li, Y., & Ding, Y. (2009). Progress in electrical energy storage system: A critical review. *Progress in Natural Science*, 19(3), 291–312. <https://doi.org/10.1016/j.pnsc.2008.07.014>
- [27] Chen, Y. J., Lai, Y. S., & Lin, Y. H. (2020). BIM-based augmented reality inspection and maintenance of fire safety equipment. *Automation in Construction*, 110(December 2019),

Article 103041. <https://doi.org/10.1016/j.autcon.2019.103041>

- [28] Chen, C., & Tang, L. (2019). BIM-based integrated management workflow design for schedule and cost planning of building fabric maintenance. *Automation in Construction*, 107(July), Article 102944. <https://doi.org/10.1016/j.autcon.2019.102944>
- [29] Chen, Y., Wang, Y., Kirschen, D., & Zhang, B. (2018). Model-free renewable scenario generation using generative adversarial networks. *IEEE Transactions on Power Systems*, 33(3), 3265–3275.
- [30] Chen, Z., Yang, L., Zhao, X., Wang, Y., & He, Z. (2019). Online state of charge estimation of Li-ion battery based on an improved unscented Kalman filter approach. *Applied Mathematical Modelling*, 70, 532–544.
- [31] Chirino, H., Xu, B., Xu, X., & Guo, P. (2018). Generalized diagrams of energy storage efficiency for latent heat thermal storage system in concentrated solar power plant. *Applied Thermal Engineering*, 129, 1595–1603.
- [32] Del Pero, G., Aste, N., Paksoy, H., Haghighat, F., & Leonforte, F. (2018). Energy storage key performance indicators for building application. *Sustainable Cities and Society*, 40, 54–65.
- [33] Dong, G., Wei, J., Zhang, C., & Chen, Z. (2016). Online state of charge estimation and open circuit voltage hysteresis modeling of LiFePO₄ battery using invariant imbedding method. *Applied Energy*, 162, 163–171.
- [34] Dounis, A. I., & Caraiscos, C. (2009). Advanced control systems engineering for energy and comfort management in a building environment-A review. *Renewable and Sustainable Energy Reviews*, 13(6–7), 1246–1261. <https://doi.org/10.1016/j.rser.2008.09.015>
- [35] Duarte, C. L. M., Ramos Zemero, B., Dias Barreto de Souza, A. C., de Lima Tostes, M. E., & Holanda Bezerra, U. (2021). Building Information Modeling approach to optimize energy efficiency in educational buildings. *Journal of Building Engineering*, 43 (October 2020). <https://doi.org/10.1016/j.jobbe.2021.102587>
- [36] Erol-Kantarci, M., & Mouftah, H. T. (2011). Wireless sensor networks for cost-efficient residential energy management in the smart grid. *IEEE Transactions on Smart Grid*, 2 (2), 314–325. <https://doi.org/10.1109/TSG.2011.2114678>
- [37] Evans, A., Strezov, V., & Evans, T. J. (2012). Assessment of utility energy storage options for increased renewable energy penetration. *Renewable and Sustainable Energy Reviews*, 16(6), 4141–4147. <https://doi.org/10.1016/j.rser.2012.03.048>
- [38] Fang, X., Kutkut, N., Shen, J., & Batarseh, I. (2011). Analysis of generalized parallelseries ultracapacitor shift circuits for energy storage systems. *Renewable Energy*, 36 (10), 2599–2604. <https://doi.org/10.1016/j.renene.2010.05.003>
- [39] Gan, D., Wang, Y., Yang, S., & Kang, C. (2018). Embedding based quantile regression neural network for probabilistic load forecasting. *Journal of Modern Power Systems and Clean Energy*, 6(2), 244–254.
- [40] Gil, A., Medrano, M., Martorell, I., Lazaro, A., Dolado, P., Zalba, B., & Cabeza, L. F. (2010). State of the art on high temperature thermal energy storage for power generation. Part 1-Concepts, materials and modellization. *Renewable and Sustainable Energy Reviews*, 14(1), 31–55. <https://doi.org/10.1016/j.rser.2009.07.035>
- [41] Golpîra, H., & Bahramara, S. (2020). Internet-of-things-based optimal smart city energy

- management considering shiftable loads and energy storage. *Journal of Cleaner Production*, 264. <https://doi.org/10.1016/j.jclepro.2020.121620>
- [42] Gomez, J., Glatzmaier, G. C., Starace, A., Turchi, C., & Ortega, J. (2011). High Temperature Phase Change Materials for Thermal Energy Storage Applications: Preprint. August (p. 10 pp.). Medium: ED; Size. Retrieved from <http://www.osti.gov/bridge/servlets/purl/1024059-4FhcXb/>.
 - [43] Griful, S. R., Welling, U., & Jacobsen, R. H. (2016). Multi-modal Building Energy Management System for Residential Demand Response. In *Proceedings - 19th Euromicro Conference on Digital System Design, DSD 2016* (pp. 252–259). <https://doi.org/10.1109/DSD.2016.10>
 - [44] Guo, C., Luo, F., Cai, Z., Dong, Z. Y., & Zhang, R. (2021). Integrated planning of internet data centers and battery energy storage systems in smart grids. *Applied Energy*, 281. <https://doi.org/10.1016/j.apenergy.2020.116093>
 - [45] Guo, H., Xu, Y., Zhu, Y., Chen, H., & Lin, X. (2022). Unsteady characteristics of compressed air energy storage systems with thermal storage from thermodynamic perspective. *Energy*, 244, Article 122969.
 - [46] He, Y. X., Liu, Y. Y., Xia, T., & Zhou, B. (2014). Estimation of demand response to energy price signals in energy consumption behaviour in Beijing, China. *Energy Conversion and Management*, 80, 429–435.
 - [47] Homssi, B. A., Hourani, A. A., Krusevac, Z., & Rowe, W. S. T. (2021). Machine Learning Framework for Sensing and Modeling Interference in IoT Frequency Bands. *IEEE Internet of Things Journal*, 8(6). March 15, 2021.
 - [48] Hong, T., Pinson, P., Wang, Y., Weron, R., Yang, D., & Zareipour, H. (2020). Energy forecasting: A review and outlook. *IEEE Open Access Journal of Power and Energy*, 7, 376–388.
 - [49] How, D. N., Hannan, M. A., Lipu, M. H., & Ker, P. J. (2019). State of charge estimation for lithium-ion batteries using model-based and data-driven methods: A review. *IEEE Access*, 7, 136116–136136.
 - [50] Hrisko, J., Ramamurthy, P., & Gonzalez, J. E. (2021). Estimating heat storage in urban areas using multispectral satellite data and machine learning. *Remote Sensing of Environment*, 252, Article 112125.
 - [51] Hu, S., Xiang, Y., Zhang, H., Xie, S., Li, J., Gu, C., Sun, W., & Liu, J. (2021). Hybrid forecasting method for wind power integrating spatial correlation and corrected numerical weather prediction. *Applied Energy*, 293(January), Article 116951. <https://doi.org/10.1016/j.apenergy.2021.116951>
 - [52] Hubicka, K., Marcjasz, G., & Weron, R. (2018). A note on averaging day-ahead electricity price forecasts across calibration windows. *IEEE Transactions on Sustainable Energy*, 10(1), 321–323.
 - [53] Hyndman, R. J., Lee, A. J., & Wang, E. (2016). Fast computation of reconciled forecasts for hierarchical and grouped time series. *Computational statistics & data analysis*, 97, 16–32.
 - [54] Iddianozie, C., & Palmes, P. (2020). Towards smart sustainable cities: Addressing semantic heterogeneity in Building Management Systems using discriminative models. *Sustainable Cities and Society*, 62(September 2019), Article 102367. <https://doi.org/10.1016/j.scs.2020.102367>
 - [55] Jalaei, F., & Jrade, A. (2015). Integrating building information modeling (BIM) and LEED system at the conceptual design stage of sustainable buildings. *Sustainable Cities and Society*, 18, 95–

107. <https://doi.org/10.1016/j.scs.2015.06.007>
- [56] Jiang, B., Dai, H., Wei, X., & Xu, T. (2019). Joint estimation of lithium-ion battery state of charge and capacity within an adaptive variable multi-timescale framework considering current measurement offset. *Applied Energy*, 253, Article 113619.
 - [57] Kaiwen, C., Kumar, A., Xavier, N., & Panda, S. K. (2017). An intelligent home appliance control-based on WSN for smart buildings. *IEEE International Conference on Sustainable Energy Technologies, ICSET*, 0, 282–287. <https://doi.org/10.1109/ICSET.2016.7811796>
 - [58] Khatua, P. K., Ramachandramurthy, V. K., Kasinathan, P., Yong, J. Y., Pasupuleti, J., & Rajagopalan, A. (2020). Application and assessment of internet of things toward the sustainability of energy systems: Challenges and issues. In *Sustainable Cities and Society*, 53. Elsevier Ltd. <https://doi.org/10.1016/j.scs.2019.101957>
 - [59] Khodayar, M., Kaynak, O., & Khodayar, M. E. (2017). Rough deep neural architecture for short-term wind speed forecasting. *IEEE Transactions on Industrial Informatics*, 13(6), 2770–2779.
 - [60] Kim, M., Kim, K., Kim, J., Yu, J., & Han, S. (2018a). State of Charge Estimation for Lithium Ion Battery Based on Reinforcement Learning. *IFAC-PapersOnLine*, 51(28), 404–408. <https://doi.org/10.1016/j.ifacol.2018.11.736>
 - [61] Kim, S. J., Lee, S. Y., & Cho, K. S. (2012). Design of high-performance unified circuit for linear and non-linear SVM classifications. *JSTS: Journal of Semiconductor Technology and Science*, 12(2), 162–167.
 - [62] Kim, T., Makwana, D., Adhikaree, A., Vagdoda, J. S., & Lee, Y. (2018b). Cloud-based battery condition monitoring and fault diagnosis platform for large-scale lithium-ion battery energy storage systems. *Energies*, 11(1). <https://doi.org/10.3390/en11010125>
 - [63] Khumprom, P., & Yodo, N. (2019). A data-driven predictive prognostic model for lithium-ion batteries based on a deep learning algorithm. *Energies*, 12(4), 660.
 - [64] Kong, W., Dong, Z. Y., Jia, Y., Hill, D. J., Xu, Y., & Zhang, Y. (2017). Short-term residential load forecasting based on LSTM recurrent neural network. *IEEE Transactions on Smart Grid*, 10(1), 841–851.
 - [65] Lashway, C. R., & Mohammed, O. A. (2016). Adaptive battery management and parameter estimation through physics-based modeling and experimental verification. *IEEE Transactions on Transportation Electrification*, 2(4), 454–464.
 - [66] Laresgoiti, I., K" abitz, S., Ecker, M., & Sauer, D. U. (2015). Modeling mechanical degradation in lithium ion batteries during cycling: Solid electrolyte interphase fracture. *Journal of Power Sources*, 300, 112–122.
 - [67] Lee, K. T., Dai, M. J., & Chuang, C. C. (2017). Temperature-compensated model for lithium-ion polymer batteries with extended Kalman filter state-of-charge estimation for an implantable charger. *IEEE Transactions on Industrial Electronics*, 65(1), 589–596.
 - [68] Li, W., Rentemeister, M., Badeda, J., Jost, " D., Schulte, D., & Sauer, D. U. (2020). Digital twin for battery systems: Cloud battery management system with online state-of-charge and state-of-health estimation. *Journal of Energy Storage*, 30(April), Article 101557. <https://doi.org/10.1016/j.est.2020.101557>
 - [69] Li, C. Z., Xue, F., Li, X., Hong, J., & Shen, G. Q. (2018). An Internet of Things-enabled BIM platform

- for on-site assembly services in prefabricated construction. *Automation in Construction*, 89(November 2017), 146–161. <https://doi.org/10.1016/j.autcon.2018.01.001>
- [70] Li, X., Zhang, L., Wang, Z., & Dong, P. (2019). Remaining useful life prediction for lithium-ion batteries based on a hybrid model combining the long short-term memory and Elman neural networks. *Journal of Energy Storage*, 21, 510–518.
 - [71] Li, C. Z., Zhong, R. Y., Xue, F., Xu, G., Chen, K., Huang, G. G., & Shen, G. Q. (2017). Integrating RFID and BIM technologies for mitigating risks and improving schedule performance of prefabricated house construction. *Journal of Cleaner Production*, 165, 1048–1062. <https://doi.org/10.1016/j.jclepro.2017.07.156>
 - [72] Liu, J., & Chen, Z. (2019). Remaining useful life prediction of lithium-ion batteries based on health indicator and Gaussian process regression model. *Ieee Access*, 7, 39474–39484.
 - [73] Liu, J., Chen, X., Yang, H., & Li, Y. (2020). Energy storage and management system design optimization for a photovoltaic integrated low-energy building. *Energy*, 190, Article 116424. <https://doi.org/10.1016/j.energy.2019.116424>
 - [74] Liu, C., Tan, J., Shi, H., & Wang, X. (2018). Lithium-ion cell screening with convolutional neural networks based on two-step time-series clustering and hybrid resampling for imbalanced data. *IEEE Access*, 6, 59001–59014.
 - [75] Liu, J., Zhang, N., Kang, C., Kirschen, D., & Xia, Q. (2017). Cloud energy storage for residential and small commercial consumers: A business case study. *Applied Energy*, 188, 226–236. <https://doi.org/10.1016/j.apenergy.2016.11.120>
 - [76] Liu, D., Zhou, J., Pan, D., Peng, Y., & Peng, X. (2015). Lithium-ion battery remaining useful life estimation with an optimized relevance vector machine algorithm with incremental learning. *Measurement*, 63, 143–151.
 - [77] Llatas, C., Soust-Verdaguer, B., & Passer, A. (2020). Implementing Life Cycle Sustainability Assessment during design stages in Building Information Modelling: From systematic literature review to a methodological approach. *Building and Environment*, 182(July), Article 107164. <https://doi.org/10.1016/j.buildenv.2020.107164>
 - [78] Lucu, M., Martinez-Laserna, E., Gandiaga, I., Liu, K., Camblong, H., Widanage, W. D., & Marco, J. (2020). Data-driven nonparametric Li-ion battery ageing model aiming at learning from real operation data-Part B: Cycling operation. *Journal of Energy Storage*, 30, Article 101410.
 - [79] Luo, X., Wang, J., Dooner, M., & Clarke, J. (2015). Overview of current development in electrical energy storage technologies and the application potential in power system operation. *Applied Energy*, 137, 511–536. <https://doi.org/10.1016/j.apenergy.2014.09.081>
 - [80] Luo, J., Mastani, M., Panchabikesan, K., Sun, Y., Haghighat, F., Moreau, A., & Robichaud, M. (2020). Performance of a self-learning predictive controller for peak shifting in a building integrated with energy storage. *Sustainable Cities and Society*, 60, Article 102285.
 - [81] Ma, G., Zhang, Y., Cheng, C., Zhou, B., Hu, P., & Yuan, Y. (2019). Remaining useful life prediction of lithium-ion batteries based on false nearest neighbors and a hybrid neural network. *Applied Energy*, 253, Article 113626.
 - [82] Mariano-Hernandez, D., Hernandez-Callejo, L., Zorita-Lamadrid, A., Duque-Pérez, O., & Santos García, F. (2021). A review of strategies for building energy management system: Model predictive control, demand side management, optimization, and fault detect & diagnosis.

- Journal of Building Engineering, 33(July 2020). <https://doi.org/10.1016/j.jobbe.2020.101692>
- [83] Marzouk, M., & Hisham, M. (2014). Implementing earned value management using bridge information modeling. *KSCE Journal of Civil Engineering*, 18(5), 1302–1313. <https://doi.org/10.1007/s12205-014-0455-9>
 - [84] Matos, R., Rodrigues, F., Rodrigues, H., & Costa, A. (2021). Building condition assessment supported by Building Information Modelling. *Journal of Building Engineering*, 38(September 2020). <https://doi.org/10.1016/j.jobbe.2021.102186>
 - [85] Mehrjerdi, H. (2021). Resilience oriented vehicle-to-home operation based on battery swapping mechanism. *Energy*, 218. <https://doi.org/10.1016/j.energy.2020.119528>
 - [86] Mellado, F., & Lou, E. C. W. (2020). Building information modelling, lean and sustainability: An integration framework to promote performance improvements in the construction industry. *Sustainable Cities and Society*, 61(May), Article 102355. <https://doi.org/10.1016/j.scs.2020.102355>
 - [87] Motlagh, N. H., Mohammadrezaei, M., Hunt, J., & Zakeri, B. (2020). Internet of things (IoT) and the energy sector. In *Energies*, 13. MDPI AG. <https://doi.org/10.3390/en13020494>
 - [88] Muenzel, V., de Hoog, J., Brazil, M., Vishwanath, A., & Kalyanaraman, S. (2015). A multi-factor battery cycle life prediction methodology for optimal battery management. In *Proceedings of the 2015 ACM Sixth International Conference on Future Energy Systems* (pp. 57–66).
 - [89] Nazaripouya, H., Wang, B., Wang, Y., Chu, P., Pota, H. R., & Gadh, R. (2016). Univariate time series prediction of solar power using a hybrid wavelet-ARMA-NARX prediction method. In *2016 IEEE/PES Transmission and Distribution Conference and Exposition (T&D)* (pp. 1–5). IEEE.
 - [90] Nowotarski, J., Liu, B., Weron, R., & Hong, T. (2016). Improving short term load forecast accuracy via combining sister forecasts. *Energy*, 98, 40–49.
 - [91] Ortega-Vazquez, M. A. (2014). Optimal scheduling of electric vehicle charging and vehicle-to-grid services at household level including battery degradation and price uncertainty. *IET Generation, Transmission & Distribution*, 8(6), 1007–1016.
 - [92] Pan, H., Lü, Z., Lin, W., Li, J., & Chen, L. (2017). State of charge estimation of lithium-ion batteries using a grey extended Kalman filter and a novel open-circuit voltage model. *Energy*, 138, 764–775.
 - [93] Pan, H., Lü, Z., Wang, H., Wei, H., & Chen, L. (2018). Novel battery state-of-health online estimation method using multiple health indicators and an extreme learning machine. *Energy*, 160, 466–477.
 - [94] Patel, K. K., Patel, S. M., & Scholar, P. G. (2016). Internet of Things-IOT: Definition, Characteristics, Architecture, Enabling Technologies, Application & Future Challenges. *International Journal of Engineering Science and Computing*. <https://doi.org/10.4010/2016.1482>
 - [95] Patil, M. A., Tagade, P., Hariharan, K. S., Kolake, S. M., Song, T., Yeo, T., & Doo, S. (2015). A novel multistage Support Vector Machine based approach for Li ion battery remaining useful life estimation. *Applied energy*, 159, 285–297.
 - [96] Pernsteiner, D., Schirrer, A., Kasper, L., Hofmann, R., & Jakubek, S. (2021). State estimation concept for a nonlinear melting/solidification problem of a latent heat thermal energy storage. *Computers & Chemical Engineering*, 153, Article 107444.

- [97] Pishdad-Bozorgi, P., Gao, X., Eastman, C., & Self, A. P. (2018). Planning and developing facility management-enabled building information model (FM-enabled BIM). *Automation in Construction*, 87(February 2017), 22–38. <https://doi.org/10.1016/j.autcon.2017.12.004>
- [98] Presser, M., Zhang, Q., Bechmann, A., & Beliatas, M. J. (2018). The internet of things as driver for digital business model innovation. *Digital Business Models: Driving Transformation and Innovation*, 27–55. https://doi.org/10.1007/978-3-319-96902-2_2
- [99] Qin, Q., Xie, K., He, H., Li, L., Chu, X., Wei, Y. M., & Wu, T. (2019). An effective and robust decomposition-ensemble energy price forecasting paradigm with local linear prediction. *Energy Economics*, 83, 402–414.
- [100] Rahman, F., Rehman, S., & Abdul-Majeed, M. A. (2012). Overview of energy storage systems for storing electricity from renewable energy sources in Saudi Arabia. *Renewable and Sustainable Energy Reviews*, 16(1), 274–283. <https://doi.org/10.1016/j.rser.2011.07.153>
- [101] Rani, R., Kumar, N., Khurana, M., Kumar, A., & Barnawi, A. (2021). Storage as a service in Fog computing: A systematic review. *Journal of Systems Architecture*, 116. <https://doi.org/10.1016/j.sysarc.2021.102033>
- [102] Ren, W., Tong, X., Du, J., Wang, N., Li, S., Min, G., & Zhao, Z. (2021). Privacy Enhancing Techniques in the Internet of Things Using Data Anonymisation. *Information Systems Frontiers*. <https://doi.org/10.1007/s10796-021-10116-w>
- [103] Rezaei, F., Bulle, C., & Lesage, P. (2019). Integrating building information modeling and life cycle assessment in the early and detailed building design stages. *Building and Environment*, 153(February), 158–167. <https://doi.org/10.1016/j.buildenv.2019.01.034>
- [104] Rezaei, M., Sameti, M., & Nasiri, F. (2021). Biomass-fuelled combined heat and power: integration in district heating and thermal-energy storage. *Clean Energy*, 5(1), 44–56.
- [105] Riaz, Z., Arslan, M., Kiani, A. K., & Azhar, S. (2014). CoSMoS: A BIM and wireless sensor based integrated solution for worker safety in confined spaces. *Automation in Construction*, 45, 96–106. <https://doi.org/10.1016/j.autcon.2014.05.010>
- [106] Richardson, R. R., Birkel, C. R., Osborne, M. A., & Howey, D. A. (2018). Gaussian process regression for in situ capacity estimation of lithium-ion batteries. *IEEE Transactions on Industrial Informatics*, 15(1), 127–138.
- [107] Salerno, I., Anjos, M. F., McKinnon, K., & Gomez-Herrera, J. A. (2021). Adaptable Energy Management System for Smart Buildings. *Journal of Building Engineering*, 102748. <https://doi.org/10.1016/j.jobbe.2021.102748>
- [108] Salimi, S., & Hammad, A. (2019). Critical review and research roadmap of office building energy management based on occupancy monitoring. *Energy and Buildings*, 182, 214–241. <https://doi.org/10.1016/j.enbuild.2018.10.007>
- [109] Sarmah, S. B., Kalita, P., Garg, A., Niu, X. D., Zhang, X. W., Peng, X., & Bhattacharjee, D. (2019). A review of state of health estimation of energy storage systems: Challenges and possible solutions for futuristic applications of li-ion battery packs in electric vehicles. *Journal of Electrochemical Energy Conversion and Storage*, 16(4), Article 040801.
- [110] Scarabaggio, P., Grammatico, S., Carli, R., & Dotoli, M. (2021). Distributed demand side management with stochastic wind power forecasting. *IEEE Transactions on Control Systems Technology*, 30(1), 97–112.

- [111] Schlueter, A., & Thesseling, F. (2009). Building information model based energy/exergy performance assessment in early design stages. *Automation in Construction*, 18(2), 153–163. <https://doi.org/10.1016/j.autcon.2008.07.003>
- [112] Severson, K. A., Attia, P. M., Jin, N., Perkins, N., Jiang, B., Yang, Z., ... Braatz, R. D. (2019). Data-driven prediction of battery cycle life before capacity degradation. *Nature Energy*, 4(5), 383–391.
- [113] Sharda, S., Singh, M., & Sharma, K. (2021). Demand side management through load shifting in IoT based HEMS: Overview, challenges and opportunities. *Sustainable Cities and Society*, 65(2021), Article 102517.
- [114] Sharifi, A. H., & Maghouli, P. (2019). Energy management of smart homes equipped with energy storage systems considering the PAR index based on real-time pricing. *Sustainable Cities and Society*, 45(October 2017), 579–587. <https://doi.org/10.1016/j.scs.2018.12.019>
- [115] Shen, S., Sadoughi, M., Li, M., Wang, Z., & Hu, C. (2020). Deep convolutional neural networks with ensemble learning and transfer learning for capacity estimation of lithium-ion batteries. *Applied Energy*, 260, Article 114296.
- [116] Shi, H., Xu, M., & Li, R. (2017). Deep learning for household load forecasting—A novel pooling deep RNN. *IEEE Transactions on Smart Grid*, 9(5), 5271–5280.
- [117] Shi, Y., Xu, B., Tan, Y., Kirschen, D., & Zhang, B. (2018). Optimal battery control under cycle aging mechanisms in pay for performance settings. *IEEE Transactions on Automatic Control*, 64(6), 2324–2339.
- [118] Shirzadi, N., Nasiri, F., El-Bayeh, C., & Eicker, U. (2021). Optimal dispatching of renewable energy-based urban microgrids using a deep learning approach for electrical load and wind power forecasting. *International Journal of Energy Research*, 1–16. <https://doi.org/10.1002/er.7374>. September.
- [119] Singh, P., & Sadhu, A. (2019). Multicomponent energy assessment of buildings using building information modeling. *Sustainable Cities and Society*, 49(May), Article 101603. <https://doi.org/10.1016/j.scs.2019.101603>
- [120] Song, X., Yang, F., Wang, D., & Tsui, K. L. (2019). Combined CNN-LSTM network for state-of-charge estimation of lithium-ion batteries, 7 pp. 88894–88902). *Ieee Access*.
- [121] Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: a simple way to prevent neural networks from overfitting. *The journal of machine learning research*, 15(1), 1929–1958.
- [122] Sun, Y., Lampe, L., & Wong, V. W. S. (2018a). Smart Meter Privacy: Exploiting the Potential of Household Energy Storage Units. *IEEE Internet of Things Journal*, 5(1), 69–78. <https://doi.org/10.1109/JIOT.2017.2771370> Sun, Y., Panchabikesan, K., Mastani, M., Olsthoorn, D., Moreau, A., Robichaud, M., & Haghighat, F. (2018b). Enhancement in peak shifting and shaving potential of electrically heated floor residential buildings using extraction system. *Journal of Energy Storage*, 18, 435–446. August 2018.
- [123] Tang, X., Liu, K., Wang, X., Gao, F., Macro, J., & Widanage, W. D. (2020). Model migration neural network for predicting battery aging trajectories. *IEEE Transactions on Transportation Electrification*, 6(2), 363–374.
- [124] Tien, P. W., Wei, S., Liu, T., Calautit, J., Darkwa, J., & Wood, C. (2021). A deep learning approach towards the detection and recognition of opening of windows for effective management of

- building ventilation heat losses and reducing space heating demand. *Renewable Energy*, 177, 603–625. <https://doi.org/10.1016/j.renene.2021.05.155>
- [125] Tlake, L. C., Markus, E. D., & Abu-Mahfouz, A. M. (2021). A Review of Interference Challenges on Integrated 5G NR and NB-IoT Networks. 2021 IEEE AFRICON, 1–6. <https://doi.org/10.1109/AFRICON51333.2021.9570861>. 2021.
- [126] Tong, S., Lacap, J. H., & Park, J. W. (2016). Battery state of charge estimation using a load-classifying neural network. *Journal of Energy Storage*, 7, 236–243.
- [127] Wang, Y., Chen, Q., Sun, M., Kang, C., & Xia, Q. (2018). An ensemble forecasting method for the aggregated load with subprofiles. *IEEE Transactions on Smart Grid*, 9(4), 3906–3908.
- [128] Wang, Y., Chen, Y., Liao, X., & Dong, L. (2019). Lithium-ion battery face imaging with contactless Walabot and machine learning. In 2019 IEEE International Conference on Mechatronics and Automation (ICMA) (pp. 1067–1072). IEEE.
- [129] Wang, S., Jin, S., Deng, D., & Fernandez, C. (2021). A Critical Review of Online Battery Remaining Useful Lifetime Prediction Methods. *Frontiers in Mechanical Engineering*, 71.
- [130] Wang, Y., Tian, J., Sun, Z., Wang, L., Xu, R., Li, M., & Chen, Z. (2020). A comprehensive review of battery modeling and state estimation approaches for advanced battery management systems. *Renewable and Sustainable Energy Reviews*, 131, Article 110015.
- [131] Wang, H. Z., Wang, G. B., Li, G. Q., Peng, J. C., & Liu, Y. T. (2016a). Deep belief network based deterministic and probabilistic wind speed forecasting approach. *Applied Energy*, 182, 80–93. <https://doi.org/10.1016/j.apenergy.2016.08.108>
- [132] Wang, J., Wu, H., Duan, H., Zillante, G., Zuo, J., & Yuan, H. (2016b). Combining life cycle assessment and Building Information Modelling to account for carbon emission of building demolition waste: A case study. *Journal of Cleaner Production*, 172, 3154–3166. <https://doi.org/10.1016/j.jclepro.2017.11.087>
- [133] Wassiliadis, N., Adermann, J., Frericks, A., Pak, M., Reiter, C., Lohmann, B., & Lienkamp, M. (2018). Revisiting the dual extended Kalman filter for battery state-of-charge and state-of-health estimation: A use-case life cycle analysis. *Journal of Energy Storage*, 19, 73–87.
- [134] Wei, Z., Xiong, B., Ji, D., & Tseng, K. J. (2017). Online state of charge and capacity dual estimation with a multi-timescale estimator for lithium-ion battery. *Energy Procedia*, 105, 2953–2958.
- [135] Wen, D. S., Chen, H. S., Ding, Y. L., & Dearman, P. (2006). Liquid nitrogen injection into water: Pressure build-up and heat transfer. *Cryogenics*, 46(10), 740–748. <https://doi.org/10.1016/j.cryogenics.2006.06.007>
- [136] Weng, C., Cui, Y., Sun, J., & Peng, H. (2013). On-board state of health monitoring of lithium-ion batteries using incremental capacity analysis with support vector regression. *Journal of Power Sources*, 235, 36–44.
- [137] Wu, W., Li, W., Law, D., & Na, W. (2015). Improving Data Center Energy Efficiency Using a Cyber-physical Systems Approach: Integration of Building Information Modeling and Wireless Sensor Networks. *Procedia Engineering*, 118, 1266–1273. <https://doi.org/10.1016/j.proeng.2015.08.481>
- [138] Wu, W., & Peng, M. (2017). A data mining approach combining k -means clustering with bagging neural network for short-term wind power forecasting. *IEEE Internet of Things Journal*,

- 4(4), 979–986.
- [139] Wu, J., Zhang, C., & Chen, Z. (2016). An online method for lithium-ion battery remaining useful life estimation using importance sampling and neural networks. *Applied energy*, 173, 134–140.
 - [140] Xiao, B., Liu, Y., & Xiao, B. (2019). Accurate state-of-charge estimation approach for lithium-ion batteries by gated recurrent unit with ensemble optimizer. *IEEE Access*, 7, 54192–54202.
 - [141] Xie, J., & Hong, T. (2016). Temperature scenario generation for probabilistic load forecasting. *IEEE Transactions on Smart Grid*, 9(3), 1680–1687.
 - [142] Xie, J., & Hong, T. (2017). Variable selection methods for probabilistic load forecasting: Empirical evidence from seven states of the united states. *IEEE Transactions on Smart Grid*, 9(6), 6039–6046.
 - [143] Xu, Z., Guan, X., Jia, Q. S., Wu, J., Wang, D., & Chen, S. (2012). Performance analysis and comparison on energy storage devices for smart building energy management. *IEEE Transactions on Smart Grid*, 3(4), 2136–2147. <https://doi.org/10.1109/TSG.2012.2218836>
 - [144] Xu, B., Zhao, J., Zheng, T., Litvinov, E., & Kirschen, D. S. (2017). Factoring the cycle aging cost of batteries participating in electricity markets. *IEEE Transactions on Power Systems*, 33(2), 2248–2259.
 - [145] Yan, C., Wang, F., Pan, Y., Shan, K., & Kosonen, R. (2020). A multi-timescale cold storage system within energy flexible buildings for power balance management of smart grids. *Renewable Energy*, 161, 626–634. <https://doi.org/10.1016/j.renene.2020.07.079>
 - [146] Yan, W., Zhang, B., Zhao, G., Tang, S., Niu, G., & Wang, X. (2018). A battery management system with a Lebesgue-sampling-based extended Kalman filter. *IEEE transactions on industrial electronics*, 66(4), 3227–3236.
 - [147] Yang, A., Han, M., Zeng, Q., & Sun, Y. (2021). Adopting Building Information Modeling (BIM) for the Development of Smart Buildings: A Review of Enabling Applications and Challenges. *Advances in Civil Engineering*. <https://doi.org/10.1155/2021/8811476>. 2021.
 - [148] Yang, X., Hu, M., Wu, J., & Zhao, B. (2018). Building-information-modeling enabled life cycle assessment, a case study on carbon footprint accounting for a residential building in China. *Journal of Cleaner Production*, 183, 729–743. <https://doi.org/10.1016/j.jclepro.2018.02.070>
 - [149] Yang, M., Lin, Y., & Han, X. (2016). Probabilistic wind generation forecast based on sparse Bayesian classification and Dempster–Shafer theory. *IEEE Transactions on Industry Applications*, 52(3), 1998–2005.
 - [150] Yao, Q., Lu, D. D. C., & Lei, G. (2018). A simple internal resistance estimation method based on open circuit voltage test under different temperature conditions. In *2018 IEEE International Power Electronics and Application Conference and Exposition (PEAC)* (pp. 1–4). IEEE.
 - [151] Yao, L., Xiao, Y., Gong, X., Hou, J., & Chen, X. (2020). A novel intelligent method for fault diagnosis of electric vehicle battery system based on wavelet neural network. *Journal of Power Sources*, 453, Article 227870.
 - [152] Yoon, S. H., Kim, S. Y., Park, G. H., Kim, Y. K., Cho, C. H., & Park, B. H. (2018). Multiple power-based building energy management system for efficient management of building energy. *Sustainable Cities and Society*, 42(May), 462–470. <https://doi.org/10.1016/j.scs.2018.08.008>
 - [153] You, G. W., Park, S., & Oh, D. (2017). Diagnosis of electric vehicle batteries using recurrent neural

- networks. *IEEE Transactions on Industrial Electronics*, 64(6), 4885–4893.
- [154] Yuan, K., Zhang, K., Zheng, Y., Li, D., Wang, Y., & Yang, Z. (2018). Irregular distribution of wind power prediction. *Journal of Modern Power Systems and Clean Energy*, 6(6), 1172–1180.
 - [155] Zainuddin, N., Daud, M., Ahmad, S., Maslizan, M., & Abdullah, S. A. L. (2021). A study on privacy issues in internet of things (IoT). In *2021 IEEE 5th International Conference on Cryptography, Security and Privacy, CSP 2021* (pp. 96–100). <https://doi.org/10.1109/CSP51677.2021.9357592>
 - [156] Zhang, Y., Song, W., Lin, S., & Feng, Z. (2014). A novel model of the initial state of charge estimation for LiFePO₄ batteries. *Journal of Power Sources*, 248, 1028–1033.
 - [157] Zhang, W., Quan, H., Gandhi, O., Rajagopal, R., Tan, C. W., & Srinivasan, D. (2020). Improving probabilistic load forecasting using quantile regression NN with skip connections. *IEEE Transactions on Smart Grid*, 11(6), 5442–5450.
 - [158] Zhang, D., Zhang, J., Guo, J., & Xiong, H. (2019). A semantic and social approach for real-time green building rating in BIM-based design. *Sustainability (Switzerland)*, 11 (14), 1–16. <https://doi.org/10.3390/su11143973>
 - [159] Zhao, Y., Liu, P., Wang, Z., Zhang, L., & Hong, J. (2017). Fault and defect diagnosis of battery for electric vehicles based on big data analysis methods. *Applied Energy*, 207, 354–362.
 - [160] Zheng, L., Zhang, L., Zhu, J., Wang, G., & Jiang, J. (2016). Co-estimation of state-of-charge, capacity and resistance for lithium-ion batteries based on a high-fidelity electrochemical model. *Applied Energy*, 180, 424–434.
 - [161] Zhou, C., Qian, K., Allan, M., & Zhou, W. (2011). Modeling of the cost of EV battery wear due to V2G application in power systems. *IEEE Transactions on Energy Conversion*, 26 (4), 1041–1050.
 - [162] Zhou, Y., Huang, M., Chen, Y., & Tao, Y. (2016). A novel health indicator for on-line lithium-ion batteries remaining useful life prediction. *Journal of Power Sources*, 321, 1–10.
 - [163] Zhou, X., Hsieh, S. J., Peng, B., & Hsieh, D. (2017). Cycle life estimation of lithium-ion polymer batteries using artificial neural network and support vector machine with time-resolved thermography. *Microelectronics Reliability*, 79, 48–58.
 - [164] Zhou, P., He, Z., Han, T., Li, X., Lai, X., Yan, L., & Zheng, Y. (2020). A rapid classification method of the retired LiCoNiMn_{1-x}–yO₂ batteries for electric vehicles. *Energy Reports*, 6, 672–683.
 - [165] Zhou, Y., Huang, M., & Pecht, M. (2020). Remaining useful life estimation of lithium-ion cells based on k-nearest neighbor regression with differential evolution optimization. *Journal of Cleaner Production*, 249, Article 119409.
 - [166] Zhou, K., Zhou, K., & Yang, S. (2022). Reinforcement learning-based scheduling strategy for energy storage in microgrid. *Journal of Energy Storage*, 51, Article 104379.
 - [167] Zhu, L., Sun, Z., Dai, H., & Wei, X. (2015). A novel modeling methodology of open circuit voltage hysteresis for LiFePO₄ batteries based on an adaptive discrete Preisach model. *Applied energy*, 155, 91–109.
 - [168] Zhu, S., Zhao, N., & Sha, J. (2019). Predicting battery life with early cyclic data by machine learning. *Energy Storage*, 1(6), e98.
 - [169] Zhuang, D., Zhang, X., Lu, Y., Wang, C., Jin, X., Zhou, X., & Shi, X. (2021). A performance data integrated BIM framework for building life-cycle energy efficiency and environmental

- optimization design. *Automation in Construction*, 127(April), Article 103712. <https://doi.org/10.1016/j.autcon.2021.103712>
- [170] Ziel, F., & Steinert, R. (2018). Probabilistic mid-and long-term electricity price forecasting. *Renewable and Sustainable Energy Reviews*, 94, 251–266.
 - [171] Zou, Y., Zhao, J., Ding, D., Miao, F., & Sobhani, B. (2021). Solving dynamic economic and emission dispatch in power system integrated electric vehicle and wind turbine using multi-objective virus colony search algorithm. *Sustainable Cities and Society*, 67 (September 2020), Article 102722. <https://doi.org/10.1016/j.scs.2021.102722>
 - [172] Ali, N., & Yongfeng, T. (2020). Keywords: Renewable energy, wind power, electrical power, doubly fed induction generator (DFIG), 2 pp. 235–245).
 - [173] Cai, L., Gu, J., & Jin, Z. (2019). Two-layer transfer-learning-based architecture for shortterm load forecasting. *IEEE Transactions on Industrial Informatics*, 16(3), 1722–1732.
 - [174] Davis, P. R. (2015). Monitoring and control of thermal energy storage systems. *Advances in Thermal Energy Storage Systems* (pp. 419–440). Woodhead Publishing.
 - [175] Li, Z., Liu, Y., Shin, K. G., Liu, J., & Yan, Z. (2019). Interference Steering to Manage Interference in IoT. *IEEE Internet of Things Journal*, 6(6). December 2019.
 - [176] Murnane, M., & Ghazel, A. (2017). A closer look at state of charge (SOC) and state of health (SOH) estimation techniques for batteries. *Analog devices*, 2, 426–436.
 - [177] Nowotarski, J., & Weron, R. (2018). Recent advances in electricity price forecasting: A review of probabilistic forecasting. *Renewable and Sustainable Energy Reviews*, 81, 1548–1568.
 - [178] Ortiz, J. P., Valladolid, J. D., Garcia, C. L., Novillo, G., & Berrezueta, F. (2018). Analysis of machine learning techniques for the intelligent diagnosis of ni-mh battery cells. In *2018 IEEE International Autumn Meeting on Power, Electronics and Computing (ROPEC)* (pp. 1–6). IEEE.
 - [179] Ren, Y., Suganthan, P. N., & Srikanth, N. (2014). A novel empirical mode decomposition with support vector regression for wind speed forecasting. *IEEE transactions on neural networks and learning systems*, 27(8), 1793–1798.
 - [180] Sahinoglu, G. O., Pajovic, M., Sahinoglu, Z., Wang, Y., Orlik, P. V., & Wada, T. (2017). Battery state-of-charge estimation based on regular/recurrent Gaussian process regression. *IEEE Transactions on Industrial Electronics*, 65(5), 4311–4321.
 - [181] Wang, L., Zhang, Z., & Chen, J. (2016c). Short-term electricity price forecasting with stacked denoising autoencoders. *IEEE Transactions on Power Systems*, 32(4), 2673–2681.

3 Subtask A Forecasting for Control of Smart Energy Storage Systems

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3.1 Introduction

The purpose of energy storage in building energy systems is to improve their performances and conducted by allowing energy to be arbitrated between points in time. This enables improvements in the operational performance of a building energy system, as the net energy usage of the system can be altered to meet operational targets such as expenditure on electricity, embodied carbon emissions, or grid impact, either instantaneously or to improve average performance. For example, in buildings with distributed solar generation, at times when local generation exceeds energy usage in the building, the excess low-carbon energy can be stored and then used at a later date, reducing energy consumption from the grid and the embodied carbon emissions incurred.

The operational performance improvements that are achieved for a given smart energy system are dependent on the controller used to schedule the battery. Therefore, the design of effective control schemes is critically important to achieving the goals of building energy management, such as the minimization of energy usage, and ensuring occupant comfort. When scheduling battery operation there is a fundamental trade-off between improving instantaneous performance and arbitrating energy to improve mean performance over the future. The benefit of storing energy to arbitrage depends strongly on the future operational conditions the building will face. Hence, improving the controller's information on future operational conditions allows for better management of this trade-off and so more effective scheduling. Whilst some modern control schemes, such as Reinforcement Learning [1], account for predictions of operational conditions implicitly, the provision of high-quality explicit predictions can be used to increase their performance. Furthermore, control methods which exploit explicit forecasts, such as Model Predictive Control (MPC), are found to provide excellent performance [2] as well as clear interpretability. The performance of these methods is dependent on the quality of forecasts available for the planning horizon they consider, as the better the prediction of the true future conditions, the more effectively the trade-off of arbitrage can be estimated and managed.

Therefore, the development of high accuracy prediction models for forecasting the operational conditions of building energy systems is a key requirement for achieving effective control of smart energy storage systems.

The development of prediction models is a data-driven task. Measurement data is required to train and calibrate models, as well as assess their performance and determine their suitability for a given application. When an energy storage control system is installed, a suitable prediction model must be trained, selected, or calibrated, requiring data from the building system being controlled. Developing a set of high accuracy prediction models for a particular building energy system requires an understanding of the data needed to achieve this. Only if the appropriate data is available can high accuracy forecasting be achieved. So, the design of prediction models must be coupled with the design of data collection strategies.

However, data has a cost. Many factors contribute to this cost, including the installation and

maintenance cost of monitoring systems, the infrastructure costs of data processing & storage, the computational cost of exploiting this data in prediction models, and the cost of delays to smart energy system projects caused by the time needed to gather sufficient data.

When determining the most appropriate prediction models for forecasting in the context of smart energy storage system control, the overall performance and cost of both the model and the data required to support it must be considered. This raises the following questions which must be answered to evaluate the effectiveness of different prediction approaches.

- How much data is required? I.e. What is the cost-performance trade-off of supporting data?
- Which variables are most important to achieving effective control? And so where should effort be prioritised in prediction?
- How well does collected data generalise between buildings and over time? I.e. What is the value of previously collected data? And how does this depend on the relationship between its source and intended application?
- How can existing data be exploited most effectively? Which prediction models use data most efficiently? And can analysis guide how existing data can be used to best effect?

This sub-task investigates the role of data in enabling high accuracy forecasting for smart energy storage systems. To achieve this, the performance of a selection of prediction models is studied in the context of providing forecasts for a Linear MPC controller operating batteries within a simulation of a multi-building energy system. This framework is used to analyse how different aspects of the supporting data impact prediction performance, and the implications this has for the joint design of forecasting models and data collection strategies.

3.2 Prediction Task

The study of prediction models for smart energy storage systems is contextualised within the task of providing forecasts for a Linear Model Predictive Controller (MPC) used to schedule battery storage units in a multi-building energy system with embedded battery storage and solar generation. This allows the quality of the prediction models to be quantified using the building energy control performance they enable. A simulation environment for performing these experiments is constructed using the CityLearn framework [3-4], which is a building energy control simulation framework designed for assessing the performance of building energy coordination algorithms for district energy systems. A schematic of the energy flows within the multi-building energy system model used in the simulations is provided in Figure 3.2.

During simulations, observation/measurement data is provided to the prediction models. The prediction models then use this observation data to produce forecasts of the required variables, which are passed to the linear predictive control model. The resulting linear optimisation problem is solved to determine the optimal control action, which is then applied to the battery. The combination of prediction model and linear predictive control model comprise the Linear MPC controller. This simulation and control loop is summarised in Figure 3.1. The linear predictive control model is described by Equation 1, with Table 3.1 providing descriptions of the parameters of the model. Due to the linearity of the simulation setup, this model provides a perfect prediction of the system dynamics over the planning horizon considered, i.e. the predictive models perfectly matches the true system model. The optimisation objective is comprised of three weighted contributions which correspond to the cost of grid electricity consumed by the buildings (assuming no net electricity metering), the embodied carbon emissions associated with the grid electricity use of the buildings, and the ramping of the grid electrical demand which represents the impact on the grid. All contributions are normalised by the values they would have if no battery storage were present in the buildings, denoted by $\tilde{O}^k$, lower bounded at 1. This clipping is performed to prevent ill conditioning of the objective when the no-storage objective values are small.

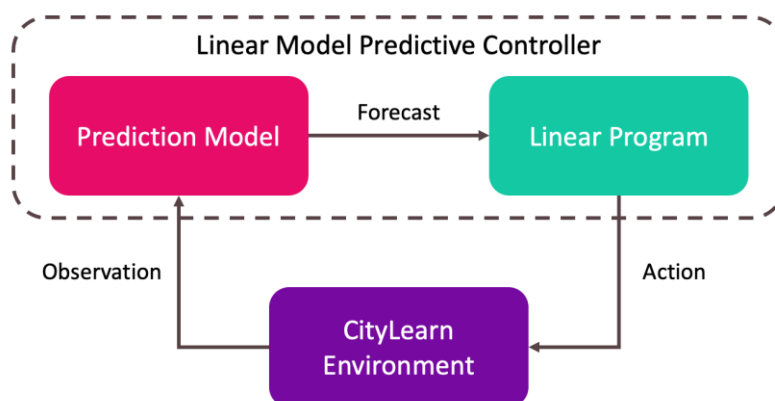


Figure 3.1: Control loop of building energy system simulation

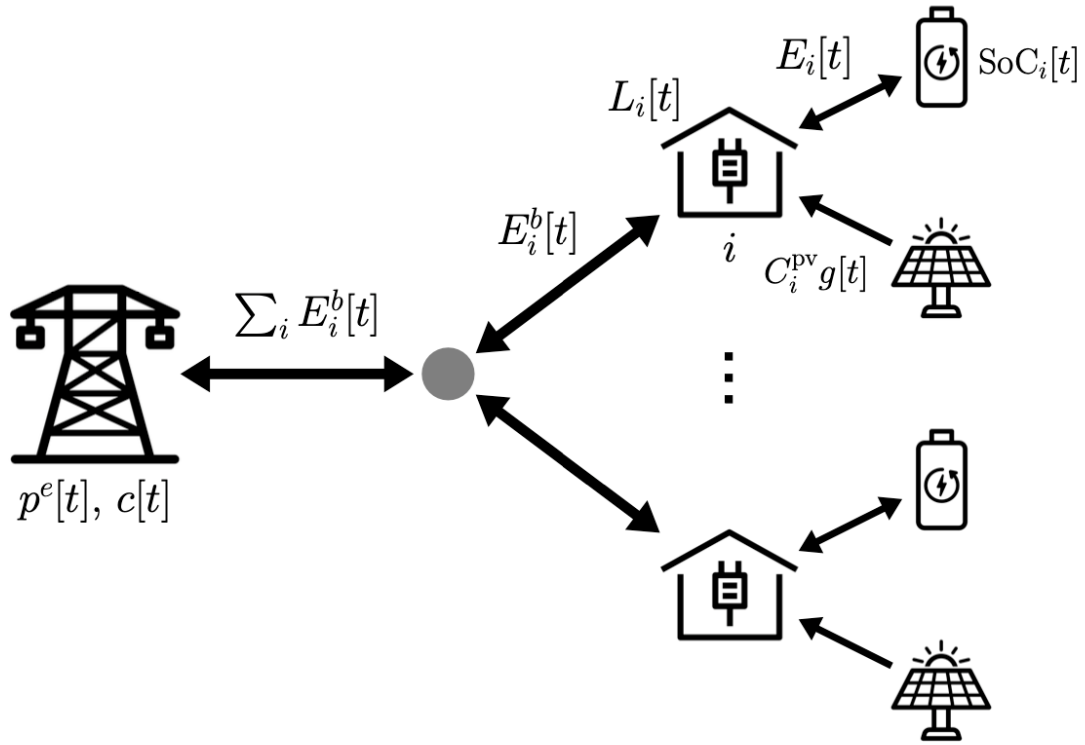


Figure 3.2: Energy flow schematic of district-level building energy system studied. (Icon credits: [Symbolon](#))

From the Linear MPC formulation it can be seen that the prediction models are required to provide forecasts of the following variables over the planning horizon T : the electrical demand of each building $L_i[t]$, the price of grid electricity $p^e[t]$, and the carbon intensity of grid electricity $c[t]$. Forecasting of normalised solar generation will not be considered, as in practical systems prediction models for this variable will rely on external meteorological forecasts, which are not available in the framework and are outside the scope of this study. In simulations the controller will be provided with perfect predictions of solar generation.

The overall performance of the Linear MPC controller is evaluated using the same objective function, from Equation 1, computed for the complete duration of the simulation. In all experiments performed the following objective contribution weights are used when evaluating the control performance, $(\gamma^p, \gamma^c, \gamma^r) = (0.45, 0.45, 0.1)$. From preliminary tests of the Linear MPC controller performance using perfect forecasts it is found that a planning horizon of $T = 48$ provides an appropriate trade-off of control performance and computation time, and so this prediction horizon length is used for the study of the prediction models.

Therefore, the prediction task is to forecast the following variables:

- electrical demand for each building $L_i[t]$
- price of grid electricity $p^e[t]$
- carbon intensity of grid electricity $c[t]$

at each time instance of the simulation for the following $T = 48$ time steps.

$$\begin{aligned}
& \min \quad \frac{\gamma^p \sum_{\tau} p^e[t+\tau] \sum_i \left(\max \left[0, E_i^b[t+\tau] \right] \right)}{\max \left[1, \tilde{O}^p \right]} \\
& \quad + \frac{\gamma^c \sum_{\tau} c[t+\tau] \sum_i \left(\max \left[0, E_i^b[t+\tau] \right] \right)}{\max \left[1, \tilde{O}^c \right]} \\
& \quad + \frac{\gamma^r \sum_{\tau} \left| \left(\sum_i E_i^b[t+\tau] \right) - \left(\sum_i E_i^b[t+\tau-1] \right) \right|}{\max \left[1, \tilde{O}^r \right]} \\
& \text{over} \quad E_i[\tau], \text{SoC}_i[\tau+1] \quad \forall i, \tau \\
& \text{subject to} \quad \text{SoC}_i[\tau+1] \leq \text{SoC}_i[\tau] + \min \left[E_i[\tau] \sqrt{\eta_i}, E_i[\tau] / \sqrt{\eta_i} \right] \quad (1a) \\
& \quad - P_i^{\max} \Delta t \leq E_i[\tau] \leq P_i^{\max} \Delta t \quad (1b) \\
& \quad 0 \leq \text{SoC}_i[\tau+1] \leq C_i^s \quad (1c) \\
& \quad \text{SoC}_i[\tau=0] = \text{SoC}_i^t \quad (1d) \\
& \quad E_i^b[\tau] = L_i[\tau] - C_i^{\text{pv}} g[\tau] + E_i[\tau] \quad (1e) \\
& \text{for all} \quad i \in [0, B-1], \tau \in [0, T-1] \\
& \text{take} \quad E_i[\tau=0] \quad \forall i
\end{aligned} \tag{Equation 1}$$

Parameter	Type	Units	Description
$E_i[t]$	Var.	kWh	Energy <i>intake</i> to battery unit in building i at time t
$\text{SoC}_i[t]$	Var.	kWh	State-of-charge of battery unit in building i at time t
Δt	Data	hrs	Time step of simulation data
C_i^s	Var.	kWh	Energy capacity of battery unit in building i
C_i^{pv}	Var.	kWp	Peak power capacity of solar PV unit in building i
η_i	Data	–	Round-trip efficiency of battery unit in building i
$P_i^{\max}$	Data	kW	Power capacity of battery unit in building i
SoC_i^t	Data	kWh	State-of-charge of battery unit in building i at time t
$L_i[t]$	Data	kWh	Electrical demand of building i at time t
$g[t]$	Data	kW/kWp	Normalised generation power from solar PV at time t
$p^e[t]$	Data	£/kWh	Grid electricity price at time t
$c[t]$	Data	kgCO ₂ /kWh	Carbon intensity of grid electricity at time t
γ^p	Data	–	Fractional contribution of electricity cost to objective
γ^c	Data	–	Fractional contribution of carbon emissions to objective
γ^r	Data	–	Fractional contribution of grid ramping to objective

Var. indicates the parameter is a decision variable of the Linear Program

Table 3.1: Description of Linear Program model parameters

The forecasts produced by the prediction models are assessed in two ways. Firstly, the prediction quality of the forecasts is quantified using the following error metrics, the normalised Mean Absolute Error (nMAE, Equation 3a), and the normalised Root Mean Squared Error (nRMSE, Equation 3b). Secondly, the performance of the forecasts is evaluated in the context of the control task by computing the control objective (see Equation 1) achieved by the system simulation.

$$\frac{\sum_{t=0}^{N-1} \frac{1}{T} \sum_{\tau=1}^T |f_{t,\tau}^v - v_{t+\tau}|}{\sum_{t=0}^{N-1} v_t} \quad \text{Equation 3a}$$

$$\frac{\sum_{t=0}^{N-1} \sqrt{\frac{1}{T} \sum_{\tau=1}^T (f_{t,\tau}^v - v_{t+\tau})^2}}{\sum_{t=0}^{N-1} v_t} \quad \text{Equation 3b}$$

where $f_{t,\tau}^v$ is the forecast of variable v made at time t for time instance τ in the planning horizon, and $v_{t+\tau}$ is the true value of the target variable τ time instances after the time t at which the forecast is made.

All code used to perform the experiments for this report is available at https://github.com/EECi/Annex_37/tree/EECi.

3.3 Cambridge Estates Building Energy Usage Dataset

For the simulations, a dataset of historic building electricity usage measurements from a set of buildings across the Cambridge University Estates covering the period 2010 to 2019 is used [5]. The dataset was created to be compatible with the CityLearn framework and contains 10 years of electricity usage data for 30 buildings of various use types from the University Estate, such as lecture blocks, offices, laboratories, and museums, alongside weather observations and grid electricity price and carbon intensity data. The dataset consists of: building electrical load data from the Cambridge Estates building monitoring systems, weather data for Cambridge from the Met Office MIDAS dataset [6] (temperature and relative humidity) and renewables.ninja reanalysis model [7-8] (direct and diffuse solar irradiance), normalised solar generation powers from the renewables.ninja reanalysis model [7-8], dynamic electricity pricing tariff data from Energy Stats UK [9], grid electricity carbon intensity from the National Grid ESO Data Portal [10], and temporal information including hour, day, and month indices, as well as daylight savings status. All data is available at hourly resolution. Further detail on the data sourcing and processing is available in reference [5].

The 10 years of available data is initially split into training, validation, and test datasets covering the following periods: train (2010 to 2015), validate (2016 to 2017), test (2018 to 2019). For all experiments performed the test data is kept the same, however the periods of data used to train the prediction

models is altered in Section 8. Of the 30 available buildings, 15 are selected¹ for use in the experiments, such that they provide a good mix of similarity and dissimilarity between the building electrical load training datasets, as defined by the similarity metrics presented in the following Data Analysis section.

3.4 Data Analysis – Similarity Metrics

Initially the set of historic building electrical load profiles is analysed to assess the range of energy usage behaviours present in the district energy system model studied. A similarity metric is proposed to enable the efficient comparison of load profiles. The potential of this metric to provide a data analysis based methodology for estimating prediction model generalisation performance is investigated in Section 7.

3.4.1 Approach

A Functional Data Analysis (FDA) approach is used to analyse and compare the building electrical load datasets. In this approach, functional principal components are extracted from the data, such that each data sample can be constructed from an equation of the form:

$$f(t) = \mu(t) + \sum_i \alpha_i v_i(t)$$

i.e. the data sample $f(t)$ is constructed from a linear sum of a mean function, $\mu(t)$ and a weighted sum of i functional principal components (fPCs), $v_i(t)$, with weightings or ‘scores’ α_i . In this approach, the mean function and fPCs are the same across all data samples, whereas the weightings are unique to each data sample. This has the benefit that to compare data samples, which are functions of time, it suffices to compare the weightings – a set of discrete values – that can be analysed statistically using standard techniques.

For this study, the datasets have been pre-processed into daily time histories, such that each data sample is a 24 hour profile of electricity consumption, starting at midnight. For each building, the training dataset comprises 6 years of data and hence 2191 data samples, and the validation and test datasets are both 2 years and hence 731 and 730 data samples respectively (2016 was a leap year).

The fPCA approach used here involves first aligning the data samples to a common mean, $\mu(t)$. This generates a warping function and an amplitude function for each data sample that describe how the data sample maps to the mean function. The warping function describes the phase relationship, i.e. the variation in time, and the amplitude function describes changes in magnitude. The warping and amplitude functions are then analysed separately and fPCs generated for both. The approach is illustrated schematically in Figure 3.3, and full details of the approach are described in (Ward, 2021) [11].

¹ Building numbers: 0, 3, 9, 11, 12, 15, 16, 25, 26, 32, 38, 44, 45, 48, 49.

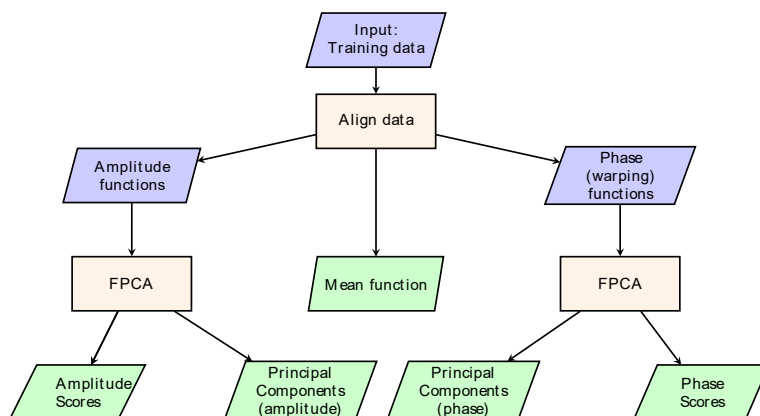


Figure 3.3: Schematic process for functional principal component analysis (fPCA)

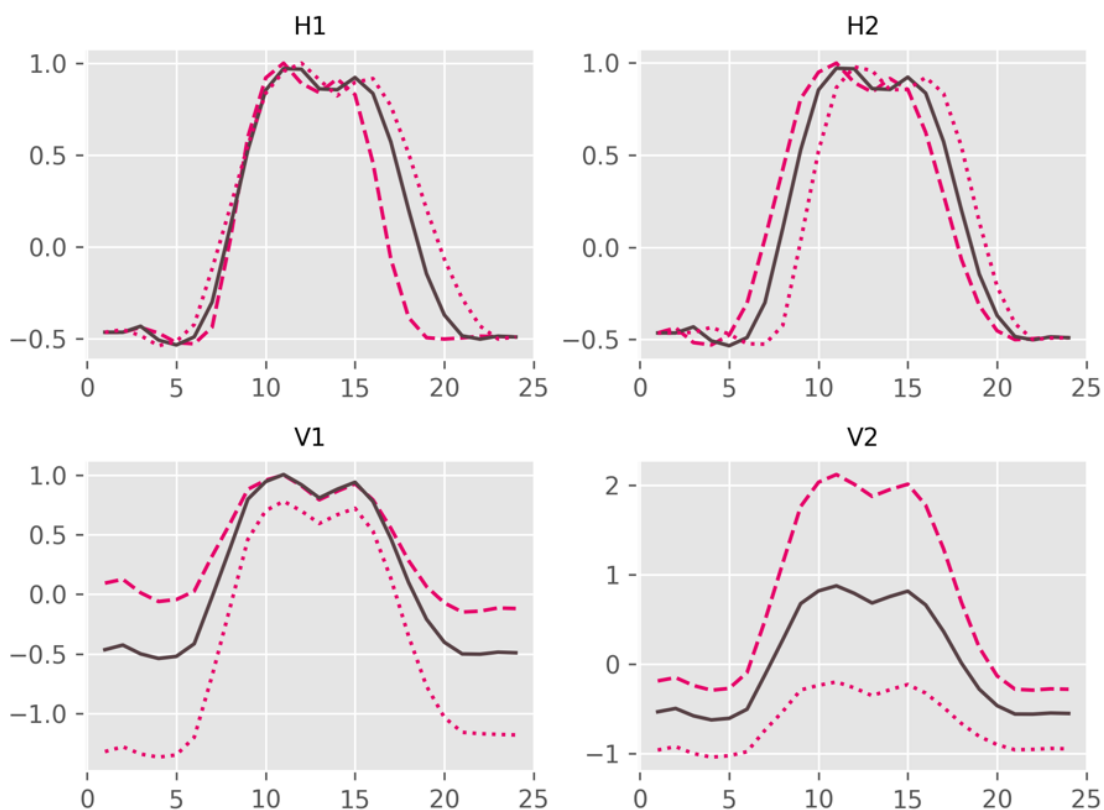


Figure 3.4: First 2 Phase (H) and Amplitude (V) PCs. The solid black line is the mean function, $\mu(t)$. The dashed line (-) indicates the impact of a +ve coefficient and the dotted line (.) a negative coefficient.

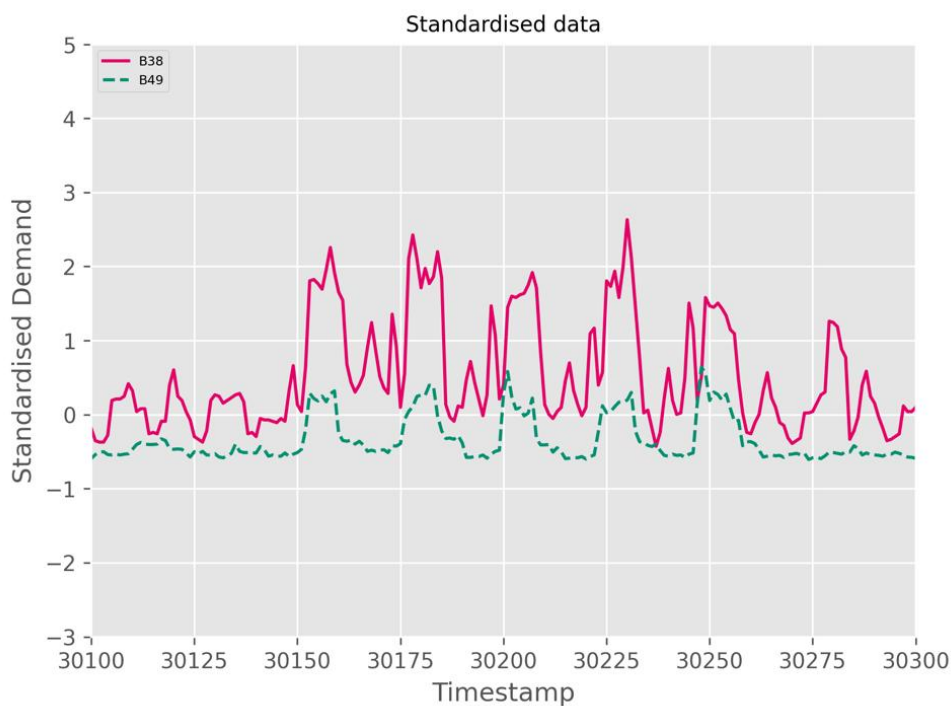


Figure 3.5: Sample data for buildings 38 and 49

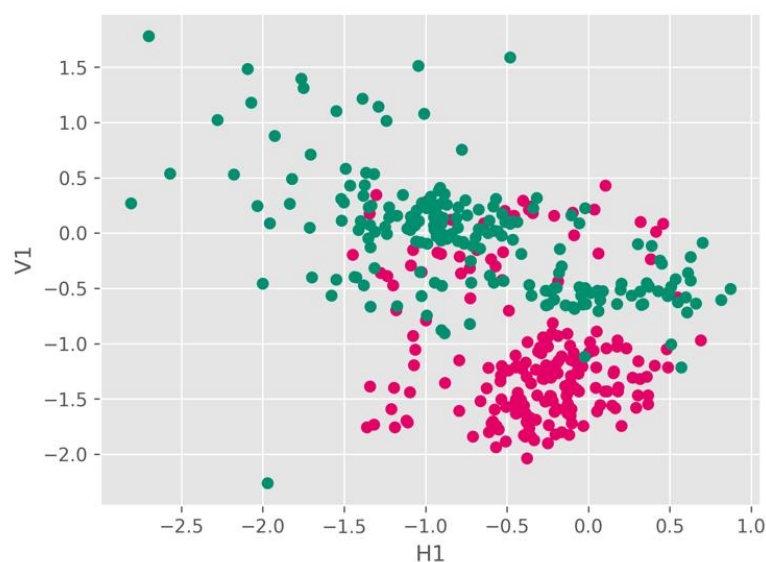


Figure 3.6: Example PC coefficients for Buildings 38 and 49

As an example, Figure 3.4 illustrates the first two phase (H1, H2 - top) and amplitude (V1, V2 - bottom) PCs. In the figure, the solid line shows the mean function. The dashed line indicates the impact of a positive PC coefficient and dotted line a negative PC coefficient. Figure 3.5 and Figure 3.6 show

example data and PC scores for two buildings respectively. The data for Building 49 in Figure 3.5 exhibits a much lower load range than the data for Building 38 – this corresponds to the less negative V1 scores in Figure 3.6 which generate a lower load range when used as a multiplier on the V1 PC.

3.4.2 Calculation of similarity

Having deconstructed the data as described above, it is possible to use statistical techniques to obtain a measure of similarity between the sets of scores for each dataset. For this we have used an optimal transport approach, i.e. an approximation to the Wasserstein, or Earth-mover's, distance, computed using the Geomloss python package². This gives a measure of the ease with which one probability distribution may be transformed into another and can be interpreted as one measure of the similarity between distributions. As an example, Figure 3.7 shows the kernel density distributions for the V1 scores for Buildings 38 and 49 – the Wasserstein distance calculated for these two distributions is 0.05.

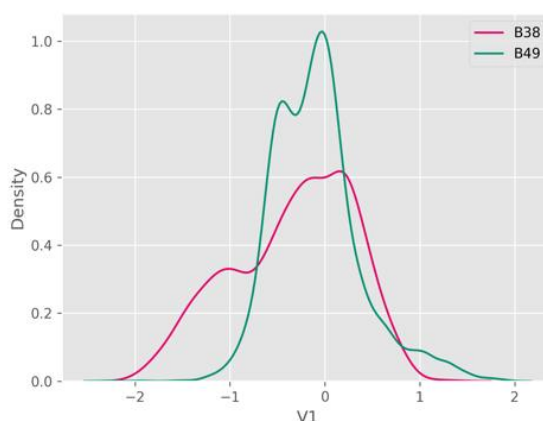


Figure 3.7: Kernel density plot of V1 scores for buildings 38 and 49. The Wasserstein distance between these two distributions is 0.05.

This calculation is performed for different datasets:

- Comparing the training data for all 15 buildings, to identify similarity between different buildings
- Comparing the training and validation datasets for each building
- Comparing the validation and test datasets for each building
- Comparing the training and test datasets for each building

The results of these calculations are shown in Table 3.2 and Table 3.3.

² <https://www.kernel-operations.io/geomloss/index.html>

	L0	L3	L9	L11	L12	L15	L16	L25	L26	L32	L38	L44	L45	L48	L49
L0	0.000	1.888	5.037	0.480	1.019	2.368	0.425	0.296	0.255	0.464	1.903	0.344	0.273	0.484	1.817
L3	1.888	0.000	2.744	1.900	1.527	1.651	1.598	1.625	1.894	2.035	1.149	1.819	1.924	1.873	2.150
L9	5.037	2.744	0.000	5.135	4.748	3.138	4.581	4.409	5.290	5.303	2.811	5.149	4.953	5.096	3.413
L11	0.480	1.900	5.135	0.000	0.967	2.455	0.441	0.510	0.432	0.299	1.810	0.395	0.530	0.314	1.831
L12	1.019	1.527	4.748	0.967	0.000	2.378	0.679	0.895	1.046	1.032	1.345	0.784	0.917	0.786	1.417
L15	2.368	1.651	3.138	2.455	2.378	0.000	2.228	2.150	2.692	2.390	2.120	2.454	2.480	2.363	1.892
L16	0.425	1.598	4.581	0.441	0.679	2.228	0.000	0.467	0.472	0.488	1.497	0.441	0.454	0.439	1.400
L25	0.296	1.625	4.409	0.510	0.895	2.150	0.467	0.000	0.350	0.615	1.557	0.312	0.304	0.420	1.575
L26	0.255	1.894	5.290	0.432	1.046	2.692	0.472	0.350	0.000	0.466	1.964	0.321	0.254	0.474	2.144
L32	0.464	2.035	5.303	0.299	1.032	2.390	0.488	0.615	0.466	0.000	1.936	0.490	0.555	0.399	1.871
L38	1.903	1.149	2.811	1.810	1.345	2.120	1.497	1.557	1.964	1.936	0.000	1.683	1.862	1.753	1.735
L44	0.344	1.819	5.149	0.395	0.784	2.454	0.441	0.312	0.321	0.490	1.683	0.000	0.364	0.307	1.755
L45	0.273	1.924	4.953	0.530	0.917	2.480	0.454	0.304	0.254	0.555	1.862	0.364	0.000	0.506	1.717
L48	0.484	1.873	5.096	0.314	0.786	2.363	0.439	0.420	0.474	0.399	1.753	0.307	0.506	0.000	1.583
L49	1.817	2.150	3.413	1.831	1.417	1.892	1.400	1.575	2.144	1.871	1.735	1.755	1.717	1.583	0.000

Table 3.2: Similarity across training datasets for 15 buildings

	L0	L3	L9	L11	L12	L15	L16	L25	L26	L32	L38	L44	L45	L48	L49
train_validation	0.213	0.600	0.412	0.215	0.537	0.851	0.633	0.453	0.281	0.184	0.783	0.202	0.245	0.390	0.422
validation_test	0.256	0.721	1.622	0.319	0.328	0.319	0.571	0.345	0.295	0.219	0.518	0.263	0.312	0.151	0.722
train_test	0.249	1.041	1.426	0.362	0.621	0.905	0.508	0.690	0.319	0.244	1.157	0.281	0.266	0.408	0.658

Table 3.3: Similarity across training/validation/test datasets for each individual building

3.5 Prediction Methods

To study the suitability of prediction models for forecasting in smart energy systems, the performance of a range of different prediction methods is investigated. The studied methods are selected to span a range of model characteristics, such as complexity & computational cost, information requirements (i.e. use of covariates), and structural characteristics, which impact a model's ability to represent different types of underlying patterns within timeseries. All of the methods studied are Machine Learning (ML) based models, as recent developments in ML techniques for timeseries forecasting have shown they can outperform classical methods in many applications. Additionally, ML techniques have advantages for practical deployment as they are well suited to retraining on new datasets, as well as online training, and require little to no hand tuning.

In time series forecasting, two strategies can be used: Iterated Multi-Step Forecasting (IMS) and Direct Multi-Step Forecasting (DMS). In the former, a single-step forecaster is iteratively used to generate multi-step predictions. Conversely, DMS directly predicts all forthcoming time steps within a predetermined forecasting window. (Zeng et al., 2023) [12] demonstrates that simple models employing DMS forecasting can surpass the performance of complex transformer-based models using IMS forecasting. These performance gains were shown to be predominantly attributed to the DMS forecasting strategy. As a result, three simple neural architectures using DMS forecasting, with varying neural structures, are investigated:

- Linear: A Multi-Layer Perceptron (MLP) model that maps the inputs directly to the output without an activation function (non-linearity).
- Conv: A Convolutional Neural Network (CNN) model that contains convolution layers followed by a linear layer. The architecture used comprises two layers with kernel sizes of 6 and 12, with five and one channels, respectively.
- ResMLP: A Residual MLPSkip model (MLP model with skip-connections), comprised of a single hidden layer with 128 neurons.

To contrast these simple neural models, the following three high complexity, state-of-the-art ML models are also studied:

- TFT: The Temporal Fusion Transformer (TFT) model [13], developed by Google, is an attention-based architecture that enables the fusion of data from multiple input sources to inform predictions. The neural structure contains features which allow for the learning of multiple underlying relationships across temporal scales, and the attention mechanism allows for interpretation of the model predictions, i.e. which data the model is exploiting to produce its forecasts. The model uses categorical covariates of datetime information, as well as temperature information for predicting building loads.
- NHITS: Neural Hierarchical Interpolation for Time Series Forecasting (NHITS) [14] is an MLP model which learns a set of basis functions at different frequencies that describe the underlying patterns in the training data, and produces forecasts by using hierarchical interpolation to combine predictions from the basis functions in a computationally efficient manner. It uses categorical covariates of datetime information.

- DeepAR: DeepAR is a Recurrent Neural Network (RNN) based model developed by Amazon [15], which has been widely applied in a range of research areas. It is a probabilistic forecasting model, but for this study only the mean prediction is used. The model uses categorical covariates of datetime information.

3.6 Method Performance Comparison

Initially, each of the prediction models is trained using the full training dataset – 6 years of training data, 2 years of validation data. These trained models are then used for forecasting in the simulator, and the quality of the forecasts provided is evaluated using the nMAE and nRMSE metrics defined in Equation 3a and Equation 3b respectively. Figure 3.8 shows the forecast quality results for the nMAE metric for each variable predicted by the models. Note that lower metric values indicate better forecast quality. The nRMSE results show identical trends, with some scaling differences³.

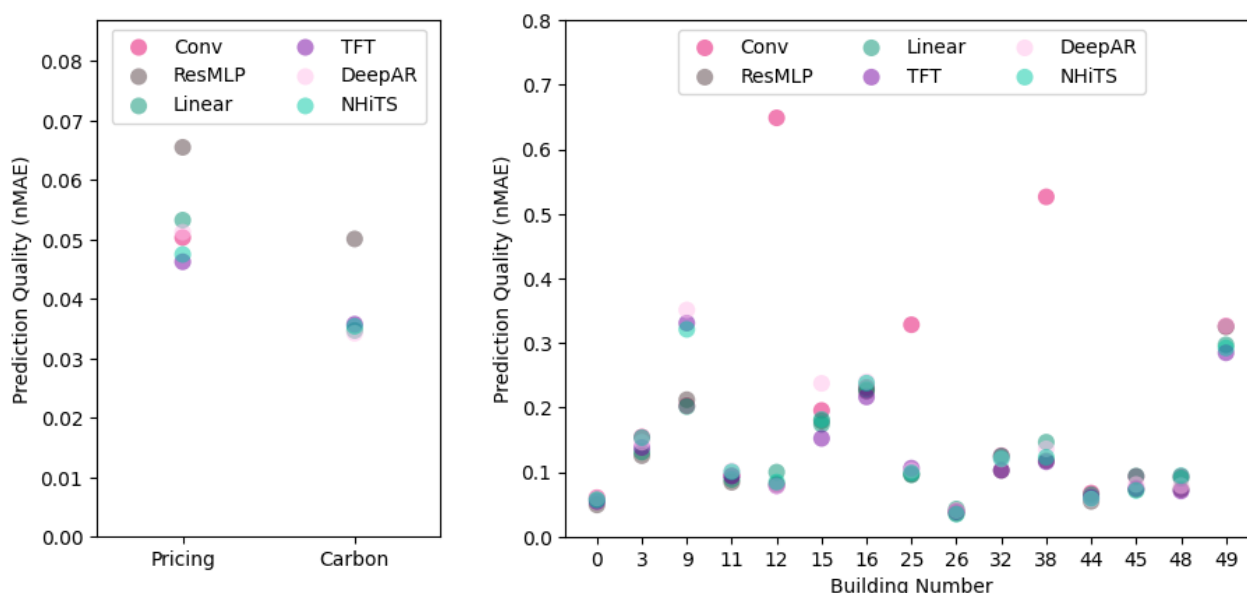


Figure 3.8: Comparison of forecasting performance of prediction models

The key result from the forecast quality assessment is that all of the models achieve broadly similar forecasting performance across the prediction variables. There are a few exceptions to this overarching behaviour. For instance, the high complexity, state-of-the-art models provide better prediction performance for electricity pricing, indicating they are better suited to representing the underlying trends in this data. Additionally, the Conv model shows anomalously poor performance on some building load variables, suggesting it is not a reliable model to use for load prediction. However

³ Figures showing nRMSE results are left out of the report for brevity, but are available to view at https://github.com/EECi/Annex_37/tree/EECi.

overall these results demonstrate that simple neural DMS models provide analogous prediction performance to high complexity models for the forecasting of building load and carbon intensity.

Table 3.4 presents the computation time⁴ required to train each of the prediction models and perform the inference required for forecasting. It shows that, with the training parameters used, all of the models required similar amounts of time to train, but that the inference time of the simple neural models is roughly 3 orders of magnitude less than the high complexity models. The computational efficiency of these simple models is advantageous for practical applications, as it allows these models to be used in systems with shorter prediction intervals, leading to higher frequency control, and allows for the use of lower cost compute hardware. Additionally, these models achieve analogous performance with lower data requirements as they do not use covariate data, avoiding the cost of procuring and handling this data.

Model	Training Time (hours)	Prediction Inference Time (s)
Conv	52.5	238
ResMLP	15.2	109
Linear	22.8	38
TFT	13.7	38,647
DeepAR	22.9	127,783
NHiTS	30.9	26,430

Table 3.4: Computational cost of prediction models

Comparing the prediction quality scores between prediction variables, it is observed that for some building electrical loads substantially better prediction quality is achieved across all models tested compared to other buildings. This consistent difference in forecast quality across models indicates that the underlying behaviours in energy usage in certain buildings makes its forecasting more challenging. Further investigation of the features that cause this difficulty of forecasting is required, as this impacts the achievable performance of battery system controllers for the building, and hence the benefits of installing a smart energy storage system. Determining the suitability of embedded storage for different buildings is necessary to properly prioritise investment in storage assets. The combined similarity metric and generalisation performance analyses performed in Sections 4 & 7 respectively provide an initial methodology for achieving this, as buildings with load profiles that have low similarity metric distances are found to have good generalisation performance. This means that if a building's load profile is found to be similar to that of a building with low forecasting difficulty, then it is likely to also have a low forecasting difficulty. This allows the forecasting difficulty of a building's electrical load profile to be estimated by comparison to load profiles of existing buildings.

⁴ Numerical experiments were performed using a high-performance desktop computer – 2.90GHz Intel Xenon 6226R with 256GB of RAM.

Additionally, it is found that forecasting the grid electricity pricing and carbon intensity variables is an easier task than predicting building loads, as the models achieve better performance than the average for building loads. However, it should be noted that for the test dataset the pricing variable is static for substantial durations due to the energy price cap introduced by the UK government in 2022, which reduces the difficulty of the price prediction task compared to normal circumstances.

Finally, the performance of the prediction models with respect to enabling effective control of the smart energy storage system is evaluated using the simulation framework, the results of which are presented in Figure 3.9. It is found that, as with the forecast quality comparison, all models provide similar overall control performance. The relationship between forecast accuracy and control performance is explored further in Section 9.

The forecasting performance comparison results show that the simple neural models achieve similar prediction performance to the high complexity models at a substantially lower computational cost, and that forecasting electrical loads is significantly more difficult for some buildings compared to others.

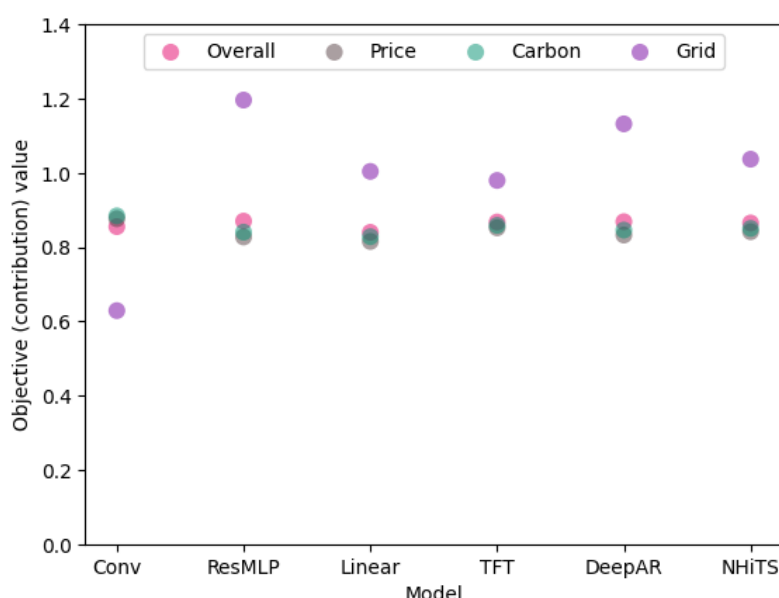


Figure 3.9: Comparison of control performance of prediction models

3.7 Generalisation Performance

In many cases where new smart energy storage systems are deployed, long durations of historic electrical load monitoring data for the building energy system are not available. Gathering multi-year load profiles for every new storage system to train prediction models would lead to a substantial cost, from both the expense of collecting, handling, and storing the data, and the cost associated with either delaying the project or the wasted operational expense from using an inefficient Rule Based Controller (RBC) in the meantime. A far more cost effective and data efficient approach is to reuse monitoring data from existing buildings, and the prediction models trained from it. However, this requires that the prediction performance achieved by the reused models, and the resulting control performance, is sufficiently good that the cost savings achieved by the data reuse are not outweighed by the wasted

operational expense from not having a bespoke prediction model⁵.

The generalisation performance of the electrical load prediction models in this study is analysed to investigate whether model reuse can enable the data savings outlined. For each model type, the prediction model trained on the load training dataset for each building is used to forecast the electrical load of every other building over the test dataset. Due to the computational cost of the high complexity models, only the TFT model is studied in the generalisation analysis, and data efficiency analysis in the next section, as it provides the best overall performance of the three models with a good balance of training and inference time. Figure 3.10 presents the results of this analysis via a violin plot of the distribution of forecast quality metrics achieved by the application of each trained model to each building (including the building the model was trained on). It shows that the Linear model provides the best generalisation performance, and so is most amenable to model reuse in practical systems. The ResMLP and TFT models show slightly worse generalisation performance, but would likely still be appropriate for model reuse, whereas the Conv model is found to generalise extremely poorly. For all models the tails of the distributions are very long, indicating that models trained on some buildings do not generalise well to certain others.

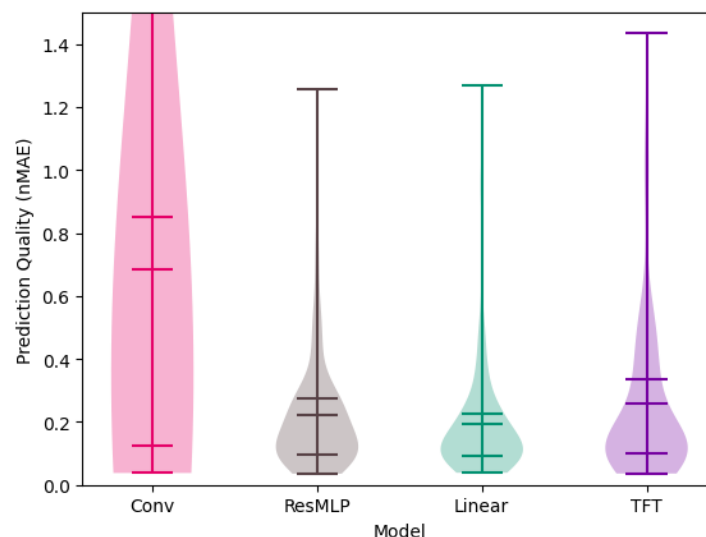


Figure 3.10: Generalisation performance of prediction models – distribution of prediction performance over model reuse

However, whilst the overall distribution of generalisation performance is important for model selection, in the context of deploying a new smart storage system, an understanding is required of whether existing trained models will provide appropriate prediction performance for the particular building being controlled, and if so, which trained model is likely to provide the best performance. [It is proposed that the building load profile similarity metrics analysed in Section 4 could provide a method](#)

⁵ Reused prediction models can be tailored to the new building system using online training, so the duration over which this wasted operational expense occurs is only that required to gather sufficient monitoring data to train a bespoke model for the building (either from new or by online training). There are several ways of performing the accounting for this counterfactual cost.

for determining whether existing trained models are appropriate for reuse for a new building, and selecting the best available model. Even in this case, fine tuning is still required. To investigate the hypothesis of whether models trained on load profiles that are similar to that of the target building (as defined by the similarity metrics) provide good prediction performance, the correlation between generalisation performance and the similarity metrics is observed. Figure 3.11 plots the correlation between the Wasserstein similarity metric and the prediction performance of the reused models, normalised by the prediction performance of the model trained on the target building, indicating the factor by which the prediction performance is worsened by reusing a model compared to the case where the true building data is collected. It shows that for the ResMLP, Linear, and TFT models there is a positive correlation between the prediction quality and the Wasserstein similarity metric. For Wasserstein metric scores less than 1, the generalisation performance of reused models is close to that of the model trained on data from the target building. With the Linear model, the prediction performance penalty of model reuse is under 50% in most cases for a Wasserstein metric less than 1, however in a few cases it is up to 150%. As the Wasserstein metric increases, the variance of the prediction performance increases, indicating that the trained model is less likely to provide good prediction performance for the target building. Similar correlations are found for both the MAE similarity metric (plotted for the Linear model in Figure 3.13) and RMSE similarity metric, however they exhibit higher prediction performance variance at low metric values, suggesting that the Wasserstein metric provides the best indication of whether good generalisation performance will be achieved by a reused model.

These results show that prediction models can be reused with a reasonable prediction performance penalty. Further, the Wasserstein similarity metric between building load profiles provides an appropriate indication of whether a trained model is likely to be suitable for use in a new building system, and can be used for the selection of a trained model for deployment.

However, before this metric can be used for decision making on model reuse in practical systems, the quantity of load data from the target building needed to accurately estimate the similarity metric must be determined, and compared against the performance of a prediction model trained using that data volume. Additionally, the implications of the prediction accuracy penalty incurred in model reuse on control performance will determine whether the cost savings from the reduced data requirements outweigh the additional operational costs incurred. This relationship between prediction accuracy and control performance is explored in Section 9.

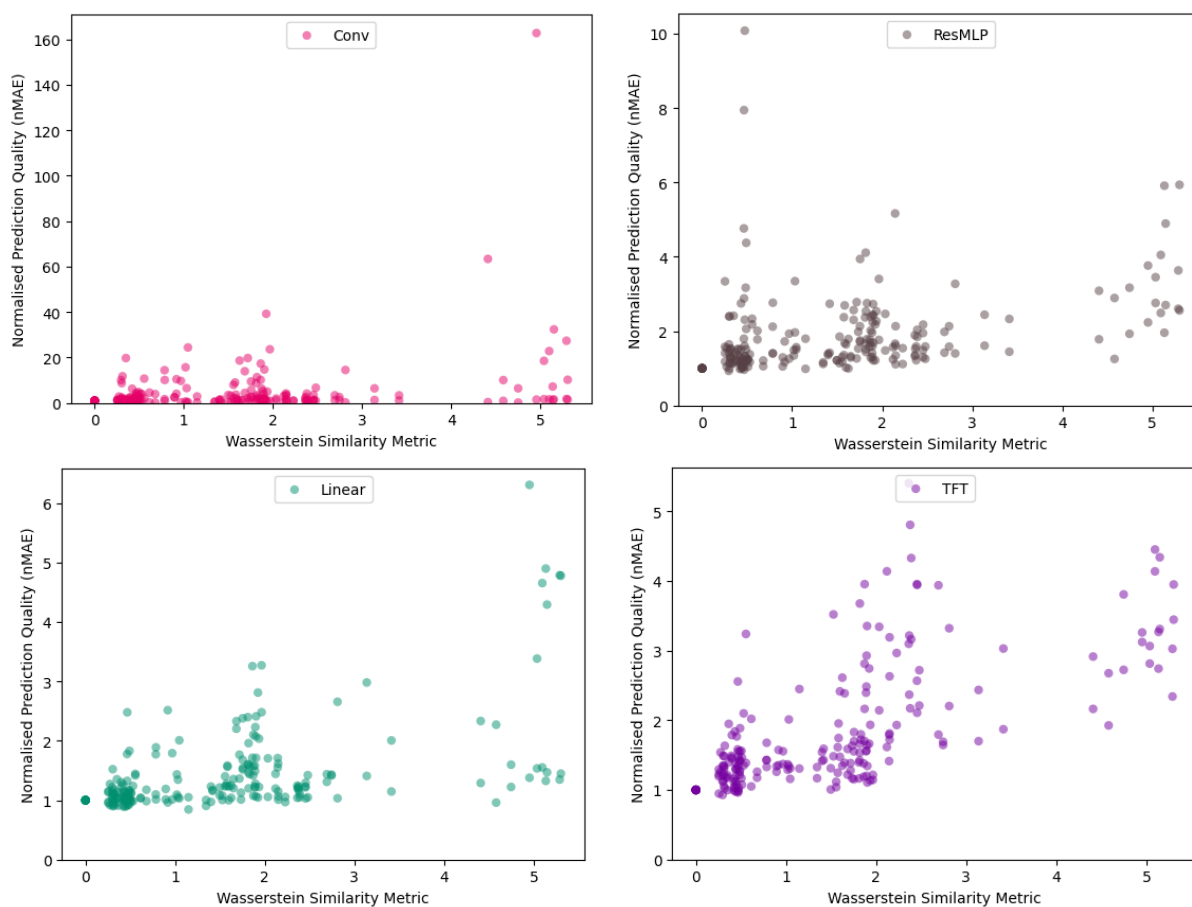


Figure 3.11: Correlation between model generalisation performance and Wasserstein similarity metric

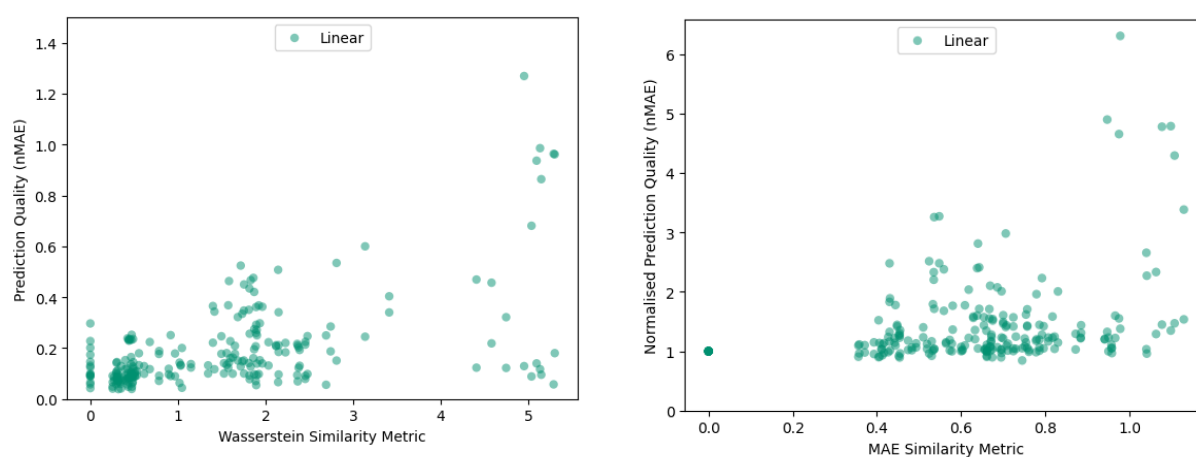


Figure 3.13: Correlation between model generalisation performance and Wasserstein similarity metric for Linear model using absolute prediction quality scale

Figure 3.13: Correlation between model generalisation performance and MAE similarity metric for Linear model

3.8 Data Efficiency

3.8.1 Impact of Training Data Volume on Prediction Performance

Another option for reducing the data requirements of prediction models is to use a shorter duration of historic measurement data for training. However, using less training data can reduce a model's ability to identify and properly learn the underlying patterns in the true data timeseries, reducing the model's prediction performance. In a similar way to model reuse, there is a trade-off between the cost of data used to train a prediction model and the performance that model achieves.

This data-performance trade-off is investigated by re-training each model type⁶ using shorter durations of combined train & validation datasets, from the initial 8 years of data down to 3 months⁷, all finishing at the end of 2017 as with the base training case in Section 6. Figure 3.14 shows how the prediction performance for the pricing and carbon variables, and the mean prediction performance over the electrical load variables, varies with the duration of training data used. The figure shows that the simple neural models are impacted very little by reductions in training data volumes down to 1 year, retaining a very similar prediction performance, whereas the performance of the TFT model is more sensitive to training data volumes, degrading rapidly in performance for load predictions. However, this rapid performance degradation does not occur for every building load variable, in some cases the performance sensitivity is analogous to that of the Linear model. Additionally, for some buildings, there is significant noise in the ResMLP and Linear model performances, with anomalously poor metric scores for certain training data durations.

Overall the results indicate that the simple neural models are far better suited to training using lower data volumes. For the Linear model, reducing from 8 years of training data to 1 year results in a 2.7% worsening in mean prediction performance over electrical load variables, increasing to 6.8% for 6 months of training data. Hence, substantial savings in data requirements can be made with a limited reduction in prediction quality if simple neural models are used, which is a significant benefit for practical smart energy storage systems.

⁶ The Conv model is not considered in this analysis due to its poor generalisation performance identified in the previous section, and its high computational cost for training.

⁷ For the TFT model, the minimum training data duration that could be used is 2 years, as the use of time information covariates requires all values of the categorical month variable in the validation set to be present in the training set.

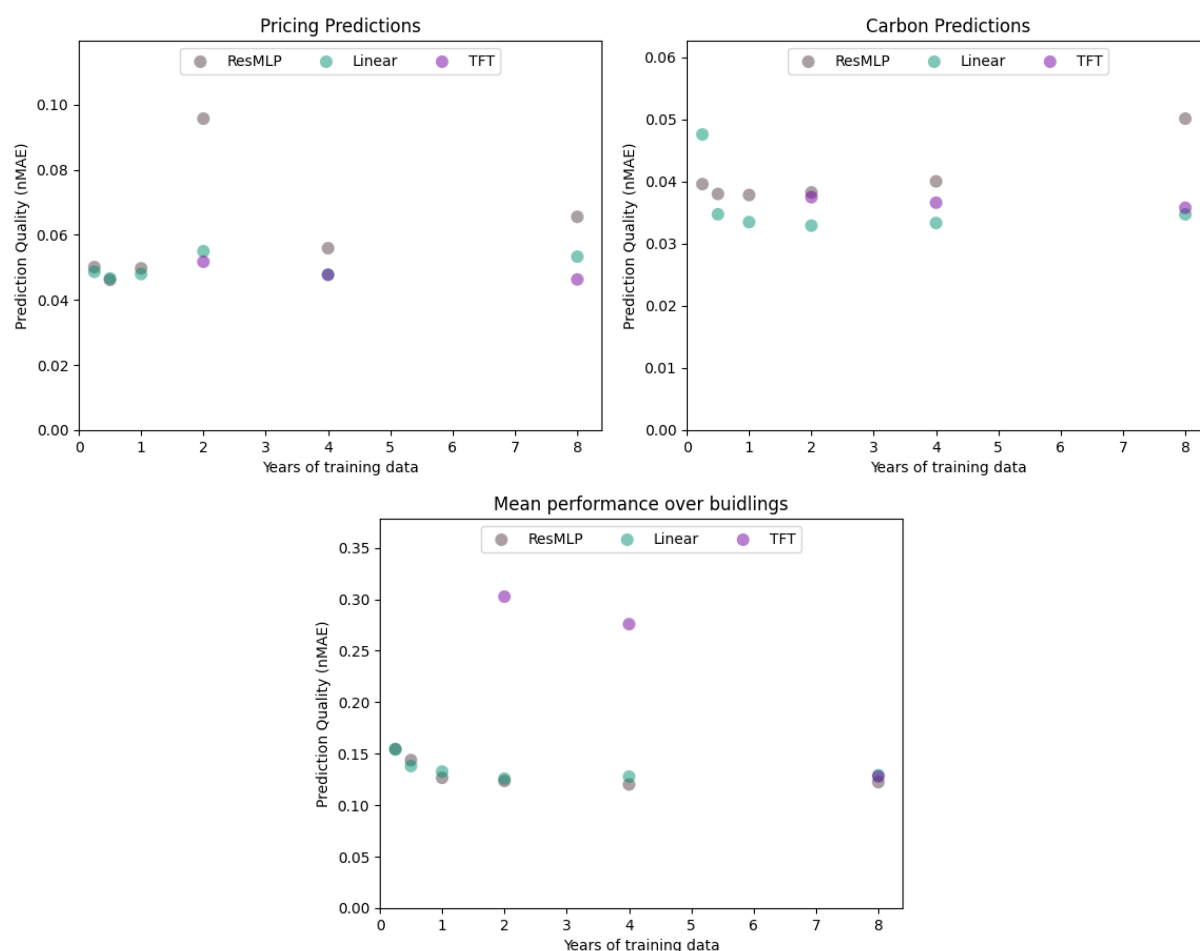


Figure 3.14: Variation of prediction quality with volume of training data used (combined train & validation)

3.8.2 Impact of Data Features/Covariates on Prediction Performance

The efficacy of feature selection on model prediction performance is also investigated by quantifying the performance disparity between models utilising a single feature and those incorporating 11 features. A single layer perceptron (linear) model is used for this performance comparison. For the 1-feature model, the forecast label served as the sole input; for instance, if carbon intensity was the variable to be forecasted, only past carbon intensity data were employed as inputs. Conversely, the 11-feature model included the variables: building load, normalised solar power generation, grid electricity price & carbon intensity, outdoor air temperature, relative humidity, diffuse solar irradiance, direct solar irradiance, month, day, and hour.

As shown in Figure 3.15, the model trained using a single feature outperforms its counterpart trained on 11 features. Several factors could contribute to this observed phenomenon:

- i. Overfitting [16]: The incorporation of an excessive number of features may lead the model to overfit the training data, thereby diminishing its performance on unseen data.
- ii. Multicollinearity [17]: The presence of highly correlated features can destabilize the model, resulting in a decline in predictive performance.

- iii. Curse of Dimensionality [18]: An increase in the number of features elevates the dimensionality of the data, which can lead to data sparsity and consequently degrade model performance.

These findings suggest that feature selection is a critical aspect of model optimisation, and that the inclusion of additional features does not necessarily translate to enhanced predictive accuracy.

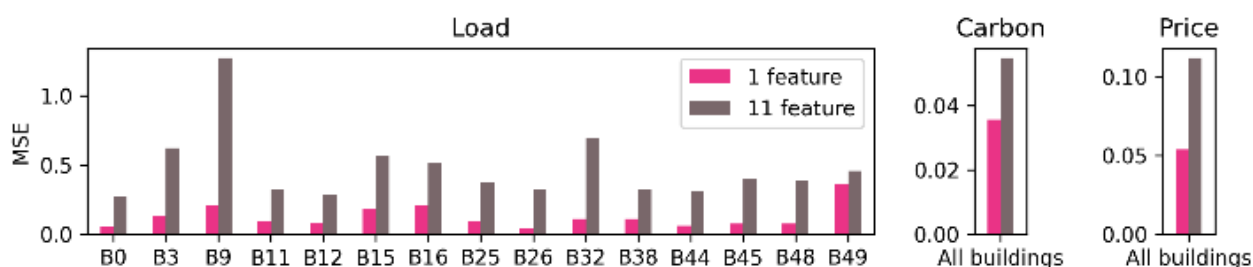


Figure 3.15: Variation of prediction quality with input features (linear model)

3.8.3 Online Training

Building behaviour can change during operation due to external factors such as weather & climate, occupancy, and equipment degradation & maintenance. Continuous online training updates the predictive models using the collected monitoring data, improving the model's ability to adapt to dynamic changes in building behaviour.

An analysis is conducted to evaluate the impact of different online training frequencies on the predictive accuracy of the single layer perceptron model, the results of which are presented in Figure 3.16. It is observed that higher frequencies of online training led to increased prediction accuracy for all prediction variables. For instance, compared to a base case without online training, the model's predictive performance for grid carbon intensity improved by 22%, 18%, 15%, and 10% when updated monthly, quarterly, semi-annually, and annually, respectively. As a result, it is anticipated that integrating online training into MPC frameworks will provide improved adaptability and robustness.

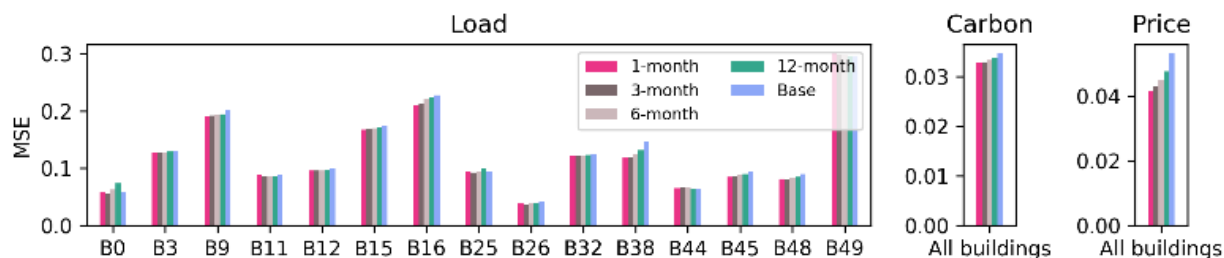


Figure 3.16: Variation of prediction quality with online training (linear model)

Using simple neural models can drastically reduce the volume of supporting data required to achieve high accuracy forecasts. The Linear model provides substantially better prediction performance when

training using a single feature, compared to the full set of 11 features. Additionally, it suffers only a 2.7% reduction in prediction performance when trained using 1 year of historic measurement data compared to the base case of 8 years, and a roughly 20% improvement in prediction performance can be achieved by updating the model online on a monthly basis.

3.9 Sensitivity of Control Performance to Forecast Accuracy

The goal of forecasting in smart energy storage systems is to enable improved energy management by increasing the performance of the battery controllers by providing them with more accurate estimates of operational conditions over the planning horizon. The preceding sections investigate the performance of prediction models in terms of their mean prediction error compared to the true operational conditions over the planning horizon. However, when assessing the benefits of prediction models, determining whether the cost trade-off of improved prediction accuracy, and the associated data requirements, requires a quantification of how the prediction accuracy maps to control performance and the incurred operational cost.

To investigate the relationship between prediction accuracy and control performance in a controlled manner, the Linear MPC controller is provided with forecasts created by adding a Gaussian Random Walk (GRW) noise component⁸ to the ground truth values of the operational variables, as described by Equation 4. This noise is added initially to all prediction variables, and then each of the variable types (load, pricing, carbon) in turn. Figure 3.17 shows the correspondence between the amplitude (standard deviation) of the noise added to create the forecast, and the nMAE prediction accuracy metric. All electrical load variables are found to have the same relationship.

$$f_{\text{GRW}}^v[t, \tau] = v_{t+\tau} + \sum_{j=1}^{\tau} w_j^{\sigma} \quad \text{s.t. } w_j^{\sigma} \text{ i.i.d. } \mathcal{N}(\mu=0, \sigma^2) \quad \text{Equation 4}$$

Figure 3.18 shows how the overall control performance, and each of the objective contributions, varies with the amplitude of the GRW noise added to each of the variable types. The results show that whilst the accuracy of the electrical load forecasts has the lowest impact on the overall control objective, it has the greatest effect on the electricity cost (price) and embodied carbon emissions contributions, greater than that of the forecasts of the pricing and carbon variables themselves. Whereas, the prediction accuracy of the pricing and carbon variables has a substantially greater effect on the grid load ramping objective contribution, which is much more sensitive to prediction accuracy than the other two contributions. This provides guidance as to where modelling effort and expenditure on data should be prioritised depending on the building system manager's weighting of these three objectives.

It is suggested that the sensitivity of the price and carbon objectives to electrical load prediction accuracy is a result of the controller misidentifying when high loads will occur, causing it to fail to store

⁸ The results of this analysis depend on the additive noise model used.

low-cost and/or low-carbon energy to meet these loads, meaning that comparatively high-cost, high-carbon grid electricity is required to satisfy the remaining unmet load when it occurs. However, up to the maximum level of noise used for testing, the controller achieves objective values of less than 1 for these two contributions, indicating that the battery still provides benefit to the building energy system for these operational metrics.

The results from Figure 3.17 and Figure 3.18 can be used to estimate the operational cost savings resulting from improved prediction accuracy, and so determine whether expenditure on data and compute to enable better forecasting is a cost effective strategy for a building system operator.

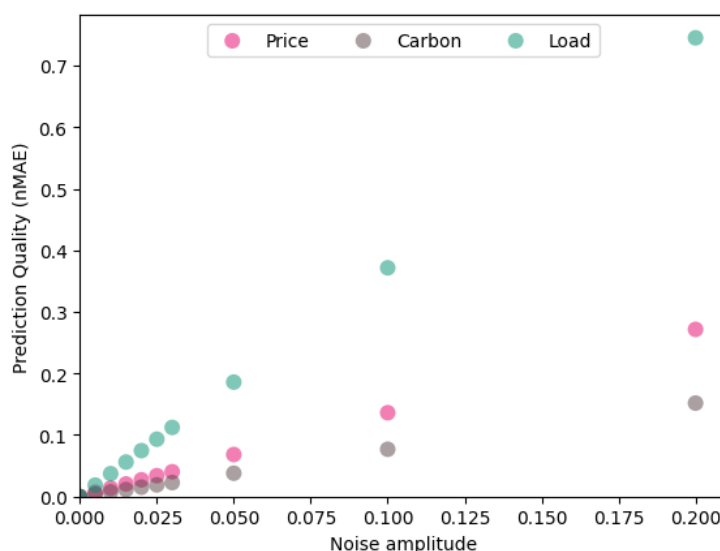


Figure 3.17: Variation of prediction performance with amplitude (standard deviation) of Gaussian Random Walk noise

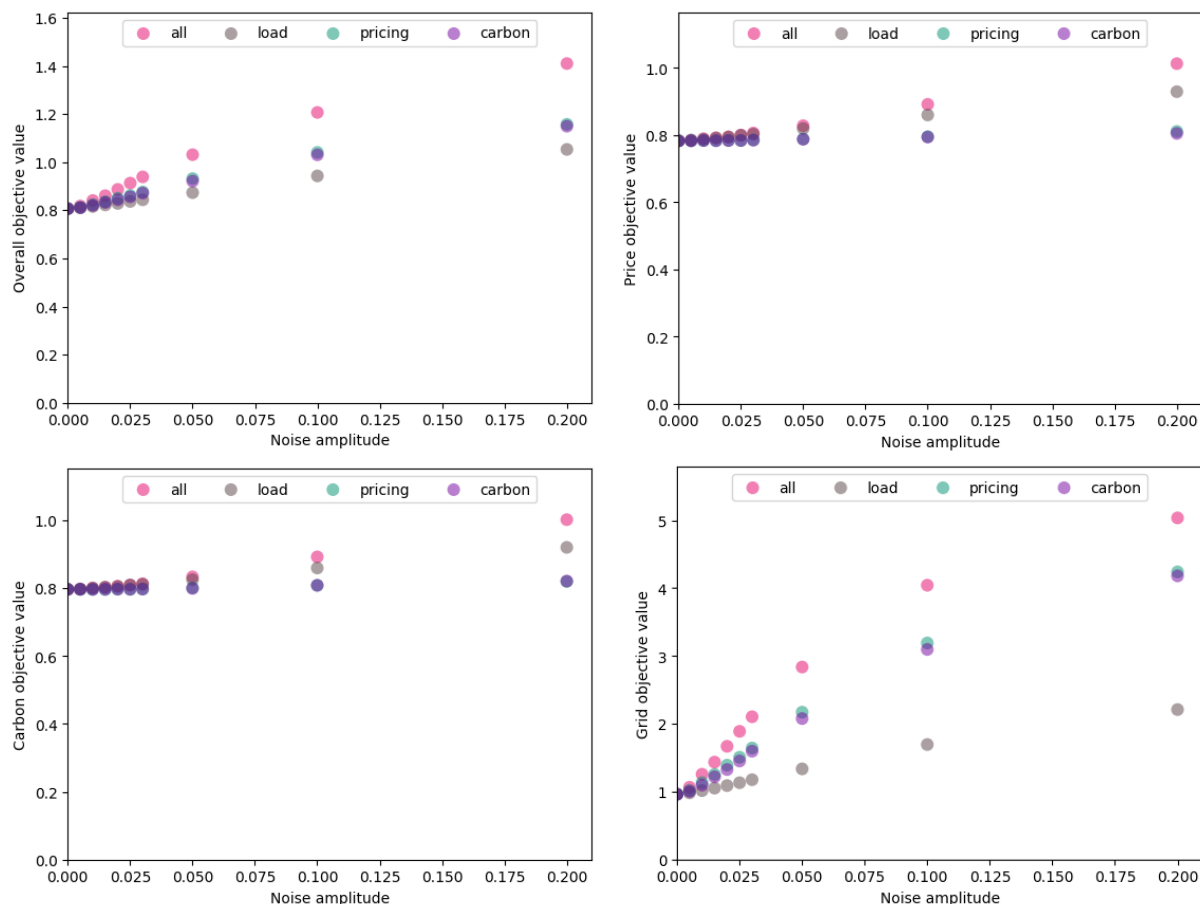


Figure 3.18: Impact of forecast noise on control performance

3.10 Summary

This chapter investigates the role of data in enabling high accuracy forecasting for smart energy storage systems. It studies the capability of different Machine Learning models to provide forecasts of electricity demand, and grid electricity cost & carbon emissions for a Linear Model Predictive Controller used to schedule battery storage units in a multi-building energy system with embedded storage and solar generation. The performance of the prediction models is assessed using both the accuracy of the forecasts provided and the quality of battery scheduling control enabled. Prediction performance of the models is assessed against their computational expense, data requirements, and generalisability.

The key finding is that simple neural DMS models provide analogous prediction performance to high complexity, state-of-the-art ML models with significantly lower computational cost, and have substantial data efficiency advantages.

Simple neural models achieve similar prediction quality scores to high complexity models across all price, carbon, and electrical load prediction variables, with roughly similar training times, but 3 orders of magnitude lower inference times. This is advantageous for practical applications as it allows for the use of higher control frequencies and cheaper compute hardware. Further, these simple models are found to be significantly more data efficient and far better suited to applications where data

availability is restricted. They perform substantially better than high complexity models when limited quantities of training data are available, with the Linear model suffering only a 2.7% reduction in prediction performance when trained using 1 year of data compared to a baseline of 8 years, and provide better prediction performance when trained using a single input feature, compared to the full set of 11 features. Additionally, online training can further improve model performance, with prediction quality of the Linear model increasing by approximately 20% when updated monthly. It is anticipated that integrating online training into MPC frameworks will provide improved adaptability and robustness.

The data collection requirements for new battery control systems can be reduced by reusing measurement data and trained models from existing buildings. For certain combinations of buildings, prediction models achieve good generalisation performance, with the reused models providing high accuracy forecasts. However, the variance in generalisation performance is substantial, with some reused models performing 6 times worse in terms of prediction quality compared to a model trained using the true building data. The Wasserstein distance between fPCA component weight distributions of building load profiles provides a data analysis based approach for determining whether model reuse will provide suitable prediction accuracy, and for selecting the best pretrained model for use in a new building system. For values of this similarity metric less than 1, the prediction performance penalty for model reuse using the Linear model is under 50% in most cases.

Forecasting grid electricity price and carbon intensity is found to be an easier task than forecasting building electrical load, with all models achieving higher prediction accuracy on average. However, the difficulty of forecasting electrical load varies significantly between buildings, with the set of models tested differing in prediction quality by a factor of 6 across the buildings. This indicates that in practical data collection strategies it may be beneficial to target expenditure on supporting data on certain buildings where the load profile is more difficult to predict.

The impact of reduced data usage on prediction accuracy can be mapped through to control performance to determine whether the savings in data costs outweigh the increased operational cost due to the impact on battery scheduling capability. This provides a methodology for determining the most cost effective data collection strategies for smart energy storage systems.

3.11 References

- [182] J. Vazquez-Canteli, G. Henze, and G. Z. Nagy. (2020). "MARLISA: Multi-Agent Reinforcement Learning with Iterative Sequential Action Selection for Load Shaping of Grid-Interactive Connected Buildings," In Proceedings of the 7th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation (BuildSys '20). [Online]. Available: <https://doi.org/10.1145/3408308.3427604>
- [183] K. Nweye, S. Siva, and G. Z. Nagy. (2023). "The CityLearn Challenge 2022," [Online]. Available: <https://doi.org/10.18738/T8/0YLJ6Q>
- [184] J. R. Vázquez-Canteli, J. Kämpf, G. Henze, and Z. Nagy. (2019). "Citylearn v1.0: An openai gym environment for demand response with deep reinforcement learning," in Proceedings of the 6th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation, ser. BuildSys '19. [Online]. Available: <https://doi.org/10.1145/3360322.3360998>
- [185] J. R. Vazquez-Canteli, S. Dey, G. Henze, and Z. Nagy. (2020). "Citylearn: Standardizing re- search in multi-agent reinforcement learning for demand response and urban energy management,"
- [186] Max Langtry and Ruchi Choudhary. (2023, July). "Cambridge University Estates building electricity usage 2010-2019," [Online]. Available: <https://github.com/EECi/Cambridge-Estates-Building-Energy-Archive>
- [187] Met Office. (2022, September). "MIDAS Open: UK hourly weather observation data, v202207, NERC EDS Centre for Environmental Data Analysis," [Online]. Available: <https://catalogue.ceda.ac.uk/uuid/6180fb7ed76a442eb1b8f3f152fd08d7>
- [188] Stefan Pfenninger and Iain Staffell. (2016). "Long-term patterns of european pv output using 30 years of validated hourly reanalysis and satellite data," *Energy*, 114:1251–1265
- [189] Iain Staffell and Stefan Pfenninger. (2016). "Using bias-corrected reanalysis to simulate current and future wind power output," *Energy*, 114:1224–1239
- [190] Energy Stats UK. (2023, July). "Historical Pricing Data – Octopus Agile Eastern England," [Online]. Available: <https://energy-stats.uk/download-historical-pricing-data/>
- [191] National Grid ESO. (2020, March). "Historic Generation Mix Carbon Intensity," [Online]. Available: <https://data.nationalgrideso.com/carbon-intensity1/historic-generation-mix>
- [192] Ward, Rebecca. (2021). "A data-centric stochastic model for simulation of occupant-related energy demand in buildings," PhD diss., University of Cambridge.
- [193] Zeng, A., Chen, M., Zhang, L. and Xu, Q. (2023, June). "Are transformers effective for time series forecasting?," In Proceedings of the AAAI conference on artificial intelligence (Vol. 37, No. 9, pp. 11121-11128).
- [194] Lim, Bryan, Sercan Ö. Arik, Nicolas Loeff, and Tomas Pfister. (2021). "Temporal fusion transformers for interpretable multi-horizon time series forecasting," *International Journal of Forecasting* 37, no. 4, 1748-1764.
- [195] Salinas, David, Valentin Flunkert, Jan Gasthaus, and Tim Januschowski. (2020). "DeepAR: Probabilistic forecasting with autoregressive recurrent networks." *International Journal of Forecasting* 36, no. 3, 1181-1191.

- [196] Challu, Cristian, Kin G. Olivares, Boris N. Oreshkin, Federico Garza Ramirez, Max Mergenthaler Canseco, and Artur Dubrawski. (2023). "NHITS: Neural Hierarchical Interpolation for Time Series Forecasting." In Proceedings of the AAAI Conference on Artificial Intelligence, vol. 37, no. 6, pp. 6989-6997.
- [197] Hawkins, D. M. (2004). "The problem of overfitting," Journal of chemical information and computer sciences, 44(1), 1-12.
- [198] Farrar, D. E., & Glauber, R. R. (1967). "Multicollinearity in regression analysis: the problem revisited," The Review of Economic and Statistics, 92-107.
- [199] Verleysen, M., & François, D. (2005, June). "The curse of dimensionality in data mining and time series prediction," In International work-conference on artificial neural networks (pp. 758-770). Berlin, Heidelberg: Springer Berlin Heidelberg.

4 Subtask B: Data-driven Modelling of Energy Storage Devices using machine learning

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Abbreviations:

- AI: Artificial Intelligence
- ANN: Artificial Neural Network
- CFD: Computational Fluid Dynamics
- FNN: Feedforward Neural Network
- GMDH: Group Method of Data Handling
- LSTM: Long Short-Term Memory
- ML: Machine Learning
- PCM: Phase Change Material
- Recurrent Neural Network: RNN
- RMSE: Root Mean Squared Error

4.1 Foreword: Online questionnaire

4.1.1 Introduction

The objective of subtask B is to analyze the numerical models developed at the component scale for optimization, design and control of energy storage systems integrated in buildings and districts. In order to carry out such analysis, a comprehensive and up-to-date set of information is mandatory. It was therefore decided to build a database gathering as much information as possible on recent or ongoing research works on energy storage systems, including (at least some) modeling attempts.

The resulting database would be freely available in SQLite format and, if deemed useful, would be made accessible to queries through a web interface. By using relevant queries, it would therefore become possible to reliably identify current trends or, to the contrary, unexplored paths in energy storage system modeling. Beside other aspects, questions of interest include the intended purpose of the developed models (design, control, optimization...), the chosen modeling strategy, and the strengths and weaknesses of the models.

4.1.2 Survey

To feed the database, we chose as a main source to compose and circulate an online survey. Since we wanted to be able to point out potential correlations between the modeled energy storage systems and some characteristics of the models, we chose to gather comprehensive information regarding the systems themselves such as storage technology, intended application, and key performance indicators. The survey is divided in five parts and contains 38 questions listed below. Single choice answers are inside curly braces; multiple choice answers are inside square brackets; optional questions are typeset in italics.

- GENERAL INFORMATION
 - First name
 - Last name
 - Affiliation
 - Email address
 - Project full name
 - Project acronym
 - Website
 - Start date
 - End date
 - Type of work [Experimental, Numerical]
 - Comments
- STORAGE TECHNOLOGY
 - Type of storage {Hot storage, Cold storage, Power storage, Other}
 - Physical phenomena {Sensible heat, Latent heat, Thermochemical, Electrochemical, Mechanical, Other}
 - Comments
- STORAGE APPLICATION
 - Storage integration [Individual dwelling, Dwelling unit, Tertiary building, Industrial building, District]
 - Temperatures (TES)
 - Source minimum temperature [$^{\circ}\text{C}$]
 - Source maximum temperature [$^{\circ}\text{C}$]
 - Source flow rate [m^3/h]
 - Nominal working temperature (storage medium) [$^{\circ}\text{C}$]
 - Reference indoor environment temperature [$^{\circ}\text{C}$]
 - Size of the whole component [m^3]
 - Duration of storage {Hours, Days, Seasonal}
 - Type of storage material
 - Quantity of storage material [kg]
 - Comments
- KEY PERFORMANCE INDICATORS (KPI)
 - Storage capacity
 - Total capacity [Wh]
 - Maximum useful capacity [Wh]
 - Recharging energy [Wh]
 - Maximum charge and discharge power
 - Maximum charge power [W]
 - Maximum discharge power [W]
 - Depth of discharge (DoD) [%]
 - Durability

- Specific cost [USD/kWh]
- Maximum self-discharge rate [%]
 - 1 h
 - 10 h
 - 100 h
 - 1000 h
- Stored energy factor [%]
- Generated savings
 - *Energy saving [kWh]*
 - *Cost saving [USD]*
 - *Reference period [days]*
- NUMERICAL MODELLING
 - Modelling objectives [Design, Control, Optimization, Understanding of physical phenomena, Other]
 - Modelling strategy [Physical PDE, Reduced order model, Statistical model, Machine learning, Other]
 - Model validation [Data from literature, Laboratory experiments, In situ experiments, Other]
 - *Validation data references (URL or DOI)*
 - *Model outcomes*
 - *Model strengths*
 - *Model weaknesses*
 - *Relevant references (URL or DOI)*

The survey was implemented using the Limesurvey platform hosted by INSA Lyon and is still available at <https://limesurvey.insa-lyon.fr/index.php?r=survey/index&sid=179787&lang=en>. It is expected to require 15 to 20 min to be filled. It was advertised during annex meetings and through emails to numerous members of the energy storage community.

4.1.3 Results

Despite being online for almost one year the survey had disappointingly little success. As of the time of this writing only about twenty questionnaires have been filled (at least partially but sufficiently to be significant). This is by far insufficient to draw any conclusion. Given the small volume of data it represents, answers will be saved in a simple CSV file. Despite the fact that such questionnaire seemed a reliable and efficient strategy to gather information, we must admit the failure of our attempt. As a result, we chose to resort to a literature review which should be a more effective way to gather information although it'll largely ignore ongoing research.

In recent years, probably because of an increasing workload in many countries, more and more academics became reluctant to get involved into voluntary (and possibly time-consuming) activities such as manuscript reviewing, as pointed out by many scientific journal editors. It seems that the developed survey suffered from the same trend and we should have reflected on some kind of incentive to get a significantly broader participation.

4.2 Introduction

4.2.1 Context

The global buildings sector consumes an estimated 30% of global energy, in the form of electricity and gaseous, liquid and solid fuels and district energy for building energy uses (e.g. heating, cooling, cooking, lighting and equipment), and is responsible for around 27% of global operational related CO₂ emissions [16]. It is clear that buildings play an important role in the objective of net zero carbon emission by 2050.

Energy storage has to play an important role in energy management and rationalization in the building sector by increasing renewable energy use [52], [36], [7] and [38]. To achieve the political goals for reducing CO₂ emissions, the optimal use of energy in buildings along with the electrification of the energy systems is becoming increasingly important. Local energy systems must respond to fluctuations with increasing flexibility by using storage systems.

4.2.2 Why and how

There are numerous approaches in research for the optimal use of storages, e.g., Rule-based Control (RBC), Model Predictive Control (MPC) or Adaptive Control (AC). Most of these methods depend on accurate and fast models of the dynamics of the system.

A major obstacle for the provision of equation based (white-box) models is the possible need for engineering services. Moreover, creating such models is, even for domain experts, a very time-consuming task, which must be executed after each change in the system. One approach to reduce the modelling effort and increase model accuracy is referred to as grey-box modelling. In grey-box modelling, comparatively simple mathematical equations are calibrated with data from tables or monitoring-data. The pure data-driven approach is referred to as black-box modelling [39, 48]. Here, the system dynamics are learned purely based on monitoring-data and only the inputs and outputs of the models are defined.

Due to the increasing availability of data, computing power, and algorithms from the field of machine-learning, black-box modelling has become more and more relevant in recent years. Some case study dealing with the use of artificial intelligence for heat storage in buildings can be found in [10]. A review on artificial intelligence for thermal energy storage is given in [40] and [23].

We propose in the Subtask B to review the existing literature on data-driven modelling of energy storage devices for buildings application.

4.3 Machine learning

The first use of “Artificial intelligence” (AI) was by computer scientist McCarthy in 1954. AI is the ability to mimic the cognitive functions of humans, such as learning and problem-solving which are distinct features of the human mind [47]. In recent years AI applications in energy systems have gained more focus [15].

Machine Learning (ML) is a branch of AI which focuses on learning and modifying the process or making new decisions based on newly acquired data. Basically, there are three types of machine learning: supervised learning, unsupervised learning, and reinforcement learning.

The main goal in supervised learning is to learn a model from labeled training data that allows us to

make predictions about unseen or future data. In this context, the term "supervised" signifies a compilation of training examples, comprising data inputs for which the corresponding desired output signals or labels are already provided. Thus, supervised learning encompasses the procedure of formulating a model that captures the underlying relationship between the given data inputs and their associated labels. When confronted with discrete class labels, as exemplified by tasks like email spam filtering, this type of supervised learning is termed a classification task. An additional subset of supervised learning is regression, in which the predicted outcome signal is a continuous values.

Another type of machine learning is known as reinforcement learning. Within the framework of reinforcement learning, the objective centers around crafting a system, often referred to as an agent, which enhances its own performance through engagements with its surrounding environment. Given that data regarding the ongoing state of the environment usually incorporates what is known as a "reward" signal, we can liken reinforcement learning to the domain of supervised learning to some extent. Nevertheless, in the context of reinforcement learning, this feedback doesn't serve as the accurate, definitive label or value, but rather as an assessment of the effectiveness of an action, as gauged by a reward function.

In supervised learning, we know the right answer (the label or target variable) beforehand when we train a model, and in reinforcement learning, we define a measure of reward for particular actions carried out by the agent. In unsupervised learning, however, we are dealing with unlabeled data or data of an unknown structure. Using unsupervised learning techniques, we are able to explore the structure of our data to extract meaningful information without the guidance of a known outcome variable or reward function. Clustering stands out as an approach within exploratory data analysis and pattern discovery, allowing us to categorize a wealth of information into coherent subsets, or clusters, without any foreknowledge of their group affiliations. Another facet of unsupervised learning pertains to dimensionality reduction. Frequently, our data exhibits high dimensionality, with each instance associated with an abundance of measurements. This can pose challenges in terms of storage capacity and the computational efficiency of machine learning algorithms. The realm of unsupervised dimensionality reduction offers a widely employed technique in feature preprocessing, geared towards eliminating noise from data that might otherwise impair the predictive capabilities of certain algorithms. This process involves condensing the data onto a lower-dimensional subspace while retaining the majority of pertinent information.

Figure 4.1 shows a typical workflow for using machine learning in predictive modeling [42].

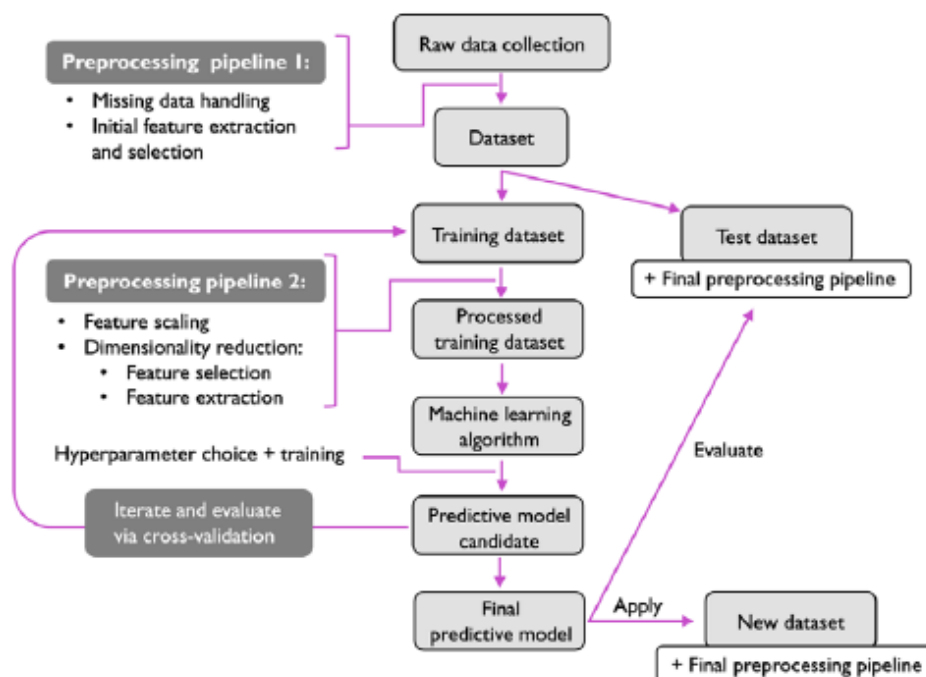


Figure 4.1: Predictive modeling workflow

Supervised ML for predictive modelling is the topic of this report. The most widely used learning algorithms for this application are:

- Regression
 - Linear regression
 - Linear discriminant analysis
 - Naive Bayes
 - Logistic regression
 - Support-vector machines
- Artificial neural network
 - Recurrent neural network
 - Elman networks and Jordan networks
 - Hopfield
 - Bidirectional associative memory
 - Echo state
 - Independently RNN (IndRNN)
 - Recursive
 - Neural history compressor
 - Second order RNNs
 - Long short-term memory
 - Gated recurrent unit
 - Bi-directional
 - Continuous-time

- Hierarchical recurrent neural network
- Recurrent multilayer perceptron network
- Multiple timescales model
- Neural Turing machines
- Differentiable neural computer
- Neural network pushdown automata
- Memristive Networks
- Feedforward Neural Network:
 - Linear neural network
 - Perceptron
 - Multilayer perceptron
- Convolutional Neural network: mainly used for image recognition
- Spiking neural network
- Bayesian neural network

Out of the various algorithms utilized in the field, the artificial neural network (see [Figure 4.2](#)) emerges as the most extensively employed. An artificial neural network, often abbreviated as ANN, operates by utilizing an assembly of interconnected units or nodes referred to as artificial neurons. These artificial neurons are a loose simulation of the neurons found in biological brains. Similar to the synapses in a biological brain, each connection in an ANN has the capacity to transmit a signal to other connected neurons. Upon receiving signals, an artificial neuron processes them, subsequently transmitting signals to its interconnected neurons. The nature of the "signal" coursing through a connection is represented by a real number, while the output of each neuron is determined through a non-linear function applied to the cumulative sum of its inputs. These connections are referred to as edges. Neurons and edges are typically assigned weights that are adjusted as the learning process unfolds. These weights serve to amplify or diminish the potency of the signal traversing a connection. Moreover, neurons may feature a threshold, ensuring that a signal is dispatched only when the cumulative signal surpasses said threshold.

Typically, neurons are aggregated into layers. Different layers may perform different transformations on their inputs. Signals travel from the first layer (the input layer), to the last layer (the output layer), possibly after traversing the layers multiple times.

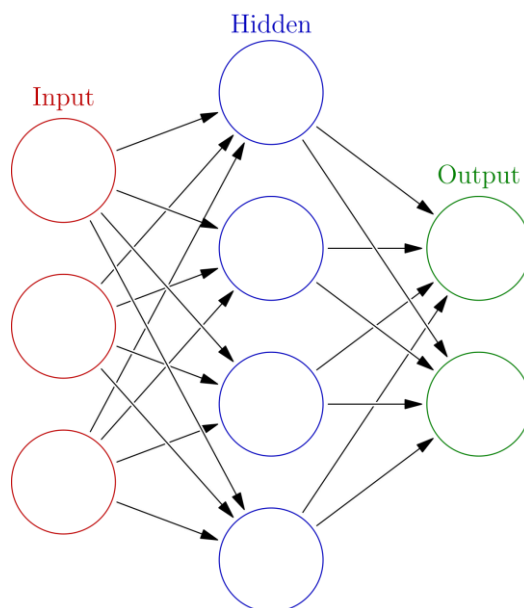


Figure 4.2: Schematic representation of an ANN – each circle is a neuron; arrows are a connection.

The bibliography on ANN shows there are two broad types of artificial neural network, characterized by direction of the flow of information between its layers:

- **Feedforward Neural Network:** It is the type where the flow of information is uni-directional, meaning that the information in the model flows in only one direction—forward—from the input nodes, through the hidden nodes and to the output nodes, without any cycles or loops
- **Recurrent neural network:** In contrast to uni-directional feedforward neural network, it is a bi-directional artificial neural network, meaning that it allows the output from some nodes to affect subsequent input to the same nodes.

The classification of Supervised ML is really important in order to 1) understand the possibilities given by this technique and 2) assess the gap between the state-of-the-art in energy storage and the state-of-the-art in ML.

4.4 Thermal energy storage systems

The following sections refer to the classification of heat storage by physical phenomena described in [33]. From a mathematical point of view, those phenomena lead to really different numerical model stiffness.

4.4.1 Sensible heat storage

The first attempt to use artificial neural network for systems including water tank is reported in 1999 [29]. The system under consideration is a solar domestic water heating system. The data were collected from tests carried out according to the Greek standard ELOT 879 for systems available to the Greek market. The data varied from collector areas between 1.81 and 4.38 m². Both open and closed systems were considered, supplied with vertical or horizontal water storage tanks. The outputs of the model are the useful energy extracted and the temperature rise in the stored water. The inputs are

the climate conditions, collector area, U-value, tank type, storage capacity and type. The feedforward ANN is implemented with three hidden slabs. Predictions within 7.1 % and 9.7 % are obtained useful energy extracted and temperature rise in the stored water. Similar application and model are also reported in [29] with an acceptable prediction capability for engineering applications.

The artificial neural network of a storage tank of a solar thermal system is developed in [21]. The model is based on the measured data of a domestic hot water system: flat-plate collector area of 1.65 m² and a solar storage tank, without electrical heater, of 0.15 m³. Measured data are gathered every minute during the period of July 5 – December 22, 2006. The model aims to estimate the temperature at different locations of a water storage tank with a five minutes resolution (i.e., thermal stratification). Inputs are mass flow rates of load and solar collector, solar irradiation and inlet temperature at the current timestep and the temperatures at the same locations at the previous timestep. The multi-layer perceptron ANN is implemented with the help of MATLAB Neural Network Toolbox. The model gives acceptable results inside the training interval as the average deviation was 0.22 °C during the training and 0.24 °C during the validation.

A solar thermal energy system is studied in [58] and ANN is used to predict the behaviour of the stratified heat storage water tank. The experimental system consists mainly of two flat-plate solar collectors, having a total surface area of 5.75 m², a thermally insulated vertical storage tank of 183-L capacity, a propane-fired tank of 189-L capacity as a source of auxiliary energy, an air handler unit, and a city water reservoir of 1000-L capacity. The experiments were conducted from March 2011 to December 2012, covering the seasons and weather condition. The quantities of interest are the ambient air temperature, the solar radiation on the horizontal and inclined planes and the preheat tank stratification temperatures T1–T6 at time $t - 1$. The outputs are the preheat tank stratification temperatures T1–T6, the heat input from the solar collectors through the heat exchanger into the system and the auxiliary heat input into the system by the propane-fired hot water tank. The neural network selected here is a multilayer feed-forward perceptron with one hidden layer. The Levenberg–Marquardt back-propagation algorithm is applied as the method for achieving fast optimisation. The preheat tank temperature predictions agreed very well with the experimental values using the testing data sets with mean relative errors in the range of 1.09–1.18 % and standard deviations of relative errors in the range of 1.04–1.87 %.

An earth air heat exchanger and seasonal storage system are under investigation in [2]. The system is composed series of two connected underground tanks coupled with a cooling floor. The cylindrical tanks are buried 3 m below ground level. Each tank was 2 m length, 1.2 m wide, and 2.5 m³ in volume. The experimental data are collected for thirteen days, starting from the 2nd of July 2015. The input data of the model are the outdoor temperature, outdoor humidity and the inlet temperature of the underground tank 1. The long-short-term-memory artificial neural network is chosen to evaluate the outlet underground tank temperature. It is worth mentioning that the training and validation dataset are the same. The results show that the mean squared error and the root means square error for the underground tank temperature are 0.165 and 0.406 respectively.

Thermal energy storage integrated into building energy systems is investigated in [34]. The experimental system is a scaled-down mock-up system for the comparative analysis of the performance of different control strategies for building energy systems that have a chilled water TES tank [35]. The system consisted of an air-source heat pump chiller, sensible TES tank, heat exchangers, and five variable-speed pumps. The quantities of interest are the water tank temperature, the temperatures of the top, middle and bottom TES tank layers, the chiller inlet and outlet temperatures, the chiller power consumption and pumps on the primary side. The inputs are the quantities of interest at the previous time-step, environmental temperatures and flowrates. The Neural Network Toolbox in

MATLAB R2020a is used to develop the AI model. The root mean square error values are less than 0.6 °C and 0.1 kW for temperature and power consumption predictions respectively on the validation dataset. It is worth mentioning that the ANN model is developed for predictive control of the system.

A physics-informed neural network for building thermal mass investigation is developed in [3]. In order to analyse the effect of thermal mass, two rooms with light and heavy thermal mass are experimentally investigated. The quantities of interest are the room temperature and thermal load demand while inputs are the outside air temperature and the states of room (temperature, AC system's action and thermal load demand) at the previous time step. The originality of the work lies in the development of a physics-informed neural network including building thermal dynamics modelling. Compared with pure data-driven model neural networks and physics-based grey-box model 2R2C, the developed hybrid model performs better in predicting thermal dynamics states with a lower prediction error of temperature (mean absolute error is less than 0.25 °C). It is also worth mentioning that the study also investigates demand response control.

Beside the use of experimental data to develop modelling of the system, some studies use physical numerical models (white-box) to derive black-box model with calculation results. For instance, [5] proposes to investigate a district cooling system with ice thermal energy storage (campus of Mississippi State University). The ice storage loop consists of a 1100-ton chiller, at the ice making setpoint temperature -5.0 °C, that is used to produce the ice in 54 ice storage modules totalling a capacity of 34,300 kW h of cooling. A numerical model is used to produce the required data. The quantities of interest are the electrical power of the plant and the ice storage heat transfer rate. The network used to model the performance is a simple feedforward network using hyperbolic activation functions due to the output of the scaled ice storage heat transfer being [-1, 1]. The final objective of the study is the optimal control of the system based on a genetic algorithm.

4.4.2 Latent heat storage

The first tentative of data based modelling of phase change heat storage is reported in [17]. The storage system is a finned tube in which ethyl-alcohol is flowing at low temperature at the inner side and water is solidifying on the outer surface of the tube. The experimental data are taken at three different inlet temperatures and six different Reynolds number. Thus, a total of 45 experimental runs are carried out. The inputs of the model are the heat transfer area, the Reynolds number, the heat transfer fluid inlet temperature and time. The calculated quantity of interest is the total thermal energy stored. A three-layer feed-forward back-propagation neural network is implemented in C++. The results show that 1) the black-box model presents a better agreement than the physical-based model of the system and 2) the model shows an absolute mean relative error of 5.58 % only.

A commercialised product manufactured by Sunamp Limited in the United Kingdom is investigated in [22]. The system comprises a dense tube-and-fin type heat exchanger made up of aluminium fins and a copper tube encased in a polymer housing. This heat exchanger is filled with a patented inorganic phase change material based on a sodium acetate trihydrate formula during the production process while in liquid form. Experimental data are collected, varying charging temperature and charging mass flow rate. The objective of the neural network model developed in this study is to approximate the outlet fluid temperature from the heat exchanger given two inputs 1) inlet fluid temperature and 2) the inlet mass flow rate. A layered digital dynamic neural network is developed using MATLAB toolbox. It is worth mentioning that the training dataset is different than the validation dataset. The coefficient of determination values for the different training and testing sets were calculated to be 0.999 and

0.889 respectively, for outlet temperature.

A solar chimney filled with phase change materials is the application studied in [19]. The experimental data come from in-situ real-scale measurements, more information can be found in [18]. The inputs are the absorber surface temperature recorded by sensors at 8 different heights while the output consists of four airflow temperatures at different heights. An ANN based on multi-layer perceptron is developed using MATLAB with the help of error backpropagation. The trained network has a high capability in predicting the process outputs; so that the average value of the relative errors, computed for the test data set, is 1.8326 %, and the maximum value of the relative error is 2.1546 %. However, it is worth mentioning that the inputs being measured temperatures, the model cannot be neither generalized nor used easily!

Phase change material mortars are experientially investigated in [41]. Paraffin, halloysite and ethylene glycol mixtures are tested from a mechanical point of view, but also from a thermodynamical aspect in an experimental building. The inputs of the model are the PCM type and the ambient air temperature. The output is the energy consumption of the air-conditioning unit. A hybrid Deep Neural Network algorithm, in which the learning algorithm was modified with Manta Ray Foraging Optimization Algorithm (MRFOA), is implemented. The training dataset is different from the validation dataset. The validation results show that the proposed model achieves an accuracy of 0.0159 root mean square error. It is worth mentioning that the neural network developed cannot be used in another room configuration.

Beside the use of experimental data to develop modelling of the system, some studies use physical numerical models (white-box) to derive black-box model with calculation results. These studies are presented hereafter.

In [13], a centralized latent heat thermal energy storage system integrated in a building mechanical ventilation system is investigated. The phase change material is paraffin RT20. A computational fluid dynamics model of the heat storage system is developed and validated in [14]. The quantity of interest is the outlet temperature from the storage system while the inputs are the heat transfer fluid, the inlet temperature, and the volume fraction. The authors chose to use feed forward group method of data handling artificial neural network. The ANN model allows a good prediction of the outlet air temperature with an impressive reduction of the computational cost compared to CFD.

Phase change material integrated in building walls is investigated in [32]. A TRNSYS numerical model is developed to evaluate the impact of PCM on the heating energy consumption. Input parameters are melting point, PCM thickness, PCM density, latent heat and thermal conductivity. The black-box is based on polynomial regression with the help of a design of experiments. Contrary to most of the literature, the black-box model is used to optimize the PCM based on existing materials database.

Phase change materials integrated in building walls are optimized in [1]. For that purpose, an ANN model is developed based on simulation carried using EnergyPlus software. It is worth mentioning that the building of interest is not a real house but the ASHRAE case 600. In this study, the quantities of interest are the heating and the cooling loads while the inputs are the thermal resistance of exterior walls, the melting temperature of PCM, the thickness of the PCM layer, the internal gain and infiltration rate. The authors chose to implement a group method of data handling artificial neural network. The heating and cooling loads root mean squared error are 0.003 kWh. The final use of the ANN model is an optimization of the PCM integrated in building walls.

A $40 \times 80 \times 80 \text{ mm}^3$ container with two enhanced heat transfer structures of fins and metal foam is filled with PCM in [6]. The experimental data are used to validate a physical-based numerical model.

The outputs of the ANN model are the liquid fraction and the average Nusselt number during the phase change process. The inputs are the melting time, the inclination number and the fin number. The authors developed an artificial neural network based on feed-forward multilayer perceptron. Excellent predictions of liquid fraction and the average Nusselt number are obtained by ANN with mean square errors of 9.6480×10^{-5} and 0.9990 respectively.

A water-PCM solar thermal storage system for domestic hot water application is studied in [12]. An experimentally validated numerical model for the system is used to generate the training and testing datasets for the ANN model. The quantity of interest is the solar fraction of the system while inputs are the collector area, the tank volume, the load temperature, the PCM melting temperature and the PCM volume fraction. A feed-forward multi-layer ANN type is chosen for this study. The optimized ANN model is then deployed to generate design maps for the system, offering accessible sizing and selection guidelines for the key design parameters: the storage tank volume, the PCM volume fraction and the PCM melting temperature. It is worth mentioning that the numerical model calculation time would be over 120 h compared to around 5 s using the ANN model.

PCM lauric acid heat storage system unit with vertical fins is studied in [8]. CFD simulations are carried for 16 cases with different fins geometries. The CFD model is validated using experimental data from the literature. The quantities of interest are liquid fraction and dimensionless stored energy while the input parameters are number of fins, dimensionless fin height, dimensionless fin spacing and Fourier number. The authors implemented a group method of data handling ANN algorithm. Training and testing dataset are different and comes from the CFD model. The proposed GMDH type of ANN predicted the thermal behavior of the storage enclosures with high accuracy. The RMSEs of liquid fraction and stored energy for test data were 0.0166 and 0.0180 respectively.

A paraffin wax multi-channel tank with metal foam is studied in [56]. HTF inlet velocity, temperature and time are employed as input data while the output is liquid fraction and temperatures. A long short-term memory back propagation neural network is chosen for the black-box modelling. The training and validation dataset are the same. The results show the correctness and reliability of the neural network.

It is also worth mentioning that neural network can be used at the material scale to predict the properties of phase change material mixtures [54], to enhance material characterization [43], to predict the thermal conductivity of carbon-based nano-enhanced PCMs [50], to predict eutectic salts properties [53].

4.4.3 Physical sorption heat storage

A high-energy-density reactor made with 40 kg of zeolite is studied in [9]. It is an open system. Experimental data are covering different ranges of hydration and dehydration temperatures, relative humidities and flow rates. The calculated quantity of interest is the outlet temperature while the input are the inlet temperature, flowrate and relative humidity. A recurrent neural network is chosen and implemented with MATLAB Deep Learning Toolbox. The results show that the model can predict the temperature evolution with a good agreement (RMSE lower than 3 K for a temperature increase of 90 K to 40 K). It is worth mentioning that, once trained, the calculation is nearly instantaneous while the physical model of the same system requires several hours!

The field of sorption cooling is also interesting to mention as the physical phenomena are identical to heat storage. A recent study from [27] addresses the use of neural networks for predicting the performance of solid desiccant cooling systems. Concerning sorption chillers, [20] developed different neural network models to predict the performance of different sorption chillers. Similarly, [26] studied

a solar-based absorption chiller cooling system, as well as in [44].

It is also worth mentioning that neural network can be used at the material scale to predict the properties of sorption material mixtures [4].

4.4.4 Chemical sorption heat storage

A study on a potassium carbonate (K_2CO_3) based complete open heat storage system was conducted in [46]. The experiments are conducted with the aim to evaluate the neural networks model under events that the sorption reactor could experience: temperature step, concentration step and real conditions. The model is designed to predict the state of charge and reactor outlet temperature evolution given the inlet reactor temperature and water vapor concentration. A model based on two neural networks architectures, a nonlinear autoregressive neural network with exogenous inputs for the prediction of the state of charge and a feedforward neural network for the prediction of the outlet temperature. The need of two different autoregressive architectures is justified by the inputs required to estimate the state of charge and outlet temperature. The model demonstrated good capabilities in predicting the dynamic evolution of the outputs for several hydration and dehydration tests, with mean squared error estimators for the state of charge and outlet temperature below 2×10^{-3} and $50^\circ C$ respectively.

It is also worth mentioning that ML can be used at the material scale to predict the properties of materials [51].

4.5 Global analysis

The number of existing ML algorithms is huge as hinted in section 4.3. but only a few algorithms are used in energy storage modelling (see Table 4.1). Two main points come to mind when observing this table. Firstly, most of the reviewed works rely on feed-forward neural networks (mainly multi-layer perceptrons). Secondly, all but one trained networks are shallow with at most 3 hidden layers.

Regarding the first point, the situation makes sense because most of the desired outputs in these studies are time-independent quantities. However a closer inspection shows that these quantities of interest are most often end values of inherently time-dependent variables. Concerning the second point, it seems that the modelling goals are usually modest enough for a simple (or even simplistic) architecture to perform in a quite satisfactory manner. One possible explanation for this situation is the common use of general ML toolboxes by non-specialists which leads more than often to default choices in terms of algorithms and architectures. The failure for some authors to follow sound training protocols, such as the absence of validation data, speaks in favour of this explanation.

We therefore trust there's ample room for improvement by exploring the vast number of well-acknowledged ML algorithms as well as deep learning approaches which are now accessible even to personal computers. As mentioned before, energy storage systems are inherently time-dependent. Hence, instead of focusing on some fixed characteristics, it would be beneficial to conceive ANNs as digital twins reproducing as much as possible of the behaviour of the storage system. Although challenging, approaches to tackle these challenges are already at hand. Beside other algorithms, recurrent neural networks are especially well-suited for such modelling task. RNNs are particularly effective for handling sequential data like time series due to their ability to retain contextual information through recurrent connections. Constructing a recurrent neural network from raw time series data is a multi-step process that involves data preprocessing, model architecture design, training, and evaluation. Therefore the implementation of a RNN requires significantly more care than for a

simple perceptron

To exemplify our last remark, we summarize below the recommended steps to create a RNN:

- **Data Preprocessing:** The first step is to prepare the raw time series data for input into the RNN. This involves tasks like data cleaning, normalization, and splitting into training, validation, and test sets. Normalization is essential to scale the data within a certain range to improve convergence during training.
- **Data Representation:** Time series data is often represented as a sequence of values over time. Depending on the complexity of the data and the task at hand, one might choose a univariate (single feature) or multivariate (multiple features) representation.
- **Sequence Creation:** The time series data needs to be transformed into sequences that the RNN can process. This is done by creating overlapping windows of data points with a certain sequence length.
- **Feature Engineering:** In addition to the raw data, one might want to include additional features or lagged values as inputs to enhance the model's performance. These could capture trends, seasonal patterns, or other relevant information.
- **Model Architecture Design:** Designing the RNN architecture is a critical step. Usual options include Simple RNN, LSTM (Long Short-Term Memory), and GRU (Gated Recurrent Unit). LSTMs and GRUs are popular choices due to their ability to handle long-range dependencies and mitigate the vanishing gradient problem.
- **Model Configuration:** Set the hyperparameters of the RNN, including the number of hidden units, the number of layers, dropout rates (to prevent overfitting), and the activation functions. The output layer's configuration will depend on the specific task – regression, classification, or forecasting.
- **Model Compilation:** Compile the RNN by specifying the loss function, optimization algorithm (e.g., Adam, RMSProp), and evaluation metrics. The loss function depends on the task: Mean Squared Error (MSE) for regression, and categorical or binary cross-entropy for classification.
- **Training:** Train the RNN using the training data sequences. During training, the model's parameters are adjusted to minimize the chosen loss function. Monitor the validation loss to detect overfitting and make adjustments accordingly.
- **Evaluation:** Once the training is complete, evaluate the RNN's performance on the test set. Calculate appropriate metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), or accuracy, depending on the task.
- **Fine-Tuning:** Depending on the evaluation results, one might need to fine-tune the model. This could involve adjusting hyperparameters, adding regularization, modifying the architecture, or revisiting data preprocessing steps.
- **Prediction and Visualization:** Use the trained RNN to make predictions on new, unseen time series data. Visualize the model's predictions against the ground truth to assess its effectiveness in capturing patterns and trends.

Table 4.1: Summary of ANN algorithm used in the bibliography

Ref	Type	Algorithm	Nb Layers	Remarks
Kalogirou et al., 1999 [29]	sensible	FNN	3 hidden slabs of 18 neurons each	Justif. by works of the authors
Géczy-Víg and Farkas, 2010 [21]	sensible	Multi-layer-perceptron	2 layers of 8 neurons	Algorithm justification Hoccoğlu et al., 2008 [24]
Yaïci and Entchev, 2014 [58]	sensible	Multi-layer-perceptron	1 layer of 20 neurons each	No justification
Benzaama et al., 2022 [2]	sensible	LSTM	?	No justification
Lee et al., 2022 [34]	sensible	?	2 hidden layers of 30 neurons each	No justification
Chen et al., 2023 [3]	sensible	Physics-informed Neural Networks	2 hidden layers of 64 neurons each	Wang and Hong, 2020 [55]
Cox et al., 2019 [5]	sensible	FNN	2 hidden layers	?
Ermis et al., 2007 [17]	latent	FNN	2 hidden layers of 8, 13 and 18 hidden neurons	Sablani et al., 2005 [45]
Ghani et al., 2018 [22]	latent	Multi-layer-perceptron	3 hidden layers of 11 hidden neurons	Medsker, 2000 [37]
Fadaei et al., 2018b [19]	latent	Multi-layer-perceptron	2 hidden layers of 4 and 5 neurons respectively	?
Rajesh and Mekala, 2023 [41]	latent	Manta Ray Foraging Optimization algorithm	2 hidden layers of 30 hidden neurons	Karaci et al., 2019 [30]
El-Sawi et al., 2014 [14]	latent	FNN group method of data handling	?	?
Bagheri-Esfah et al., 2020 [1]	latent	FNN group method of data handling	2 hidden layers	Kumar et al., 2013 [31]
Cui et al., 2022 [6]	latent	Multi-layer-perceptron	1 hidden layer of 10/12 hidden neurons	?

Eldokaishi et al., 2022 [12]	latent	FNN	3 hidden layers of 50 hidden neurons	Svozil et al., 1997 [49]
Darvishvand et al., 2022 [8]	latent	FNN group method of data handling	?	Ebtehaj et al., 2015 [11]
Xiao et al., 2023 [56]	latent	LSTM Backpropagation	?	Xu et al., 2022 [57]
Delmarre et al., 2021 [9]	physical sorption	LSTM	200 hidden layers	Hochreiter and Schmidhuber, 1997 [25]
Scapino et al., 2019 [46]	chemical sorption	nonlinear autoregressive network & FNN	SOC: 1 layer and 10/20 neurons; outlet temperature 3/4 layers 25/7 neurons	Bibliography

4.6 Main conclusions

- The current practise in energy storage modelling is far from unleashing the potential of contemporary machine learning. This situation is probably caused by the lack of the expertise needed to implement state-of-the-art ML techniques in the energy storage community. This time, we did not have enough data, but there is a credible expectation of actual benefits in subsequent practical application coming from trying these techniques.
- Few works have been developed for physical and chemical sorption while this technology is promising and requires an exact control of the system. Moreover, white-box approaches to this kind of systems are often limited since they lead to stiff differential systems, whereas ANN are extremely well suited to handle highly non-linear problems.
- ML is usually used for model prediction while many uses should be also regarded like real-time self-learning, anomaly detection, data-mining...
- More information is needed to match the system modelled and the ML algorithm.

4.7 References

- [1] Bagheri-Esfah, H., Safikhani, H., Motahar, S., 2020. Multi-objective optimization of cooling and heating loads in residential buildings integrated with phase change materials using the artificial neural network and genetic algorithm. *Journal of Energy Storage* 32, 101772. <https://doi.org/10.1016/j.est.2020.101772>
- [2] Benzaama, M.H., Menhoudj, S., Mokhtari, A.M., Lachi, M., 2022. Comparative study of the thermal performance of an earth air heat exchanger and seasonal storage systems: Experimental validation of Artificial Neural Networks model. *Journal of Energy Storage* 53, 105177. <https://doi.org/10.1016/j.est.2022.105177>
- [3] Chen, Y., Yang, Q., Chen, Z., Yan, C., Zeng, S., Dai, M., 2023. Physics-informed neural networks for building thermal modeling and demand response control. *Building and Environment* 234, 110149. <https://doi.org/10.1016/j.buildenv.2023.110149>
- [4] Çolak, A.B., Aydin, D., Al-Ghosini, A., Dalkilic, A.S., 2022. Discharging performance prediction of experimentally tested sorption heat storage materials with machine learning method. *Journal of Energy Storage* 56, 106159. <https://doi.org/10.1016/j.est.2022.106159>
- [5] Cox, S.J., Kim, D., Cho, H., Mago, P., 2019. Real time optimal control of district cooling system with thermal energy storage using neural networks. *Applied Energy* 238, 466–480. <https://doi.org/10.1016/j.apenergy.2019.01.093>
- [6] Cui, W., Si, T., Li, Xiangxuan, Li, Xinyi, Lu, L., Ma, T., Wang, Q., 2022. Heat transfer analysis of phase change material composited with metal foam-fin hybrid structure in inclination container by numerical simulation and artificial neural network. *Energy Reports* 8, 10203–10218. <https://doi.org/10.1016/j.egyr.2022.07.178>
- [7] D'Agostino, D., Mazzarella, L., 2019. What is a Nearly zero energy building? Overview, implementation and comparison of definitions. *Journal of Building Engineering* 21, 200–212. <https://doi.org/10.1016/j.jobbe.2018.10.019>
- [8] Darvishvand, L., Safari, V., Kamkari, B., Alamshenas, M., Afrand, M., 2022. Machine learning-based prediction of transient latent heat thermal storage in finned enclosures using group method of data handling approach: A numerical simulation. *Engineering Analysis with Boundary Elements* 143, 61–77. <https://doi.org/10.1016/j.enganabound.2022.06.009>
- [9] Delmarre, C., Resmond, M.-A., Kuznik, F., Obrecht, C., Chen, B., Johannes, K., 2021. Artificial Neural Network Simulation of Energetic Performance for Sorption Thermal Energy Storage Reactors. *Energies* 14, 3294. <https://doi.org/10.3390/en14113294>
- [10] Dincer, I., Erdemir, D., 2021. Chapter 6 - Artificial Intelligence in Heat Storage Applications, in: Dincer, I., Erdemir, D. (Eds.), *Heat Storage Systems for Buildings*. Elsevier, pp. 263–286. <https://doi.org/10.1016/B978-0-12-823572-0.00001-1>
- [11] Ebtehaj, I., Bonakdari, H., Zaji, A.H., Azimi, H., Khoshbin, F., 2015. GMDH-type neural network approach for modeling the discharge coefficient of rectangular sharp-crested side weirs. *Engineering Science and Technology, an International Journal* 18, 746–757. <https://doi.org/10.1016/j.jestch.2015.04.012>
- [12] Eldokaishi, A.O., Abdelsalam, M.Y., Kamal, M.M., Abotaleb, H.A., 2022. Modeling of water-PCM solar thermal storage system for domestic hot water application using Artificial neural networks. *Applied Thermal Engineering* 204, 118009.

- <https://doi.org/10.1016/j.applthermaleng.2021.118009>
- [13] El-Sawi, A., Haghighat, F., Akbari, H., 2014. Assessing long-term performance of centralized thermal energy storage system. *Applied Thermal Engineering* 62, 313–321. <https://doi.org/10.1016/j.applthermaleng.2013.09.047>
 - [14] El-Sawi, A., Haghighat, F., Akbari, H., 2013. Centralized latent heat thermal energy storage system: Model development and validation. *Energy and Buildings* 65, 260–271. <https://doi.org/10.1016/j.enbuild.2013.05.027>
 - [15] Entezari, A., Aslani, A., Zahedi, R., Noorollahi, Y., 2023. Artificial intelligence and machine learning in energy systems: A bibliographic perspective. *Energy Strategy Reviews* 45, 101017. <https://doi.org/10.1016/j.esr.2022.101017>
 - [16] Environment, U.N., 2022. 2022 Global Status Report for Buildings and Construction [WWW Document]. UNEP - UN Environment Programme. URL <http://www.unep.org/resources/publication/2022-global-status-report-buildings-and-construction> (accessed 8.22.23).
 - [17] Ermis, K., Erek, A., Dincer, I., 2007. Heat transfer analysis of phase change process in a finned-tube thermal energy storage system using artificial neural network. *International Journal of Heat and Mass Transfer* 50, 3163–3175. <https://doi.org/10.1016/j.ijheatmasstransfer.2006.12.017>
 - [18] Fadaei, N., Kasaeian, A., Akbarzadeh, A., Hashemabadi, S.H., 2018a. Experimental investigation of solar chimney with phase change material (PCM). *Renewable Energy* 123, 26–35. <https://doi.org/10.1016/j.renene.2018.01.122>
 - [19] Fadaei, N., Yan, W.-M., Mahdi Taffarj, M., Kasaeian, A., 2018b. The application of artificial neural networks to predict the performance of solar chimney filled with phase change materials. *Energy Conversion and Management* 171, 1255–1262. <https://doi.org/10.1016/j.enconman.2018.06.055>
 - [20] Frey, P., Fischer, S., Drück, H., 2014. Artificial Neural Network modelling of sorption chillers. *Solar Energy* 108, 525–537. <https://doi.org/10.1016/j.solener.2014.08.006>
 - [21] Géczy-Víg, P., Farkas, I., 2010. Neural network modelling of thermal stratification in a solar DHW storage. *Solar Energy* 84, 801–806. <https://doi.org/10.1016/j.solener.2010.02.003>
 - [22] Ghani, F., Waser, R., O'Donovan, T.S., Schuetz, P., Zaglio, M., Wortischek, J., 2018. Non-linear system identification of a latent heat thermal energy storage system. *Applied Thermal Engineering* 134, 585–593. <https://doi.org/10.1016/j.applthermaleng.2018.02.035>
 - [23] He, Z., Guo, W., Zhang, P., 2022. Performance prediction, optimal design and operational control of thermal energy storage using artificial intelligence methods. *Renewable and Sustainable Energy Reviews* 156, 111977. <https://doi.org/10.1016/j.rser.2021.111977>
 - [24] Hocaoglu, F.O., Gerek, Ö.N., Kurban, M., 2008. Hourly solar radiation forecasting using optimal coefficient 2-D linear filters and feed-forward neural networks. *Solar Energy* 82, 714–726. <https://doi.org/10.1016/j.solener.2008.02.003>
 - [25] Hochreiter, S., Schmidhuber, J., 1997. Long Short-Term Memory. *Neural Comput.* 9, 1735–1780. <https://doi.org/10.1162/neco.1997.9.8.1735>
 - [26] Hosseini, P., 2022. Deep-learning neural network prediction of a solar-based absorption chiller cooling system performance using waste heat. *Sustainable Energy Technologies and*

- Assessments 53, 102683. <https://doi.org/10.1016/j.seta.2022.102683>
- [27] Jani, D.B., Mishra, M., Sahoo, P.K., 2017. Application of artificial neural network for predicting performance of solid desiccant cooling systems – A review. *Renewable and Sustainable Energy Reviews* 80, 352–366. <https://doi.org/10.1016/j.rser.2017.05.169>
 - [28] Kalogirou, S.A., Panteliou, S., 2000. Thermosiphon solar domestic water heating systems: long-term performance prediction using artificial neural networks. *Solar Energy* 69, 163–174. [https://doi.org/10.1016/S0038-092X\(00\)00058-X](https://doi.org/10.1016/S0038-092X(00)00058-X)
 - [29] Kalogirou, S.A., Panteliou, S., Dentsoras, A., 1999. MODELING OF SOLAR DOMESTIC WATER HEATING SYSTEMS USING ARTIFICIAL NEURAL NETWORKS. *Solar Energy* 65, 335–342. [https://doi.org/10.1016/S0038-092X\(99\)00013-4](https://doi.org/10.1016/S0038-092X(99)00013-4)
 - [30] Karaci, A., Yaprak, H., Ozkaraca, O., Demir, I., Simsek, O., 2019. Estimating the Properties of Ground-Waste-Brick Mortars Using DNN and ANN. *CMES* 118, 207–228. <https://doi.org/10.31614/cmcs.2019.04216>
 - [31] Kumar, R., Aggarwal, R.K., Sharma, J.D., 2013. Energy analysis of a building using artificial neural network: A review. *Energy and Buildings* 65, 352–358. <https://doi.org/10.1016/j.enbuild.2013.06.007>
 - [32] Kuznik, F., Arzamendia Lopez, J.P., Baillis, D., Johannes, K., 2015. Phase change material wall optimization for heating using metamodeling. *Energy and Buildings, SI: IEA-ECES Annex 31 Special Issue on Thermal Energy Storage* 106, 216–224. <https://doi.org/10.1016/j.enbuild.2015.06.021>
 - [33] Kuznik, F., Johannes, K., 2020. Thermodynamic Efficiency of Water Vapor/Solid Chemical Sorption Heat Storage for Buildings: Theoretical Limits and Integration Considerations. *Applied Sciences* 10, 489. <https://doi.org/10.3390/app10020489>
 - [34] Lee, D., Ooka, R., Matsuda, Y., Ikeda, S., Choi, W., 2022. Experimental analysis of artificial intelligence-based model predictive control for thermal energy storage under different cooling load conditions. *Sustainable Cities and Society* 79, 103700. <https://doi.org/10.1016/j.scs.2022.103700>
 - [35] Lee, D., Ooka, R., Matsuda, Y., Ikeda, S., Choi, W., 2021. Experimental Investigation of Model Predictive Control for Thermal Energy Storage System Using Artificial Intelligence, in: 2021 29th Mediterranean Conference on Control and Automation (MED). Presented at the 2021 29th Mediterranean Conference on Control and Automation (MED), pp. 961–966. <https://doi.org/10.1109/MED51440.2021.9480324>
 - [36] Lizana, J., Chacartegui, R., Barrios-Padura, A., Valverde, J.M., 2017. Advances in thermal energy storage materials and their applications towards zero energy buildings: A critical review. *Applied Energy* 203, 219–239. <https://doi.org/10.1016/j.apenergy.2017.06.008>
 - [37] Medsker, L., 2000. *Recurrent Neural Networks: Design and Applications*. CRC-Press.
 - [38] Mofidi, F., Akbari, H., 2020. Intelligent buildings: An overview. *Energy and Buildings* 223, 110192. <https://doi.org/10.1016/j.enbuild.2020.110192>
 - [39] Montáns, F.J., Chinesta, F., Gómez-Bombarelli, R., Kutz, J.N., 2019. Data-driven modeling and learning in science and engineering. *Comptes Rendus Mécanique, Data-Based Engineering Science and Technology* 347, 845–855. <https://doi.org/10.1016/j.crme.2019.11.009>

- [40] Olabi, A.G., Abdelghafar, A.A., Maghrabie, H.M., Sayed, E.T., Rezk, H., Radi, M.A., Obaideen, K., Abdelkareem, M.A., 2023. Application of artificial intelligence for prediction, optimization, and control of thermal energy storage systems. *Thermal Science and Engineering Progress* 39, 101730. <https://doi.org/10.1016/j.tsep.2023.101730>
- [41] Rajesh, B., Mekala, C., 2023. Experimental investigation of influence of phase change materials in energy consumption of air-conditioning units and prediction performance evaluation of modified deep neural network model. *Construction and Building Materials* 389, 131582. <https://doi.org/10.1016/j.conbuildmat.2023.131582>
- [42] Raschka, S., Liu, Y. (Hayden), Mirjalili, V., Dzhulgakov, D., 2022. Machine Learning with PyTorch and Scikit-Learn: Develop Machine Learning and Deep Learning Models with Python. Packt Publishing.
- [43] Ren, G., Chuttar, A., Banerjee, D., 2022. Exploring efficacy of machine learning (artificial neural networks) for enhancing reliability of thermal energy storage platforms utilizing phase change materials. *International Journal of Heat and Mass Transfer* 189, 122628. <https://doi.org/10.1016/j.ijheatmasstransfer.2022.122628>
- [44] Rosiek, S., Batlles, F.J., 2011. Performance study of solar-assisted air-conditioning system provided with storage tanks using artificial neural networks. *International Journal of Refrigeration* 34, 1446–1454. <https://doi.org/10.1016/j.ijrefrig.2011.05.003>
- [45] Sablani, S.S., Kacimov, A., Perret, J., Mujumdar, A.S., Campo, A., 2005. Non-iterative estimation of heat transfer coefficients using artificial neural network models. *International Journal of Heat and Mass Transfer* 48, 665–679. <https://doi.org/10.1016/j.ijheatmasstransfer.2004.09.005>
- [46] Scapino, L., Zondag, H.A., Diriken, J., Rindt, C.C.M., Van Bael, J., Sciacovelli, A., 2019. Modeling the performance of a sorption thermal energy storage reactor using artificial neural networks. *Applied Energy* 253, 113525. <https://doi.org/10.1016/j.apenergy.2019.113525>
- [47] Schalkoff, R.J., 1990. Artificial Intelligence: An Engineering Approach. McGraw-Hill.
- [48] Schreiber, T., Netsch, C., Eschweiler, S., Wang, T., Storek, T., Baranski, M., Müller, D., 2021. Application of data-driven methods for energy system modelling demonstrated on an adaptive cooling supply system. *Energy* 230, 120894. <https://doi.org/10.1016/j.energy.2021.120894>
- [49] Svozil, D., Kvasnicka, V., Pospichal, J., 1997. Introduction to multi-layer feed-forward neural networks. *Chemometrics and Intelligent Laboratory Systems* 39, 43–62. [https://doi.org/10.1016/S0169-7439\(97\)00061-0](https://doi.org/10.1016/S0169-7439(97)00061-0)
- [50] Taheri, M., Pourfayaz, F., Hemmati, S., 2023. A highly accurate model for prediction of thermal conductivity of carbon-based nano-enhanced PCMs using an artificial neural network. *Energy Reports* 10, 1249–1258. <https://doi.org/10.1016/j.egyr.2023.07.058>
- [51] Tasneem, S., Sultan, H.S., Ageeli, A.A., Togun, H., Alamier, W.M., Hasan, N., Safaei, M.R., 2023. Machine learning modeling of reversible thermochemical reactions applicable in energy storage systems. *Journal of the Taiwan Institute of Chemical Engineers, Optimisation in Energy and Process Engineering* 148, 104926. <https://doi.org/10.1016/j.jtice.2023.104926>
- [52] Technology Roadmap - Energy Storage – Analysis [WWW Document], n.d. . IEA. URL <https://www.iea.org/reports/technology-roadmap-energy-storage> (accessed 8.22.23).
- [53] Tian, Y., Liu, X., Zhang, L., Luo, Q., Xu, Q., Yao, H., Yang, F., Wang, J., Dang, C., Xuan, Y., 2022. Prediction of thermophysical properties of chlorine eutectic salts via artificial neural network

- combined with polar bear optimization. *Journal of Energy Storage* 55, 105658. <https://doi.org/10.1016/j.est.2022.105658>
- [54] V, M.G., D, R.S., 2022. A comprehensive investigation and artificial neural network modeling of shape stabilized composite phase change material for solar thermal energy storage. *Journal of Energy Storage* 48, 103992. <https://doi.org/10.1016/j.est.2022.103992>
- [55] Wang, Z., Hong, T., 2020. Reinforcement learning for building controls: The opportunities and challenges. *Applied Energy* 269, 115036. <https://doi.org/10.1016/j.apenergy.2020.115036>
- [56] Xiao, T., Liu, Z., Lu, L., Han, H., Huang, X., Song, X., Yang, X., Meng, X., 2023. LSTM-BP neural network analysis on solid-liquid phase change in a multi-channel thermal storage tank. *Engineering Analysis with Boundary Elements* 146, 226–240. <https://doi.org/10.1016/j.enganabound.2022.10.014>
- [57] Xu, F., Xu, X., Sun, Y., Li, J., Dong, G., Wang, Y., Li, H., Wang, L., Zhang, Y., Pang, S., Yin, S., 2022. A framework for motor imagery with LSTM neural network. *Computer Methods and Programs in Biomedicine* 218, 106692. <https://doi.org/10.1016/j.cmpb.2022.106692>
- [58] Yaïci, W., Entchev, E., 2014. Performance prediction of a solar thermal energy system using artificial neural networks. *Applied Thermal Engineering* 73, 1348–1359. <https://doi.org/10.1016/j.applthermaleng.2014.07.040>

5 Subtask C: Smart Design/Integration Methodology for Energy Storage System

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5.1 Abstract

Recent research studies have focused on the optimal design of Thermal Energy Storage (TES) systems for different plants and processes, utilizing advanced optimization techniques. There are a wide range of TES technologies that can be integrated into a variety of thermal applications. Each TES technology has its own technical and economic characteristics that make it essentially suitable for a specific application. Identifying important factors and then matching an application with the most appropriate TES system is still a challenging issue. Subtask C discusses the challenges in identifying the most appropriate Thermal Energy Storage (TES) system for a specific application due to the technical and economic characteristics of each TES technology. A seven-step design methodology is proposed that can guide the process from describing the thermal process to defining the TES geometry based on the requirements and constraints of the thermal application. The steps in the proposed methodology include specifying the thermal process, thermal demand, storage technology, integration parameters, key performance indicators, optimization method, and optimization tools. The proposed methodology is implemented in seven different case studies to demonstrate its effectiveness in identifying the most appropriate TES system for a specific application. Although the case studies involve various types of applications with both sensible and latent thermal energy storage systems, the proposed design procedure is applicable. The design steps proposed in this subtask can serve as a foundation for developing a systematic approach for designing TES systems in future works.

5.2 Introduction

Buildings account for 30% of total global final energy use and 27% of all global greenhouse gas emissions [1]. Most of this energy use and greenhouse gas (GHG) emissions are related to the operation of heating and cooling systems [2], which play a vital role in buildings as they maintain a satisfactory indoor climate for the occupants.

One way to reduce the environmental impact of buildings is to integrate renewable energy sources into heating and cooling building systems. However, renewable energy sources are often intermittent, creating a time delay between energy production and demand. For example, technology such as solar collectors are only productive during the day, when domestic heating demand is at its lowest.

Thermal energy storage (TES) is a way of addressing the mismatch in supply and demand between renewable resources and energy demand. TES is a technology in which thermal energy is stored as a change in internal energy of a material to be used at a later time for heating and cooling applications [3]. Among the advantages of TES are the increase in overall efficiency and better reliability when applied in an energy system, leading to reductions in investment and operating costs, as well as reductions in GHG emissions [4] [5]. As shown in Figure 5.1, TES technologies are typically classified in three categories: sensible, latent, and thermo-chemical [6].

In sensible heat storage, thermal energy is stored by varying the temperature of the storage medium. In latent heat storage system, heat is absorbed or released in correspondence of phase change in the storage medium. Finally, in thermo-chemical storage, thermal energy is stored and retrieved by breaking and reforming molecular bonds in reversible chemical reactions [3]. Each thermal energy storage technology has its advantages and disadvantages. Sensible TES is simple and widely demonstrated, but it suffers from low energy storage density. On the other hand, thermo-chemical TES can reach high energy storage density, but this technology is still under development due to technical challenges [7].

A lot of work is being carried out in the field of thermal energy storage for buildings and several review articles have been published on the subject [8][9]. The integration of TES in building systems can bring benefits in terms of energy efficiency, increased contribution of renewable energy and peak load reduction. As shown in Figure 5.2, TES in buildings can be divided into two major categories, passive and active storage. For passive storage, the driving force for charging and discharging is only the temperature difference between the store and the surroundings. In the case of an active storage, the charging and discharging occurs with active help from pumps or fans [10].

As shown in Figure 5.2, various technologies of TES systems with different thermal properties can be utilized in buildings. On the other hand, there are various types of building requiring the integration of TES systems for different purposes e.g. increasing energy efficiency or reducing energy costs and GHG emissions. Hence, an effective design of TES system, i.e. choosing a proper TES technology with a proper size which meets the application-specific requirements can be a complex and challenging task and it depends on several factors.

In a simple traditional design, the size of the storage system can be calculated for the worst-case scenario. However, this leads to an oversized estimation of the needed capacity. Optimal design of TES systems for various plants and processes using advanced optimization techniques is a subject of many recent research studies and has received considerable attention in the literature.

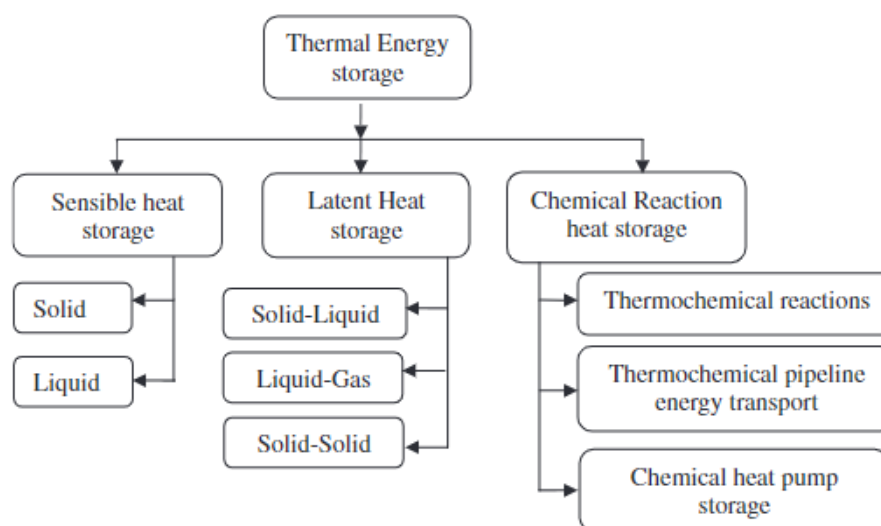


Figure 5.1: Classification of thermal storage technologies [6]

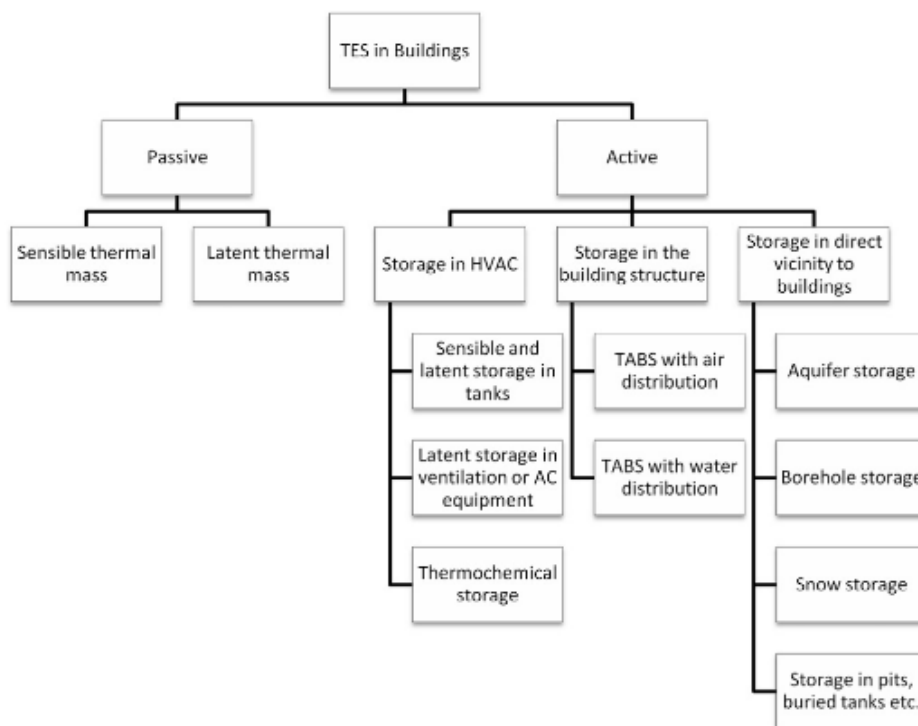


Figure 5.2: Classification of TES in buildings

The optimal design of TES can be categorized according to the level at which the optimization occurs. Some of the studies only focus on the optimization of the storage design either at component level or at system level, whereas other studies also consider the optimization of the plant operation, where the storage system will be integrated. Depending on the level of design, there are different requirements that should be considered. For instance, in [11] TES design considerations for a solar power plant at different levels have been reviewed. At the component level, the focus of the design is on the basic components of the TES, whereas at the system level, the integration of storage components with other systems e.g., pumps, heat exchanger and control systems should be considered. The plant level design focuses on the plant requirements, e.g., improving annual capacity factor of a solar power plant.

When the integration of the TES into a plant is considered, the optimal design can be categorized according to the application, whether it is a retrofit application or a greenfield application [12]. The former examines the integration of the TES into a plant which already exists, whereas the latter is about the design of TES in parallel with the rest of the plant from the beginning of the plant design. Depending on whether it is a retrofit or a greenfield application, the optimal TES technology can be different for that application. For instance, TES systems integrated in the building structure such as walls, floor and ceiling might better fit with greenfield applications. Figure 5.3 shows a general classification of TES design methodology.

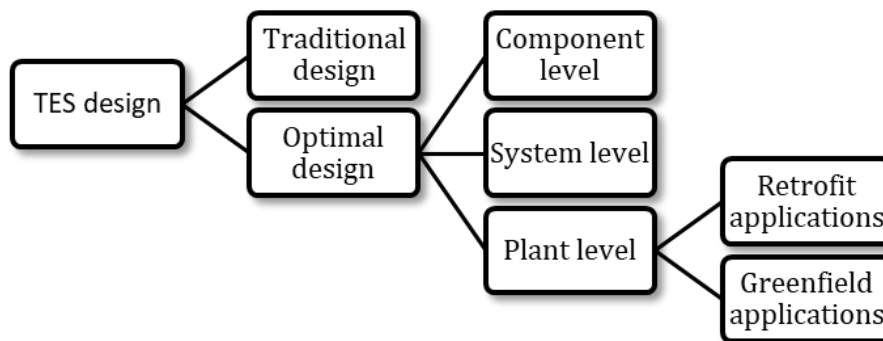


Figure 5.3: Classification of Thermal Energy Storage Systems Design

Looking at the literature of the past 20 years, Phase Change Material (PCM) is one of the most-common TES technologies designed for different applications. For instance, in a study back to 2004, a semi-empirical thermal model was developed that can be integrated into a commercial software package for design optimization of a hybrid heat sink TES with a PCM unit [13].

In recent studies, Li et. al. in [14] proposed a multi-objective optimization approach for designing a PCM thermal energy storage system, where the proposed approach was illustrated for optimizing an outdoor swimming pool heating system with PCM storage.

In another example [15], focusing on the design optimization at the system level, the impact of inlet water temperature and flow rate on the design of a water based active PCM storage was experimentally investigated.

Via a parametric study, an optimum design of a PCM storage system comprising PCM units embedded with a capillary pipe system was proposed in [16] for space cooling of nearly zero-energy residential buildings. The study showed the main parameters which affect the cooling performance, and the energy use of the system are PCM layer thickness, number of parallel pipes, diameter of pipe, night cooling duration, cooling water inlet temperature and water velocity.

The study in [17], was also examined the design optimization of an active cool PCM storage system integrated with HVAC systems. Employing a model-based design approach, this study optimized the storage capacity to maximize the cost-saving potential that can be achieved from peak load management and participation in demand response programs.

Minimizing the phase change time and maximizing the stored energy of a finned latent heat thermal energy storage system were the objectives of the design optimization in [18], where the volume fraction of fins, the number of fins and the dimensionless fin length were considered as design variables in a pareto optimal design scheme.

Another common TES technology designed for many applications is the building-integrated thermal energy storage systems, that is the use of thermally massive building fabrics e.g., concrete slabs or masonry block walls either in a passive or an active design. In a two-series publication [19] [20], Bastien and Athienitis compared several design concepts for the passive design of thermally massive elements in buildings and presented a design methodology for sizing such storage systems in solariums and greenhouses. According to [19], identifying the design objective is the most important factor that should be considered in the first place when designing a passive TES system. Depending on the design objective, different materials and configurations can be appropriate, e.g., massive exterior wall or direct-gain/isolated-gain space. This study first reviewed several design objectives such as reducing

indoor temperature swings, reducing the space heating and cooling energy consumption or delaying the peak solar gain effect. Then, the study selected the most appropriate design concepts for isolate-gain applications, such as daily average operative temperature swing and minimum and maximum operative temperature. In the second series [20], six different configurations of solaria were modeled with frequency response and finite difference thermal network modeling approaches to investigate the impact of different design variables e.g., TES material or varying thermal resistance of the insulation layer on the selected design objectives. Based on analyses of the thorough simulation results, a design methodology in 11 steps has been provided, together with recommendations to adopt the appropriate size of TES in different configurations and for satisfying different design objectives.

In another study [21], a design procedure has been provided for the active building-integrated thermal energy storage systems i.e., when passive elements embody a mechanical charging system such as hydronic systems for exchanging heat with the storage media.

As seen, a wide range of TES technologies are available that can be integrated into a variety of thermal applications. Each TES technology has its own technical and economic characteristics that make it essentially suitable for a specific application. Identifying important factors and then matching an application with the most appropriate TES system is still a challenging issue.

A group of papers merely optimizes the thermal performance of TES systems [22][23][24][25]. However, the requirements for TES systems differ significantly depending on the chosen application. As a result, it is essential to develop design methods that allow a TES system to meet the specific needs of an individual thermal application. In this regard, a second group of papers optimizes the overall performance of the application in which the TES system is integrated [26][27][28]. Nevertheless, a deep knowledge of the process under analysis is required for the second group and they rely on complex simulations that are highly time-consuming.

Current barriers to commercial deployment of TES systems include their complex design procedure that should address the specificities of both the TES system and the application under consideration. Indeed, there is a gap between the two approaches that should be filled by fast and easy to apply methodologies capable of adapting the thermal characteristics of a TES system to the needs of the thermal application. The major gap is to develop a set of methodologies to guide the process from description of the thermal process to defining TES geometry based on the requirements and constraints of thermal application [29]. In addition, developing systematic evaluation procedures for TES systems integrated in different applications is essential to advance their deployment [12]. Gibb et. al. in [12] propose a systematic methodology in three concrete steps for characterizing and evaluating thermal energy storage systems in different applications. The main step in the proposed methodology is the analysis of the thermal process which includes the structured collection and analysis of process information. In the next step, the system boundary, i.e. the point of contact between the fluid and the thermal sinks/sources as well as technical properties of the system should be specified. Finally, via determination of relevant KPIs, the benefit of the thermal energy storage system to the process is investigated in the last step. Two case studies, a concentrating solar power and a cogeneration power plant were evaluated using the proposed methodology in this research.

Taking a broader view, TES systems are a part of a wider group of flexibility alternatives. Considering the growing number of factors which are increasing system complexity, there is still much room for design of integrated energy systems as well as development of simplified building/district modeling tools and system optimization techniques. For example, systematic approaches need to be adopted in order to identify the appropriate combination of infrastructure and market signals. In this way, commercial models of TES operation as well as more efficient use cases can be developed [30].

5.3 Smart Design Methodology

Literature review reveals a lack of systematic approach for design and integration of thermal energy storage systems into buildings. To our best knowledge, the only study which addresses this topic is the study conducted by Campos-Celador et. al [29]. They propose a general methodology divided into four steps for design of thermal energy storage systems. In the first step, the thermal process should be characterized by its nominal parameters i.e., temperature and mass flow rate of the heat transfer fluid. Design parameters are then specified in the second step. Likewise, the thermal energy storage technology should be characterized in the third step that meets the specifications and constraints imposed by the first two steps. The final step is the determination of the thermal energy storage design. The proposed methodology was applied to a domestic micro-cogeneration application in this research. As emphasized by the authors, the simple methodology presented in this research can be used as starting point for design of TES and a more detailed analysis, particularly regarding the interaction between the TES and the application should be considered. Inspired by this research study, the presented methodology is further developed in this Subtask and then implemented on a few case studies. The design methodology consists of the following seven steps:

- Step 1: Specification of the thermal process
- Step 2: Specification of the thermal demand
- Step 3: Specification of storage technology
- Step 4: Specification of integration parameters
- Step 5: Specification of key performance indicators
- Step 6: Specification of optimization method
- Step 7: Specification of optimization tools

Inputs to the proposed design methodology are the parameters which characterize the thermal properties of the heat transfer fluid, namely, nominal upper and lower temperature and the nominal mass flow rate. In addition, in relation to interaction between the TES system and the application, nominal generation and demand as well as the physical available space should be given as input to the design methodology. These parameters can have an impact on the TES technology chosen for a specific application. In the following of this section, each step of the design methodology is explained.

5.3.1 Specification of the thermal process

To characterize a thermal process, three variables related to the heat transfer fluid (HTF) can be used: upper working temperature, lower working temperature and mass flow. In normal operation, the instantaneous values of such variables vary over time, and they typically oscillate around some nominal design values. Therefore, the following three nominal parameters, that is, nominal upper temperature (T_{up}), nominal lower temperature (T_{low}) and nominal mass flow ($\dot{m}$) can be used to characterize any thermal process. Together with the thermophysical properties of the heat transfer fluid, these three parameters will constrain the TES technology and act as inputs for the design methodology.

5.3.2 Specification of the thermal demand

The thermal demand and resource availability curves can be used to derive a few important parameters for designing a TES system. It is more likely that thermal demand and resource availability curves fluctuate from season to season or, or even, from day to day. A single pair of curves demonstrating the thermal demand and resource availability is essential for design purposes. One option is to exploit average conditions that represent the nominal behavior of the process. Alternatively, designers can apply the most demanding conditions corresponding to the peak conditions of the TES system. The choice is dependent on the objective that is behind the integration of the TES system, and it significantly affects the expected benefits of the TES integration. The important design parameters for the TES system are as follows:

- Charging time, i.e. the time availability for charging (t_c),
- Discharging time, i.e. time availability for discharging (t_d)
- The storage capacity (Cap)

Desirable charging and discharging thermal power can be calculated using the above parameters.

5.3.3 Specification of storage technology

TES are commonly classified by the nature of the physical contact between the storage medium and the HTF. Following this classification, TES can be divided into direct-contact TES and indirect-contact TES. Direct-contact TES systems are those where the HTF is, at the same time, the storage medium. On the other hand, indirect-contact TES systems present a container or heat exchanger that separates the storage medium and the HTF. One of the most common typologies of direct-contact TES is sensible heat TES using water as HTF, which is the working principle of storage tanks. In this case, the amount of heat stored depends on the amount of the storage material, specific heat of the medium and the difference between upper and lower nominal temperature. Charging and discharging time corresponds to the time required to fill or empty the volume of the tank. Typically, a correction factor is introduced to consider the mixing effect.

In indirect-contact TES systems, the heat transfer is based on thermal processes between the storage medium and the HTF, which differs from direct-contact TES, where the heat transfer is based on mass transfer. The capacity of indirect-contact TES technology is generally defined by a mean enthalpy variation for the storage medium added to the sensible effect of the components involved in the thermal process. The time required for storing and releasing the heat can be defined as a function of different operating parameters and design characteristics such as mass flow rate, nominal temperatures, geometry etc. Other approaches in literature introduce the concept of dimensionless time.

5.3.4 Specification of integration parameters

Along with the design parameters, there are parameters which are related to the integration of TES system within the thermal process. For instance, spatial parameters such as available volume (V_{max}) or available area (A_{max}) address opportunities or problems regarding existing space, distances between process parts, obstacles, and available infrastructure.

In addition, arrangement of the TES system boundary plays an important role in evaluating TES integration. It is defined as the point of contact between the thermal sink as well as thermal source

and the fluid streams. All components such as heat exchangers which are required for linking the TES system to the process are included in this definition.

5.3.5 Specification of key performance indicators (KPIs)

Specification of optimization strategy for integration of TES systems is dependent on defining key performance indicators (KPIs). Due to the diverse list of applications in which TES systems can be integrated, flexibility in KPIs definition is an essential aspect. In this regard, Giacone and Mancò investigated the necessity of a clear and methodical framework to identify the most relevant KPIs for integration of TES systems [31]. The identified KPIs can address a variety of criteria including energy efficiency, thermal comfort, reliability, cost, sustainability, and flexibility. Usually there is more than one KPI that should be optimized. Since these objectives are generally in conflict with each other, different technologies and configurations might be exploited. When designers face with such multi-objective optimization problems, a weighted average of KPIs is optimized as an objective function in some cases. However, previous knowledge of the system is required to select the weights. Also, tuning the weights is time-consuming. As a result, Pareto approach which leads to a set of non-dominated solutions called Pareto frontier is applied in some other studies.

5.3.6 Specification of optimization method

If the constraints and objective function of an optimization problem are a linear function of decision variables, it is called linear programming (LP). Otherwise, the problem is called nonlinear programming (NLP). Mixed-integer linear programming (MILP) is applied when there are binary or integer decision variables such as the status (on/off) of an equipment.

Typical deterministic gradient-based optimization methods such as Newton, Quasi-Newton and Steepest Descent are effective only for convex and smooth problems. Consequently, stochastic metaheuristic algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) which are population-based are more effective.

5.3.7 Specification of optimization tools

Optimization tools can be classified into two main groups: stand-alone optimization packages and simulation-based optimization tools. The most frequently stand-alone optimization packages mentioned in literature are GenOpt®, MATLAB®, modeFrontier® and Topgui®. The most mentioned two simulation-based optimization tools in literature that attempt to merge both optimization and simulation techniques are BeOpt™ and Opt-E-Plus™.

5.4 Case Studies

5.4.1 Earthbag-PCM integrated walls for temporary housings

Earthbag temporary housings are a viable solution to quickly accommodate a massive number of relocated people due to natural disasters, coercive movements, civil wars, insurgency, etc. these houses, nonetheless, faces a poor indoor condition, especially in regions with harsh climatic conditions. To enhance their indoor condition, thus, the integration of PCM to the earthbag units is proposed as a potential technique. Hence, this case study reports the development, modelling, and optimization of earthbag units for such applications.

Steps 1 and 2: Specification of the thermal process and thermal demand

In this case study, 24 earthbag unit blocks were fabricated to construct a earthbag test wall while each unit has a mixture of 30% clay and 70% well-graded soil sand [32]. The soil and the microencapsulated PCM (inertek26) and PCM composited were mixed at 2.2% of the composition of the entire unit block mixture. Water was added to the mixture up to the point where 10% moisture was achieved [33]. In a hot climate such as Nigeria, the PCM with a higher transition temperature option is preferable to reduce high temperatures [34]. The microencapsulated PCM and formed PCM composite are having 26 and 31 phase transition temperature. The heat storage capacity of the selected PCM are 182 kJ/kg and 215 kJ/kg for A31 and Inertek26. The selection process considered the comfort zone of Kano state, the region for the experiment, which was determined to be between 23°C and 32°C [35].

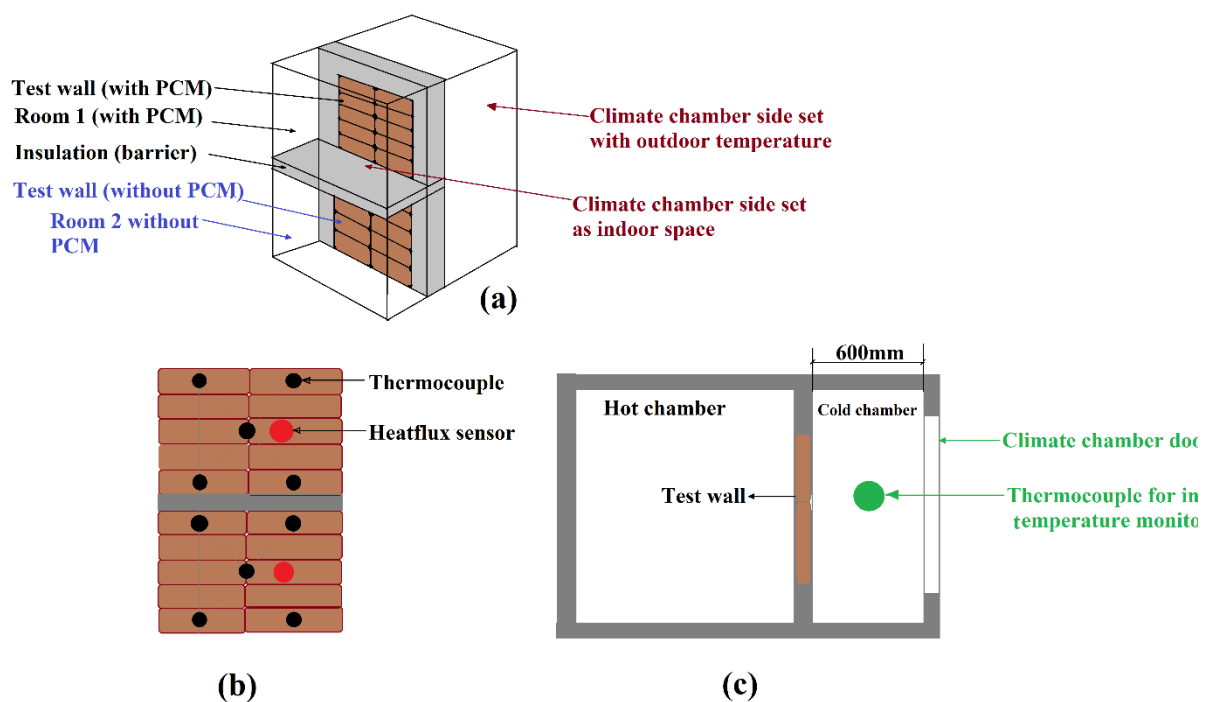


Figure 5.4: (a) Test walls prototype in climatic chamber (b) Schematic layout of thermocouples and heat flux at outer and inner surface of walls (c) Top elevation of experimental arrangement

Step 3: Specification of storage technology

To assess the behaviour of PCM in an earthbag-building model, three identical real wall-scale prototypes were built, including Wall 1 (baseline) without PCM, Wall 2 with PCM encapsulated in expanded graphite and perlite (WA31) and Wall 3 with powdered PCM (WInk26). As shown in Figure 5.4, the prototype walls are then placed in a climate-controlled thermal chamber to simulate an indoor space of an earthbag building. The climate chamber was programmed to replicate summer climatic conditions in Kano, Nigeria. Additionally, k-type thermocouples (with an accuracy of 0.05°C) were positioned at the test wall's inner and outer surfaces, and two heat flux sensors were installed on the wall to measure heat flow rates. Figure 5.4 displays a 3D sketch of the wall used for the simulation to validate the experimental work.

Step 4: Specification of integration parameters

To meet the desired requirements for designing PCM-Earthbag walls, 5 parameters were considered, as presented in Table 5.1, such as the type and quantity of PCM material used, the size and shape of the bags, the wall size and thickness, and the insulation materials thickness.

Table 5.1: Parameters and their properties

Component	Thickness (m)	Area (m ²)	Number of block/walls	Quantity (Kg)	Conductivity (W/ m. K)	Density (kg/m ³)	Specific heat (J/kg . K)
Earthbag block	0.25	0.08	10				
Earthbag wall	0.25	0.64					
A31	0.03			2.2 %w of EB*	0.2	680	2220
Inertek26	0.03			2.2 %w of EB*	0.21	790	1071
Floor (EPS expanded perlite)	0.075				1.15	1900	950
slab (EPS expanded perlite)	0.075				1.9	2300	1650

* Means 2.2% of total quantities of materials used in a single bag of earthbag unit block

Step 5: Specification of key performance indicators (KPIs)

In this investigation, two principal performance measures were considered, including (1) the inner surface temperature reduction and (2) the viable PCM charging and discharging duration. The goal was to maximize the thermal comfort resulted from the earthbag unit walls. The results of this analysis suggest that the integration of PCM into earthbag walls can help to significantly reduce the surface temperature, with the WA31 inner surface wall decreasing by up to 3.1°C when using a 6cm PCM layer. The best thermal comfort results were found using an optimised model with a PCM layer of only 1cm. The inner surface temperature reduction was found to be 5.82°C with good charging and discharging performance.

Step 6: Specification of optimization method

Genetic algorithm (GA) is implemented in this case study to optimise the average inner surface temperature of the earthbag building model to find the minimum average surface wall temperature at which the indoor of the earthbag model to fall within the thermal comfort zone of Kano state, Nigeria (selected state of the experiment). The parameters considered include the earthbag wall thickness (EGT), building orientation (BO), PCM layer thickness (PLT), PCM conductivity (PC), and PCM specific heat (PSH). Therefore, to optimise the performance of the earthbag-PCM units, 230 sets of unique simulation inputs, varying the independent operating variables, were obtained, and the corresponding output of each simulation in terms of average inner surface temperature was used for a multivariable regression analysis (MRA).

Step 7: Specification of optimization tools

In this case study, the equation of the ANOVA developed in excel data analysis is used as the objective function for GA in MATLAB software optimization tool. Once the correlation between the independent

variables has been determined as described above, the GA is used to optimise them due to their efficiency in dealing with multivariable optimisation problems. The objective is to minimise the "Average Inner surface temperature" variable. Constraints related to the problem are also imposed, with each variable's lower and upper limits given in Table 5.2. Table 5.3 details the GA parameters used in the optimisation model. After this, the GA program is executed with the specified parameters and variable constraints. Finally, the optimised values of the variables are extracted and presented in Table 5.4. Once the optimisation was done with the genetic algorithm as outlined before, the optimised values listed in Table 5.4 were utilised to perform the final simulation with the EnergyPlus model. This simulation was then compared to the parametric analysis of the original design.

Table 5.2: Variable Bound for the key building design parameters

S/N	Variables (mm)	Bound
1	Earthbag wall thickness (EGT)	$200 \leq \text{EGT} \leq 450$
2	Building orientation(BO)	$0 \leq \text{BO} \leq 90$
3	PCM layer thickness (PLT)	$10 \leq \text{PLT} \leq 70$

Table 5.3: Genetic Algorithm parameters for the present model

S/N	GA parameters	Value
1	Population size	50
2	Number of iterations	100
3	Number of bits per variable	8
4	Crossover probability	0.8
5	Mutation probability	0.05

Table 5.4: Designed model and Optimised values of the variable after analysis with GA and parametric analysis

S/N	Variables	Designed model	Parametric analysis	Optimised value (GA)
1	Earthbag wall thickness (mm)	250	250	450
2	Building orientation ($^{\circ}$)	0		90
3	PCM layer thickness (mm)	10	10-70	10

Results and Conclusion on case study 5.4.1

The case study's findings as shown in Table 5.5 demonstrate that introducing PCM into earthbag walls can lower surface temperatures by up to 1.92°C and 2.50°C for WA31 and WInk26, respectively. However, WInk26 with Inertek26 PCM proves ineffective due to surface temperatures consistently exceeding the PCM's melting point during the day, hampering charging and discharging cycles. On the other hand, A31 PCM exhibits a more favorable temperature profile, with a 19-hour charging and 3-hour discharging cycle, leading to its selection for further analysis. Parametric examination reveals that a 6cm PCM layer with 16 hours of charging and 8 hours of discharging lowers the inner surface temperature of WA31 by 3.1°C. Interestingly, the optimized model suggests that optimal thermal

comfort results can be achieved with just a 1cm PCM layer. This optimized approach reduces the inner surface temperature by 5.82°C, demonstrating desirable outcomes for a 13-hour charging and 11-hour discharging cycle as shown in Table 5.6.

Table 5.5: Inner surface temperature reduction and charging and discharging results before optimization

Earthbag wall	Temperature reduction (°C)	Charging (hr)	Discharging (hr)
Wink26_3cm layer	1.92°C	24	0
WA31_3cm layer	2.50°C	19	3
WA31_6cm layer	3.1°C	16	8

Table 5.6: Optimized result for inner surface temperature reduction and charging and discharging

Earthbag wall	Temperature reduction (°C)	Charging (hr)	Discharging (hr)
WA31_6cm layer	5.82°C	13	11

5.4.2 The feasibility study and design optimization of a solar-assisted geothermal heat pump for a real restaurant building in a mountain site

The system in this case study includes six thermal storages (see Figure 5.5 for its initial design configuration): three on the use-side storages (low temperature, high temperature, DHW) and three on the source-side (integration hot storage, Exhaust DHW storage, Ground for geothermal field). Given the total seasonal thermal energy demand resulting from the calibrated dynamic simulation of the building model, the focus of the design activity presented here is on the three source-side storages. The objective is to find their optimal integration for increasing the temperature at the source side of the heat pump and optimizing its coefficient of performance [36].

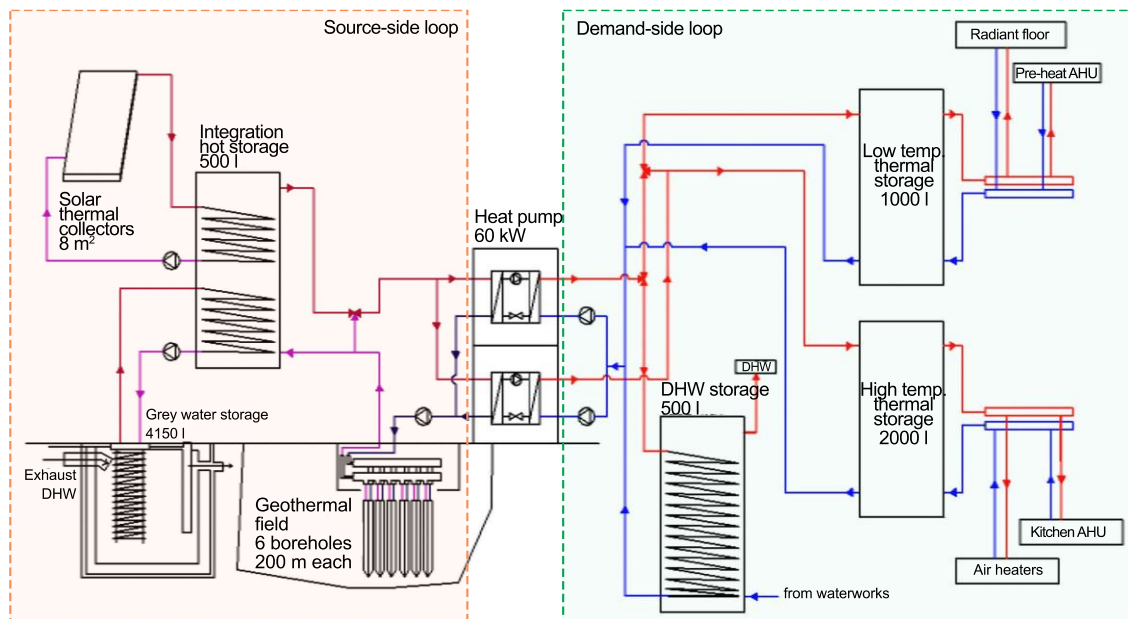


Figure 5.5: Schematics of demand side and supply side loops of the system

Step 1: Specification of the thermal process.

Regarding the characterization of the thermal process, mass flow rates of the water acting as HTF were already fixed in the initial design considering the available circulating pumps of the different loops and the nominal flow rates expected at the source side of the heat pump. However, considering the unpredictability of the different heat sources feeding the different loops (exhaust DHW depends on the building use and the solar source is subject to weather conditions), the upper and lower working temperatures were not considered as inputs. Instead, they were treated as outputs of the design optimization activity. The appropriate constraints were set through control logics to ensure the automatic shut off of a loop when temperature levels were too low to provide a positive contribution.

Step 2: Specification of the thermal demand

The storage design in this case study relies on detailed thermal demand and resource availability curves derived from a detailed dynamic simulation calibrated on real monitored weather data at the building site. Rather than focusing on peak or average conditions, the design approach aims at exploiting such detailed dynamics looking for the TES optimal sizing and system integration that optimizes the seasonal performance of the overall system.

Therefore, coherently with the characterization of the thermal process, the design parameters such as the charging and discharging time and the related thermal power and storage capacity, were not fixed but were allowed to vary in relation to the variation of optimization parameters.

Step 3: specification of storage technology

The project boundaries imposed the type of storage technology to be used in the system. One is the ground field, an indirect-contact TES that relates its storage capacity to the number and depth of boreholes, being the ground the storage medium and a water-glycol mix the HTF. The “grey water storage” is an underground water tank that is used as indirect-contact TES to store the heat recovered from exhaust DHW coming from the use-side, therefore relating its storage performance to its volume and the sizing of the heat exchanger between the exhaust DHW (the storage medium) and the water

circulating in the exchanger serpentine. The “integration hot storage” is a water tank storage acting as an indirect contact TES to integrate and store the heat coming from the three source loops (ground, solar and grey water - if and when heat is available, with accurate controls). It is done by means of proper sizing of the storage itself and of the heat exchangers. For the two water tanks, the storage medium is water and the HTF is water mixed with 40% of glycol.

Step 4. Specification of integration parameters

In this case study, integration parameters were specified as optimization parameters, defined with a Min-Max variation range and discrete steps for variation in the range (Table 5.7).

Table 5.7: Optimization parameters

	Name	Optimization parameter description	Unit	Min	Max	Step size
Spatial integration parameters	Ncoll	Number of solar thermal collectors	[-]	2	30	2
	Nbor	Number of geothermal boreholes	[-]	2	10	2
	Dbor	Depth of boreholes	[m]	50	350	25
	STVint	Volume of the Integration storage per solar collectors' area	[l/m ²]	40	100	10
	STVgw	Volume of the grey water storage	[l]	2000	8000	1000
TES system boundary parameters	Ssol	Surface of the solar heat exchanger serpentine in the integration storage	[m ²]	2.0	4.0	0.5
	Sgw,int	Surface of the grey water heat exchanger serpentine in the integration storage	[m ²]	3.0	7.0	0.5
	Sgw	Surface of the heat exchanger serpentine in the grey water storage	[m ²]	3.0	9.0	1

Regarding spatial integration parameters, the Min and Max volume of both Integration storage and DHW storages were set according to available space for installation of the tanks and the solar field, also considering detailed constraints regarding the min and max possible ration between the water storage volume and the solar field (expressed in l/m²). Also, the dimension of the ground storage, generated by the number and the depth of boreholes, was set according to available space for drilling in the project site. Regarding the TES system boundary parameters, the surfaces of the different heat exchanger serpentine as points of contact between the different loops and the storages were used as design parameters, given fixed flow rates of fluids circulating in the different loops.

Step 5. Specification of key performance indicators (KPIs)

According to the objective of the case study, the defined KPIs refers to the overall energy efficiency and cost performance of the system. The cost-related KPI is the global cost of the system within its estimated lifecycle (30 years), following the formulation provided by Standard EN 15459 for economic evaluation of energy systems in buildings:

$$C_G(\tau, P) = CI + \sum_j \left[\sum_{i=1}^{\tau} (C_{a,i}(j) * R_d(i)) - V_{f,\tau}(j) \right] \text{ [€]} \quad (1)$$

where $C_G(\tau, P)$ represents the global cost relatively to the starting year τ_0 , considering a number τ of years as the calculation period and the defined set of parameters P , CI is the initial investment cost, $C_{a,i}(j)$ is the annual cost for system component j at the year i (including operational energy costs and

costs for ordinary or extraordinary maintenance), $R_d(i)$ is the discount rate for year i , $V_{f,\tau}(j)$ is the final value of component j at the end of the period τ .

The other KPI is the seasonal performance factor of the system that was defined, as used for multipurpose systems [37], as the ratio of the total useful energy output to the total energy expense of a system as follows:

$$SPF_{SAGHP} = \frac{Q_h + Q_v + Q_{DHW}}{E_{el,HP} + E_{el,aux}} [-] \quad (2)$$

where Q_h , Q_v and Q_{DHW} are the useful energy outputs for space heating, ventilation and DHW, while $E_{el,HP}$ and $E_{el,aux}$ are the electrical energy inputs for the heat pump operation and the auxiliary systems (circulation pumps).

Given these two objectives, the final KPI driving the optimization was defined as a multi-objective optimization function as follows

$$MOF_{SAGHP} = w_1 \frac{C_G - C_{G,min}}{C_{G,max} - C_{G,min}} + w_2 \frac{SPF - SPF_{max}}{SPF_{min} - SPF_{max}} [-] \quad (3)$$

where $MOF_{SAGHP} \in [0,1]$ and weights w_1 and w_2 were initially set to 0.5. After running single-objective optimization for both minimizing and maximizing the two objectives as inputs for eq.(3), the weights could be adjusted according to the investors' preference.

Steps 6 and 7. Specification of optimization method and tools

A simulation-based optimization method was used to meet the design objectives. In details, the GenOpt® software was used as optimization tool, with a tailored coupling to the detailed system dynamic model made in TRNSYS. Given the discrete design space and the non-linearity of objective functions, the optimization runs were driven by the metaheuristic population-based PSO algorithm, selected in its binary version to deal with a discrete design space. The settings for PSO parameters were defined according to preliminary studies devoted to optimization of the algorithm performance in solving similar problems [38].

Results and discussion on case study 5.4.2

From the system efficiency point of view, it is shown that the maximum achievable increase of SPF with respect to the initial design is around 6%, but at a potential expense of a very high increase of global cost (+250%) driven by the high investment cost of boreholes. The adopted multi-objective optimization approach allowed identifying a solution leading to nearly optimal SPF but significant containment of global cost (-34%), coherently with the investor's objective of maximizing the overall efficiency of the system with a view on global cost over the system lifecycle.

In details, the higher cost-effectiveness resulted in the solar loop, whose size is maximized, while the contribution of the heat recovery from exhausted DHW resulted to be lower than expected, leading to reduce the size of its storage. The planned number of boreholes resulted to be enough to increase the temperature level of the main loop by up to 5°C without causing unsustainable increase of global cost but, in order to avoid degradation of storage capacity of the ground field (resulting from multi-yearly simulations of the overall system), in the summer period the solar system must be used for recharging the ground field.

5.4.3 Macro-encapsulated ceiling panel (MEP) with embedded pipes for water circulation

An active thermal energy storage configuration similar to Thermo active building systems (TABS) oriented to all new and retrofit building types was investigated at the Technical University of Denmark (DTU) [39]. The PCM was macro-encapsulated in a ceiling panel with embedded pipes for water circulation, referred to as MEP.

The MEP, its operation, and water circuit are shown in Figure 5.6. Its construction ensured a direct contact between the PCM and the pipe profile. The MEP was designed to condition the indoor space during occupancy by absorbing the cooling load (passive operation). Active water circulation followed a rule-based control as a function of the operative temperature (T_{op}) during un-occupied hours, 18:00 to 08:00, discharging the PCM. However, the MEP could work as a radiant panel if needed during peak cooling loads. The piping structure was based on a commercially available product.

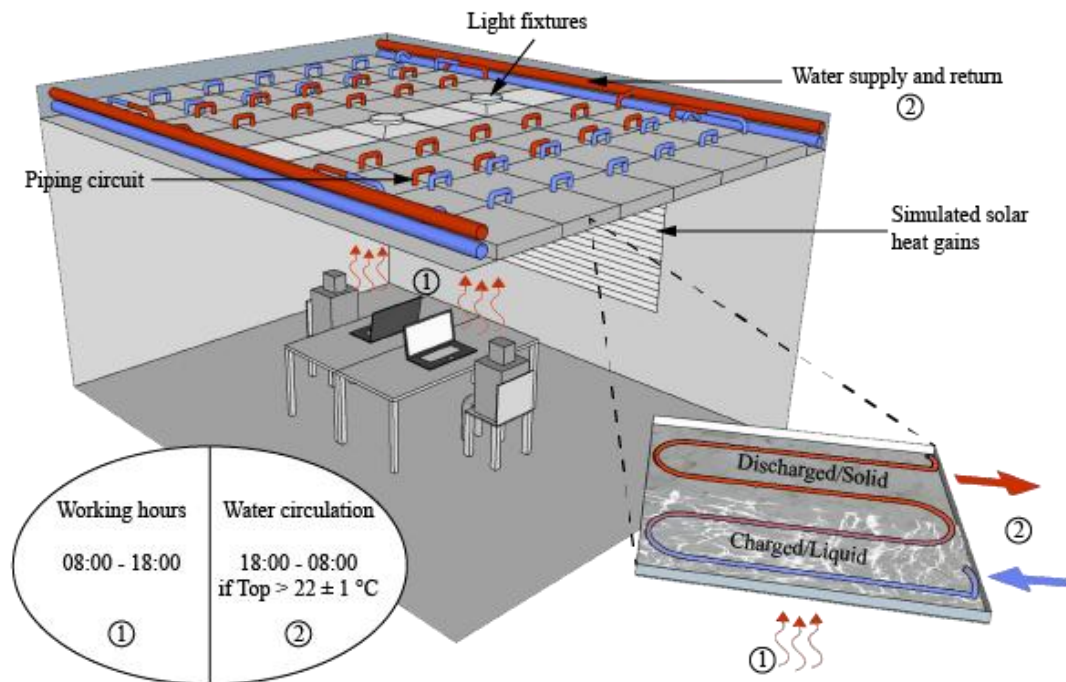


Figure 5.6: MEP panel operation principle [39]. (T_{op} : operative temperature).

Step 1: Specification of the thermal process

Water, i.e. the heat transfer fluid (HTF), is circulated through the pipes embedded in the PCM. Due to the MEP's configuration, the nominal mass flow rate was determined according to the TABS design procedure of ISO 11855-2:2015 and 11855-3:2015 [39][40]. The value was determined based on the specific heat capacity during the phase change, 242 Wh/m². The minimum and maximum water mass flow rates were 91 and 220 kg/h, respectively, to ensure a turbulent flow while avoiding noise [40]. The nominal upper temperature (T_{up}) of the water was selected according to the freezing temperature of the PCM, 21 °C. The nominal lower temperature (T_{low}) should be selected to avoid any risk of condensation [39][40].

Step 2: Specification of the thermal demand

The total specific heat capacity of the panel was approximately 242 Wh/m² within the melting range [39]. The heat capacity of a single panel was ~87 Wh [39], with a total of 4144 Wh for the 48 panels included in the climatic chamber (Figure 5.6). This was because of the maximum usable ceiling coverage in the climatic chamber, which was ~70% of the total floor area. Additionally, the volume of PCM per panel was limited by the load bearing capacity of the suspended ceiling and in order to avoid leakage [39]. The charging time represented the total occupancy time, 10 h (from 08:00 to 18:00), since the cooling load was almost equal to the total heat capacity of the PCM ceiling. The discharge time could take place over the entire un-occupied period, which was 14 h during the experiments (from 18:00 to 08:00) [39]. For a supply water temperature of 20 °C, the discharge time was 11 h with the design water flow rate of 140 kg/h and approximately 7 hours with the maximum water flow rate of 220 kg/h. For a supply temperature of 18 °C and a design water flow rate of 128 kg/h the discharge time was reduced to 6 hours [40]. Thus, the time required for storing and releasing heat can be defined as a function of the operating parameters and design characteristics, namely cooling load, mass flow rate, and supply/return temperatures.

Step 3: Specification of storage technology

The MEP represents an indirect-contact thermal energy storage (TES) prototype. The latent heat storage material was a solid-liquid phase change material (PCM), paraffin, with a peak melting temperature of 24 °C and a phase change range between 21 °C and 25 °C. The PCM was chosen based on the defined comfort limits, 20 and 26 °C [39][40].

Step 4: Specification of integration parameters

The MEP was designed as a ceiling panel with 0.6x0.6x0.03 m³ (W×L×H) dimensions, being easily integrated in regular suspended ceiling openings in Europe. Due to its design, radiant ceiling panels with PCM, the thermal storage is located next to the demand, i.e. in the occupied space. With a PCM thickness of 0.01, the volume of material per panel was 3.6 dm³ (~3 kg per panel). Therefore, the maximum number of panels can be selected as a function of the cooling demand and the available ceiling area e.g., total minus the area required for lighting fixture, fire safety, and ventilation diffusers. In the climatic chamber, the panels were connected to a heat exchanger (HEX) through a closed loop. At the other end, the HEX was connected to a chiller (cooling source).

Step 5: Specification of key performance indicators (KPIs)

The MEP was assessed in terms of energy efficiency, thermal comfort, cost, and flexibility. In terms of energy, the KPIs used were the specific cooling power during passive charging and active discharging and the primary energy use. Thermal comfort was assessed based on the indoor temperature range (e.g., operative temperature) and temperature stratification (vertical temperature difference). For flexibility, the MEP's cooling load shifting ability but also supply water temperature range were investigated. Both global cost and payback period were used as KPIs for the economic analysis.

Step 6: Specification of optimization method

Both water circulation and ventilation were investigated as discharge methods. The parameters investigated were the thermal conductivity of the PCM, air flow rate (night ventilation), water flow rate, water circulation schedule, and water supply temperature [41]. The supply water temperature and flow rate were further analysed in the climatic chamber [39][40]. Results showed that water circulation was a better discharging method than night ventilation since it increased the solidification

percentage of the PCM. The indoor thermal environment was improved for an increase in heat conductivity, a longer water circulation operation time, and a lower supply water temperature [40]. The increase in flow rate also benefitted the thermal environment as long as the water flow regime was turbulent, however having a smaller effect than the other parameters analysed [40]. When investigating the control strategy, it was determined that a control dependent on the operative temperature to reduce overcooling would benefit the thermal environment [40][41].

Step 7: Specification of optimization tools

An optimization of different operating conditions and panel properties on the discharge of PCM ceiling panels was made [40][41]. The MEP was investigated in climatic chamber experiments [39] and building performance simulations in TRNSYS [41][42].

Results and discussion on case study 5.4.3

The panel registered during the experiments a specific cooling power between 5 and 28 W/m², with 11 W/m² on average during passive charging, i.e. during occupancy. The thermal environment was maintained for 83% of the occupied time in Category II of EN 16798-1:2019 [43]. The temperature stratification was within the Category A of ISO 7730 limits, with a temperature difference between head and ankles (1.1 and 0.1 m, respectively) of a seated occupant lower than 2 K [39].

The tests confirmed the MEP's load shifting ability, being able to shift the cooling load from occupied to off-peak (un-occupied) hours [39]. Moreover, the panel presented high flexibility during discharge due to the wide range of water supply temperatures, 15 to 21 °C, making it compatible with an extensive range of renewable energy sources [39][41].

A building simulation analysis of a recently renovated room at DTU compared the PCM ceiling panel to a TABS and all-air system in terms of energy, thermal comfort, and cost. The thermal environment and primary energy use were similar to TABS. The thermal environment was slightly worse than in the experiments, however with operative temperatures within 22 and 27 °C for more than 90% of the occupied time. The PCM ceiling panel registered a primary energy use similar to TABS, 16 kWh/m², 18% lower than the all-air system for the cooling season of Copenhagen, Denmark [42]. Additionally, both PCM and TABS registered a 30% reduction in the peak cooling power compared to the all-air system [42]. From a cost perspective, the global cost and payback period were calculated and compared to the results obtained from a TABS and an all-air system. In its current state it was determined that the MEPs were only marginally more expensive than the all-air system under high cooling loads with a 20 year payback period, while TABS had the lowest cost [44].

5.4.4 Sizing-Designing Approach for Adiabatic-Compressed Air Energy Storage System Towards Self-Sufficient Building

In a conventional compressed air energy storage (CAES) system, known as diabatic-CAES (D-CAES), the thermal energy is lost during the compression process while the heat required for the expansion process is supplied by burning fossil fuel, particularly natural gas [45].

Adopting TES is a successful way to improve the D-CAES system efficiency while mitigating carbon emissions. Consequently, the second generation of CAES technology called adiabatic-CAES (A-CAES) emerged. In the A-CAES system, the heat generated during the compression process is stored in a thermal energy storage (TES) system and reused to heat the high-pressure air prior to the expansion phase. Hence, the A-CAES system can obtain up to 70% system efficiency while achieving a zero-emission system (no need to burn fossil fuels) [46]. Figure 5.7 illustrates an A-CAES in an integrated

energy system. As shown, the A-CAES system can contribute to the electricity, heating, and cooling network.

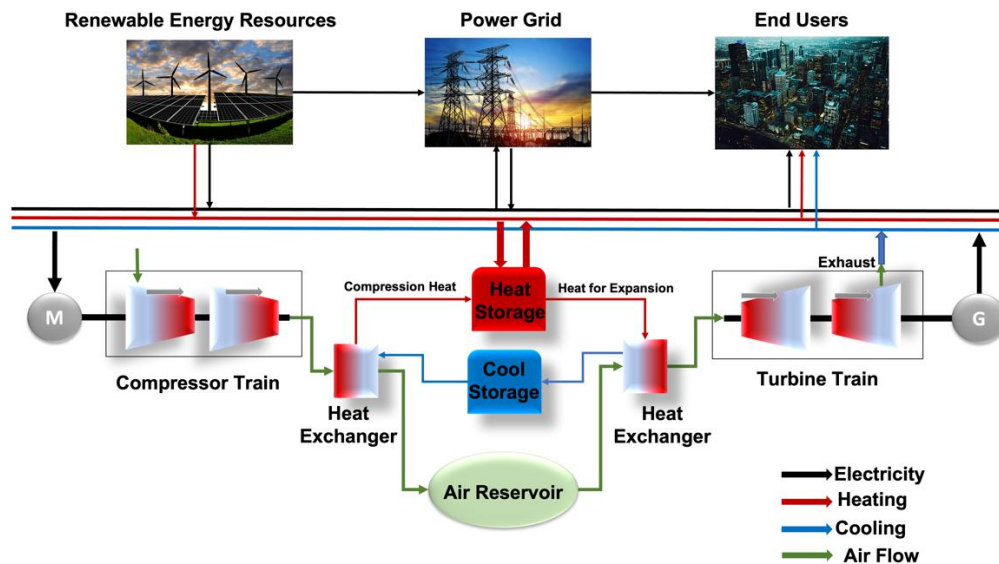


Figure 5.7: A-CAES with TES in the integrated energy system.

Recently, Bazdar et al. [47] investigated the effect of a low-temperature double hot/cold tank TES system capacity on the performance of a grid-connected with a PV/ A-CAES system designed to meet the demand of an educational building located in Montreal-Canada. They proposed a sizing-designing methodology based on the long-term transient operation of an A-CAES system in an integrated energy system to meet the application-specific requirements considering techno-economic and environmental aspects [48].

Step 1: Specification of the thermal process

The hot and cold tank temperatures (T_{up} and T_{low}) are set at 120 °C and 25 °C, respectively. During the charging process, the heat generated in the compression stage is removed from high-temperature compressed air by HTF (e.g., water) from the cold tank while passing through the cooling heat exchangers with an effectiveness of 95%. Then, thermal energy in the form of high-temperature heat transfer fluid (HTF) is stored in the hot tank and reused for heating the high-pressure air released from the air storage tank (at 25 °C) before the expansion process (with an inlet temperature of 100 °C) during the discharging phase.

Figure 5.8 presents flowcharts of the proposed optimal design approach for an A-CAES integrated with TES and renewable energy systems. This strategy can be applied to different renewable energy resources, hybrid energy systems in different modes (e.g., grid-connected, off-grid, stand-alone) and for various applications (e.g., building, district, rural area, urban area, etc.). The TES-related outcomes is expected to be an optimum capacity and charging/ discharging time for the TES corresponding to the size of solar power generation, CAES components (e.g., compressor/turbine train, air storage tank), and building load demand.

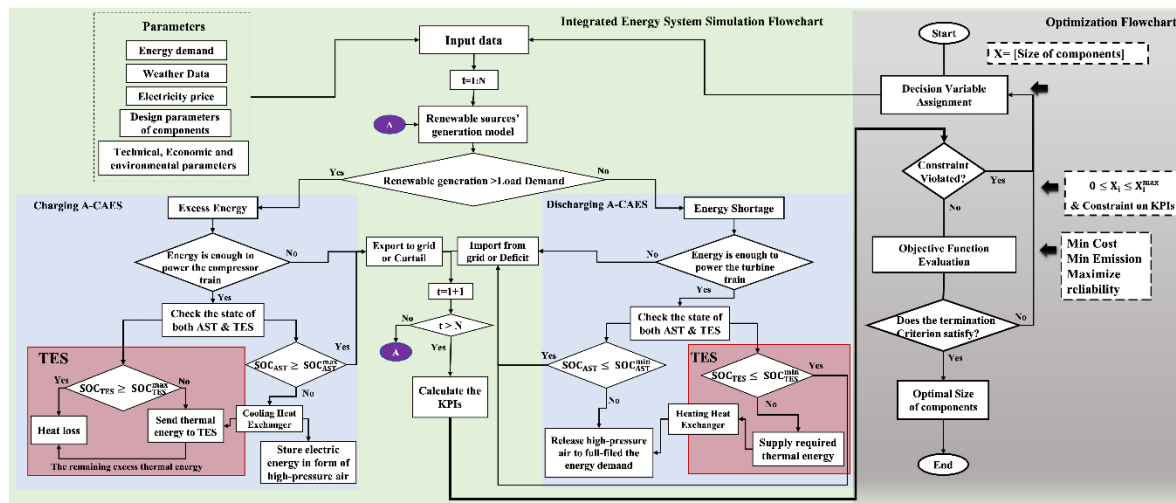


Figure 5.8: The designing flowchart for integrated energy systems, including renewables and A-CAES with TES.

Steps 2, 3 and 4: Specification of the thermal demand, storage technology and integration parameters

In the methodology, the regenerative heat system includes two groups of cooling/heating counter-current heat exchangers and a direct-contact sensible TES with double hot and cold-water tanks.

It should be noted that a maximum of 12961 PV panels (300 W each) can be installed based on the available rooftop area of the case study. For the studied building to achieve a maximum 50% self-sufficiency, a 570 kW A-CAES system, including TES with a capacity of 3000 kWh (27 m³) and charging (t_c) /discharging (t_d) time of 5.12 / 3.78 hr, is needed.

Step 5: Specification of key performance indicators (KPIs)

Depending on the user requirement and the system mode, various KPIs could be defined concerning the technical (e.g., reliability, self-sufficiency, self-consumption, etc.), economical (e.g., net present cost, cost of energy, profit, etc.), and environmental factors (e.g., carbon emission).

To investigate the effect of the presence of the TES system in CAES on optimal configuration, and the KPIs, two scenarios corresponding to the different CAES configurations, such as D-CAES (with combustion chamber) and A-CAES (with TES), were investigated. Table 5.8 shows the optimal configurations and KPIs of proposed systems designed for electrification of one of the high-energy intensive buildings of Concordia university located in downtown of Montreal-Canada with an average hourly electricity demand of 645 kWh.

Steps 6 and 7: Specification of optimization method and optimization tools

Given the economic model of each component in the integrated energy system along with the system's analytical model as a function of decision variables (components' design parameters), an MINLP optimization problem can be formulated.

The optimization problem aims to minimize the levelized cost of energy (LCOE) while achieving maximum building self-sufficiency (SSR). The PSO method (with #20 particles and #100 iterations) was applied to solve the optimization problem for annual system operation with a one-hour resolution.

The simulation-optimization model was implemented in MATLAB software (version R2022a) running on an Intel Core i7-7500U CPU @ 2.7 GHz.

Results and discussion on case study 5.4.4

As shown in Table 5.8, although PV/D-CAES has less LCOE of 0.076 \$/kWh compared to 0.084 \$/kWh for the PV/A-CAES system, thermal energy generated during the compression process recovered by around 94% in A-CAES leading to a zero-emission hybrid system compared to the PV/D-CAES with 161 tonne/year carbon emission (CE). Figure 5.9 shows the one-year operation of TES in the studied hybrid PV/A-CAES system.

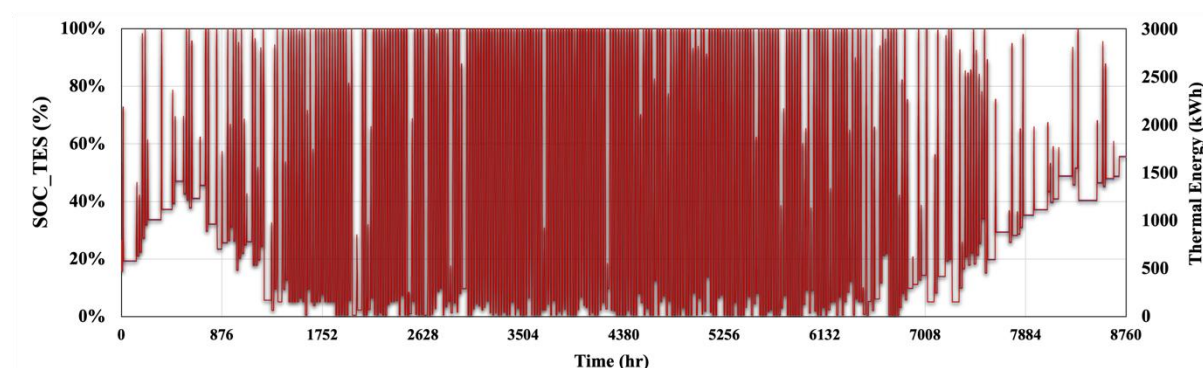


Figure 5.9: TES system dynamic behavior in the hybrid PV/A-CAES system over a year.

Table 5.8: Optimal results of sizing D-CAEA and A-CAES with TES system to meet the electric demand of an educational building in Montreal-Canada

Scenario	Optimal Configuration					KPIs' Value				
	Compressor	Turbine	AST	TES	P_{AST}^{Max}	LCOE	SSR	HRR	RTE	CE
	(kW)	(kW)	(m ³)	(kWh)	(MPa)	(\$/kWh)	(%)	(%)	(%)	(tonne/yr.)
A-CAES	585	526	300	3000	10.6	0.084	50	94	51.0	0
D-CAES	286	587	300	0	6.35	0.076	50	0	40.8	161

5.4.5 Utilization of LHTES integrated with geothermal energy system in underground engineering

Thermal energy storage systems based on phase change materials (PCM) are used to shift the peak load in buildings. An effective method to improve the performance of such system is to bury it in the soil to take advantage of soil's high thermal inertia. In this case, Zeng et al. [49] firstly proposed the model of underground buried water tank integrated with PCM panels as thermal accumulators for a heat pump system. The thermal inertia of the geothermal energy is used to remain the PCM at solid state at first and to naturally cool the tank once they are melted. The fluid is heat exchanged with the soil and the phase change plates through the phase change water tank, as shown in Figure 5.10.

Steps 1, 2 and 3: Specification of the thermal process, thermal demand and storage technology

A 2-D mathematical model was created to replicate the mechanics of phase change and heat transport in the HTF and the soil medium surrounding the tank. A symmetrical border at the middle of the fourth panel is taken to streamline the calculating process. The mathematical model is developed in MATLAB and experimentally validated with an NMBE and RMSE of less than 10% and 30%, respectively.

Prior research has focused on achieving a specified engineering load shifting using a single water-phase change material (PCM) tank, whose volume is adjusted to the required cooling or heating load. Zeng et al. [50]'s proposal for thermal storage in an underground shelter's emergency mode also includes multi-modular water-PCM tanks (MMWPT), which offer flexibility and are simple to mass-produce. The PCM are first kept in a solid form by geothermal energy, and the tank is naturally cooled after the PCM have melted.

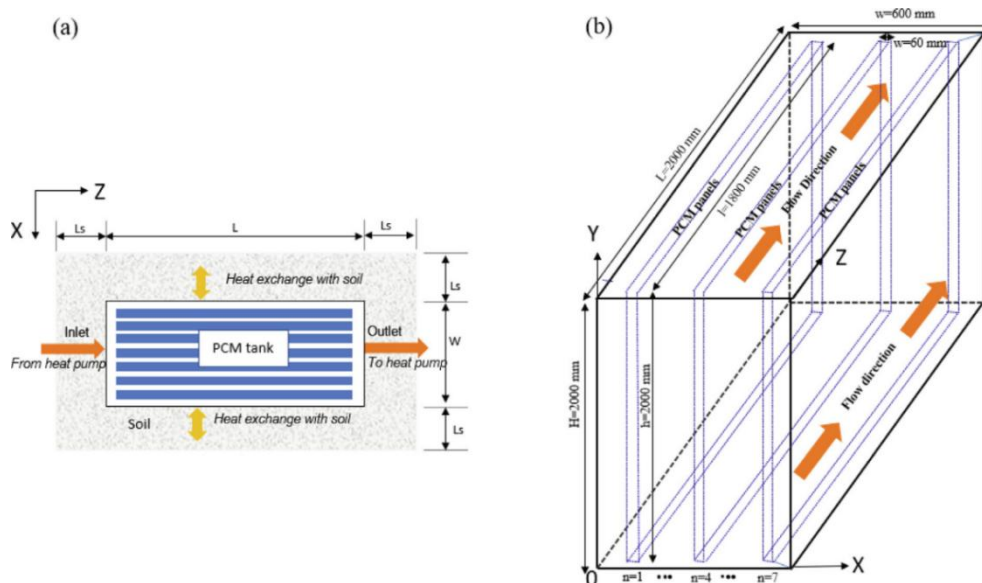


Figure 5.10: Schematic of buried water-PCM tank: (a) top view, (b) front-left view [49]

As shown in Figure 5.11 (a), water tanks are intended to be connected in an $N \times M$ matrix shape where M is the number of tanks in parallel and N is the number of tanks connected in series. A specific arrangement of PCM panels in the MMWPT was shown in Figure 5.11 (b). The water-PCM tank measures 2000 mm in length, 600 mm in width, and 2000 mm in height (height). The PCM panels inside the tank are 1800 mm in length, 60 mm in width, and 2000 mm in height (height). There is 20 mm space between the vertical PCM panels.

Step 4: Specification of integration parameters

The geothermal heat pump system (GHPS) is cascaded with multi-modular water-phase change material (PCM) tanks to cool the underground shelter in the ordinary mode and emergency mode, respectively. The hybrid system designed for the underground shelter is displayed in Figure 5.12 as a schematic diagram. MMWPT, GHEs, WLHPs, water collectors, water separators, and pumps are the key components of the proposed system. The following two operating strategies are given based on the conditions of the underground shelter in peacetime (Model.1) and emergency time (Model.2). Finally, the model was developed in TRNSYS [51]:

Model.1: The GHE offers heating and cooling to the underground shelters in ordinary mode. Based on the peak load, the maximum length of the GHE is determined.

Model.2: When compared to Model 1, the cooling load in the emergency mode exhibits a considerable

rise. Parallel cooling is provided by the two halves, GHE and MMWPT. By adding to and scaling MMWPT, the peak load difference between Models 1 and 2 is eliminated.

Step 5: Specification of key performance indicators (KPIs)

The system's key performance indicators included the outlet temperature, effective discharge duration (EDD), and total heat emitted. Due to its effect on the energy efficiency of HP systems, the temperature drop (ΔT_{water}) during the effective discharging duration (EDD) is a critical evaluation indicator. The outcome shows that the ΔT_{water} in the scenario with N (number of series tanks) $\times 5$ (number of parallel tanks) is about four times as that with $N \times 1$. The related effective discharge duration (EDD), which is increased by dividing the water into five parallel water tanks, is 1.27–1.28 times longer.

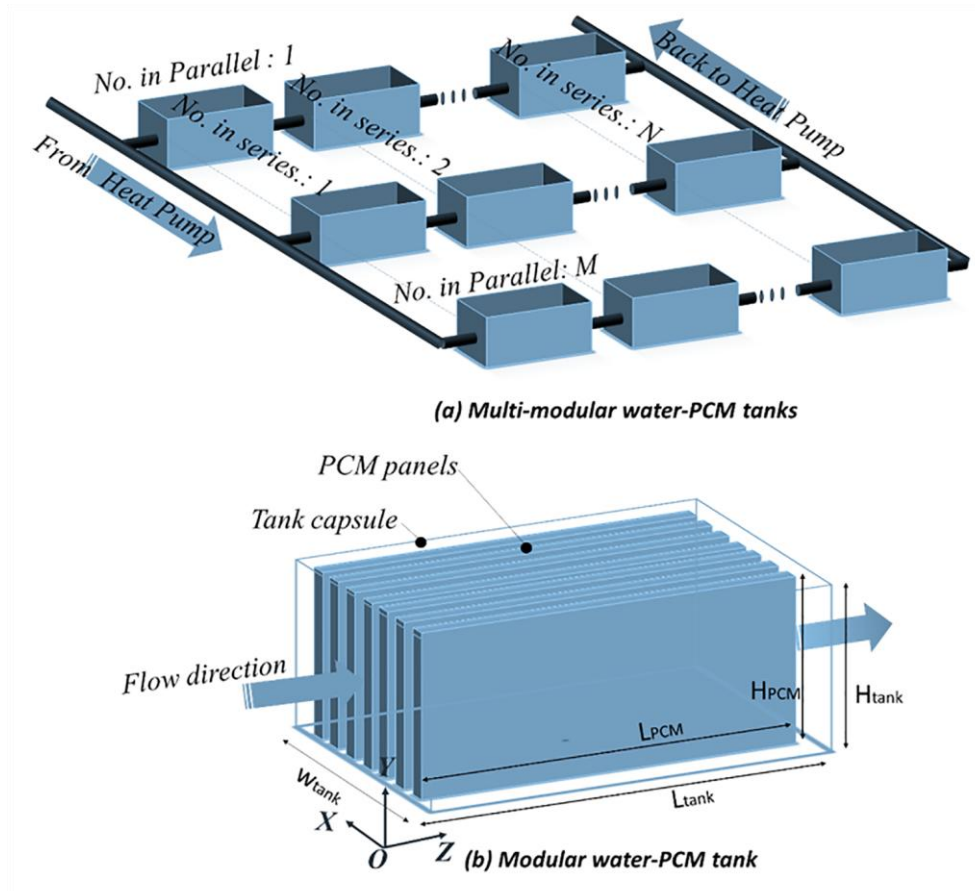


Figure 5.11: Schematic diagram of the multi-modular water-PCM tanks [50]

According to the parametric analysis, the PCM's thermal conductivity, the size and shape of the PCM panels, and the fluid's velocity of heat transfer in the spaces between the panels are the factors affecting tank performance. The primary factors affecting performance in the emergency mode for the integrated system are the ground heat exchanger length, multi-modular water-PCM tank matrix (MMWPM), and cooling water flow ratio. Table 5.9 is a list of the specific comparison criteria used in the study [51].

Table 5.9: Values of variables used in the parametric study in the emergency mode [52]

Variables	Base scenario	Values
GHE length (m)	2500	1800, 1900, 2000, 2100, 2200, 2300, 2400, 2500
MMWPM	3×5	3×5, 3×4, 2×5
Cooling water flow ratio	2:8	0:10, 1:9, 2:8, 3:7, 4:6, 5:5

Steps 6 and 7: Specification of optimization method and optimization tools

A Taguchi design, also known as an orthogonal array, was designed for simulations after listing the parameters and their levels. After that, TRNSYS 18 was used to interact with the data for simulation, and all the parameter and level combinations were set as inputs in the MATLAB code. ANOVA was also used to assess the data and find out how each influential element varied and what influence it had. The identification of factor ranking and their primary factors was reported as a result. The proper parameter combination is then displayed [52].

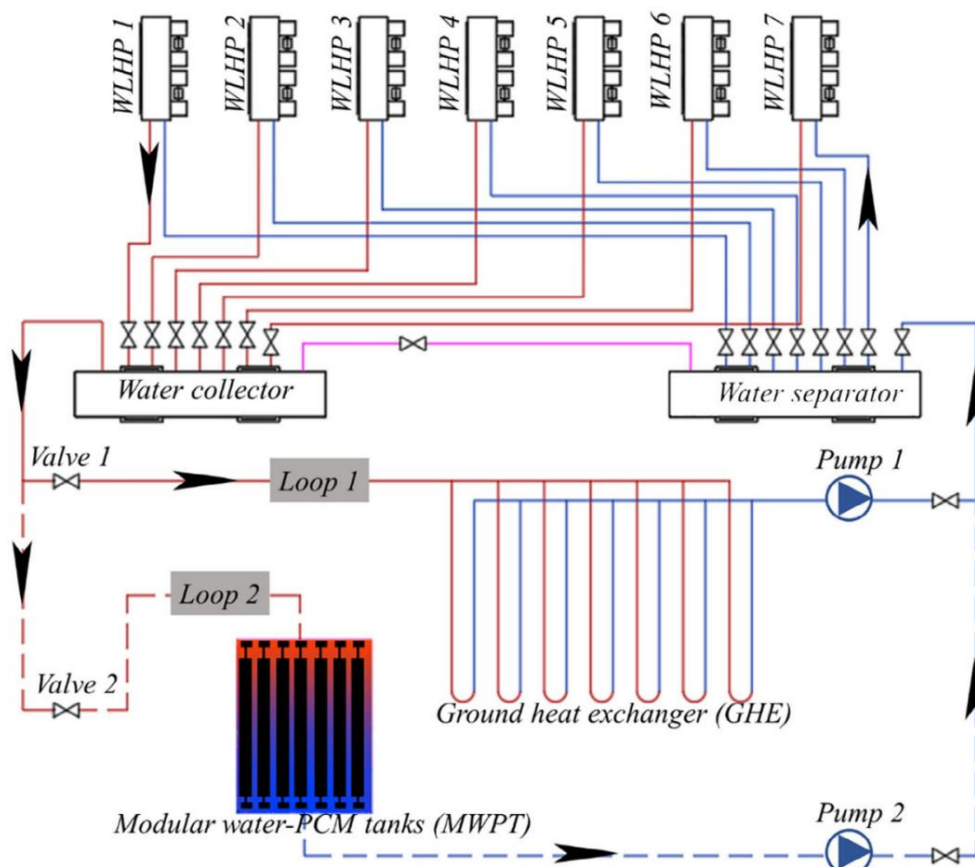


Figure 5.12: Schematic diagram of the hybrid system [51]

Results and discussion on case study 5.4.5

The implementation of the recently planned buried water-PCM tank in the underground engineering for load shifting is expected to use the system as a reference. The PCM in the tank can be kept in a solid form by burying the water-PCM tank in the ground. The tank can offer latent thermal storage capacity in times of need. According to the findings, the underground water-PCM tank's cooling capacity is 24.96% greater than that of an insulated tank.

Zeng et al. [51] additionally investigate the effect of MMWPT configuration on the HP system's cooling performance. The ideal MMWPM for the underground shelter would be 3x5. In an emergency, MMWPT is expanded and scaled to serve as the GSHP's thermal storage system in an underground shelter. The hybrid system's thermos-economic performance in both regular mode and emergency mode are carried out. The average initial cost per unit EDD in emergency mode was found to be the most pertinent evaluation metric. Flowing ratio comes before GHE length and MWT matrix in the list of factors. The initial cost per unit EDD Was dropped by 24.37% with the hybrid system's ideal design.

5.4.6 Utilization of LHTES integrated with Ground source heat pump (GSHP) in office building

An effective and environmentally friendly method of heating and cooling buildings is the ground source heat pump (GSHP). Summertime cooling storage is provided by PCM tanks, which are charged with cold by GSHP units at night. Cooling towers dissipate heat while releasing cold during the day. Cold is supplied by PCM tanks first, followed by GSHP units when PCM tanks have finished discharging, and then by GSHP units after that. The leftover heat is dispersed by a cooling tower if the building cooling load exceeds the combined capacity of the PCM tank and heat pump equipment.

Step 1: Specification of the thermal process

The exchanger provides Water and PCM with the fundamentals of heat exchange in a water tank [53]. Warm fluid from the collector transfers heat to water through a heat exchanger when the tank is in a state of heat storage. Thus, the water's temperature needs to be raised. Due to the temperature difference between water and the phase change material, some heat will be transferred from the water to the latent heat storage capsules. Similar to this, when the tank is in the heat-extracting condition, a heat exchanger uses cool fluid to remove heat from water, lowering the temperature of the water. Water will receive a portion of the heat stored in latent heat storage capsules. In this case, the water serves as a heat-transfer medium between the exchanger and PCM as well as a heat storage medium for perceptible heat.

Step 2: Specification of the thermal demand

In an office building in Wuhan, China (30.52 N, 114.32 E), a numerical study on a GSHP system combined with PCM cooling storage tank was conducted. This office building had a 5175 m² total area. In the summer, the cooling season was from June 1 to September 30 while in the winter, it was from December 1 to February 28. In Table 5.10, the annual dynamic building load was displayed.

Table 5.10: Annual dynamic building load [4].

Load type	Value	Ratio of cooling load to heating load
Design cooling load (kW)	1045.46	2.42
Design heating load (kW)	432	
Cumulative cooling load (kWh)	682695	3.6
Cumulative heating load (kWh)	189132	

Step 3: Specification of the storage technology

Both in the summer and the winter, ground heat exchangers (GHE) are employed for heat exchange. The overall length of GHE is determined by the office building's winter heating load. The GHE are single-U-shaped PE tubes. The borehole is 0.2 m in diameter, 100 m deep, and spaced 5 m apart. The tube has an internal diameter of 25 mm and an exterior diameter of 32 mm. Table 5.11 includes a list of the specific details of the Latent Heat Storage Tank.

Table 5.11: Latent heat storage tank design parameters

The size of tank	1.0. × 1.2 × 1.0 m
Heat loss coefficient U_t	0.3 W/(m ² K)
Total area of exchanger A_{he}	6 m ²
Coefficient of heat-transfer U_{he}	150 W/(m ² K)
Water volume in tank V_w	0.45 m ³
PCM type	CaCl ₂ · 6H ₂ O
PCM enclosed size	140 × 120 × 70 mm

PCM total volume V_{pm}	0.5 m ³
PCM melting point T_m	29.9
PCM melting latent heat L	187.49 kJ/kg
PCM density ρ_{pm}	1710 kg/m ³
PCM specific heat C_{Ppm}	1460 J/(kg K) (s) 2130 J/(kg K) (l)
PCM thermal conductivity λ_{pm}	1.09 W/(m K) (s) 0.54 W/(m K) (l)

Step 4: Specification of integration parameters

The GSHP systems must be connected with additional supplemental cooling/heating systems due to the year-round imbalance of cooling and heating demands in cooling- or heating-dominated locations. An efficient way to deal with issues brought on by cooling and heating imbalance in various locations is to combine a GSHP with a thermal energy storage (TES) system. The implementation of GSHP integrated with PCM cooling storage system still faces a number of difficulties. The best way to operate this combination system for various buildings in various climates is challenging. Yet, there is currently insufficient study being done on integrated system optimization. As a result, the combined system is created in TRNSYS to perform system optimization. Figure 5.13 displayed the integrated system's schematic [54].

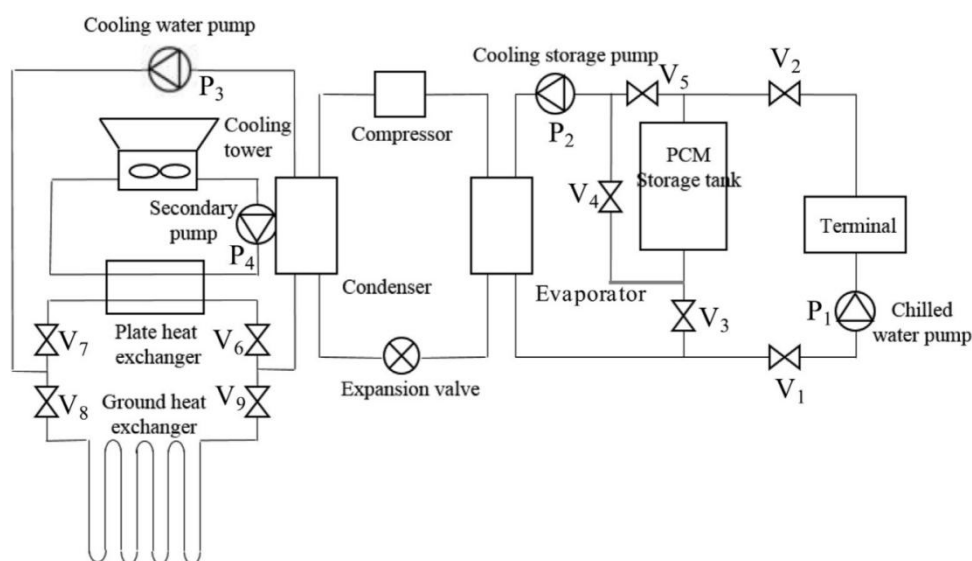


Figure 5.13: Schematic of combined system [54].

Step 5: Specification of key performance indicators (KPIs)

Under various cooling storage ratios (the ratio of PCM cooling storage tank capacity to total system cooling capacity), the energy performance and economic analyses of this combined system were examined. For this integrated system, the ideal operation mode and cooling storage ratio were found.

Steps 6 and 7: Specification of optimization method and optimization tools

Based on TRNSYS, a numerical model of the GSHP coupled with PCM cooling storage system was developed. The cooling tower's temperature difference control method is then used to simulate the system's operation under year-round continuous and intermittent (with three designs) situations for a period of 20 years [55].

Results and discussion on case study 5.4.6

The issue of soil heat accumulation can be efficiently solved by using GSHP in conjunction with a PCM cooling storage system, which also increases the heat pump unit's operational efficiency. A consistent operating performance and good energy efficiency were achieved by the GSHP with PCM cooling storage compared to that without. For this integrated system, the ideal mode of operation and cooling storage ratio were discovered. The best cooling storage ratio, according to numerical research, was 40%, considering the initial investment and operating costs. Comparing the GSHP combined PCM cooling storage system to the standard GSHP hybrid cooling tower (CT) system, the annual cost of the system under a cooling storage ratio of 40% was decreased by 34.2%.

The PCM cooling storage system employed the partial cooling storage and cooling storage before modes. In comparison to a typical GSHP hybrid cooling tower system without cooling storage, the operating mode could fully release the store cooling energy and increase the utilization efficiency of cooling storage consumption and operation cost. A key element in the combined system's ideal design and functioning is the cooling storage ratio. Varying cooling storage ratios have an impact on the combined system's operation energy performance and economy. However, factors such as building type, location, and system utilization mode affect the ideal cooling storage ratio.

This case just presents an example of the optimal usage of the combined system. The optimal design could be helpful to strengthen the theoretical and practical understandings on the combined systems and facilitate more extensive applications of the systems.

5.4.7 Utilization of LHTES integrated with solar energy system in Tibet

A well-known engineering technique for bridging the gap between the heat demand of the served building and the heat supply from the solar heating system is the integration of a latent heat energy storage.

Step 1: Specification of the thermal process

Zhao et al. [56] explored a Tibet-specific PCM-integrated solar heating system that is exceptional in terms of altitude, solar radiation, air pressure, and water boiling temperature, among other factors. The entire process entails: (1) identifying the distinct characteristics of Tibet's climate and altitude and relevant requirements for the solar system; (2) designing a PCM-integrated solar heating system based on a chosen building in Lhasa and planning the potential control strategies appropriate to such a system; (3) analyzing the system's energy performance under different operational schemes; and (4) recommending the most suitable system operational scheme and design strategy.

Step 2: Specification of the thermal demand

At a specific building in Lhasa, the phase change material (PCM) storage tank is intended to support the solar heating system [53]. The five stories of this building, each have a heating area of 3778.87 m² and a height of 3.9 m. The building's hourly heating load (from 4 November to 19 March the following year) is computed using DEST software. The supply water temperature and return water temperature of the heating system are then calculated using the load value. Based on numerical models of the SHS-PCM, the entire heating season (November to March) is chosen as the research timeframe.

Step 3: Specification of the storage technology

The minimum solar portion for building heating should be 60%, according to the Technical Code for Solar Heating Systems (GB 50495-2009) [57]. The roof space of a building, however, limits the overall area of solar heat collectors. Two rows with 44 collector panels each are finally chosen, taking into account the need for the edge wall shelter and maintenance area. The PCM storage tank is only regarded as latent heat storage, with the same heat storage capacity, in accordance with code [57]. Table 5.12 displays the selected parameters for both tanks [58].

Table 5.12: Selection parameters for ordinary water tank and PCM storage tank [58]

	Nomenclature	Units	Ordinary Tank	Water	PCM Tank	Storage
Heat storage capacity	Q_m	GJ	0.63		0.63	
Volume of tank	V_{hp}	m ³	3×2.5×4		3×2.5×0.8	
Volume PCM plate	V_{pp}	m ³	-		3×2.5×0.08	
Number of PCM plates	N_{pp}		-		6	
PCM materials					Paraffin	
Phase-transition temperature	T_m	°C	-		47	
Terminal form			fan coil		Fan coil	

Supply and return heating temperature	$T_{e,in} / T_{e,o}$	°C	45/40	45/40
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Step 4: Specification of integration parameters

The authors have put up a conceptual design for the PCM-integrated solar heating system (SHS-PCM) to match the heat load and demand of the intended building. A solar collecting system (SCS), a phase change thermal storage system (PCTSS), and an indoor heating system make up the system in Figure 5.14. The SCS includes flat plate solar thermal collectors (FSTCs), a plate heat exchanger, pump 1, valves, pipelines, etc. as the primary source of heat. As an additional heat source, the PCTSS consists of a PCM storage tank, an assistance heat source (AHS), a plate heat exchanger, pump 2, valves, and pipelines, among other components [59].

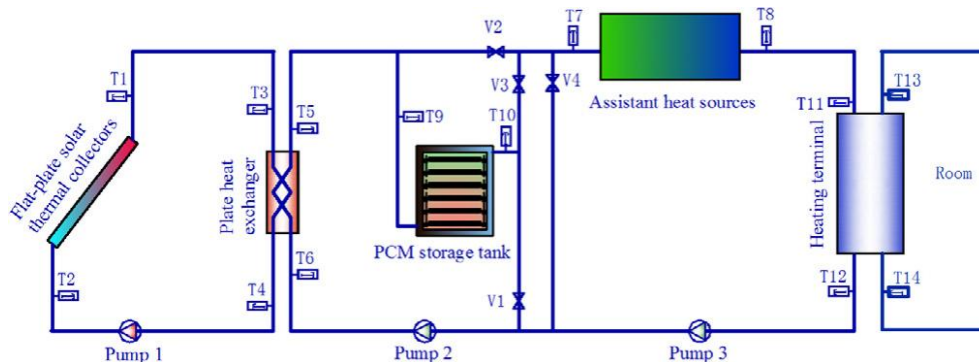


Figure 5.14: Schematic diagram of the SHS-PCM [56]

Step 5: Specification of key performance indicators (KPIs)

The heating conditions, solar energy contribution rate, and overall heating system energy-saving capabilities are examined using a public building in Lhasa as the research object. This analysis is done using various PCM storage tanks and various terminal shapes.

A control strategy and numerical models were created for the first time for each of the seven distinct operation modes that cover the whole heating season of the system, as shown in Table 5.13. The seven proposed operation modes are as follows:

- Mode 1: free cooling
- Mode 2: reservation of heat absorbed by the solar collector in the PCM storage tank when there is no heating demand
- Mode 3: direct supply of the heating demand by the solar collector
- Mode 4: use of the heat absorbed by the solar collector to meet the heating demands, with the excess heat stored in the PCM storage tank
- Mode 5: use of heat stored in the PCM storage tank to meet the heating demands
- Mode 6: combined use of heat stored in the PCM storage tank and the auxiliary heating sources to meet the heating demands
- Mode 7: exclusive use of the auxiliary heat sources in order to meet the heating demands.

Mathematical models were established for each of the above seven operation modes, taking into

consideration the effects of the outdoor meteorological parameters and terminal load on the heating system.

With reference to the valve and temperature numbering in Figure 5.14, the system operating modes and control parameters are listed in Table 5.13.

Table 5.13: Operating modes and control parameters of the SHS-PCM [58].

Mode	Detail	Flat-Plate Solar Collector	PCM Storage Tank	Auxiliary Heat Source (AHS)	Operation
Mode 1	Natural cooling	Off	Off	Off	All valves closed
Mode 2	FSC for PCM storage tank	On	On	Off	Valves V7 and V1 opened; Pumps 1 and 2 on
Mode 3	FSC for indoor heating	On	Off	Off	Valves V7, V2, V6, and V5 opened; Pumps 1 and 2 on
Mode 4	FSC for PCM storage tank and indoor heating	On	On	Off	Valves V7, V1, V2, V6, and V5 opened; Pumps 1 and 2 on
Mode 5	PCM storage tank for indoor heating	Off	On	Off	Valves V3, V6, V5, and V4 opened; Pumps 2 on
Mode 6	PCM storage tank and AHS for indoor heating	Off	On	On	Valves V3, V6, V5, V4 opened; Pumps 2 on; AHS on

Mode	AHS	for	indoor	Off	Off	On	Valves V6, V5, V4, and V2
7	heating						opened; Pumps 2 on; AHS on

Steps 6 and 7: Specification of optimization method and optimization tools

Meteorological data, hourly heating load, and design parameters were entered into MATLAB as the known conditions and the time step was adjusted to 20 minutes based on the numerical models of a SHS coupled with PCM thermal storage established in MATLAB. Calculated dynamic properties of the performance indices of the AHS, PCM storage tank, and FSTCs during the heating process (such as operation time of each mode, inlet and outlet temperature of fluids, heating quantity of assistant heat sources, phase change ratio, thermal efficiency of solar collectors, etc.).

A novel energy performance dynamic simulation model, namely, department of Housing and Urban-Rural in Tibet, was then applied to analyze the energy performance of the building and associated solar heating system at three operational schemes and two different heating selections. On these bases, optimal models and operation pattern are selected.

Results and discussion on case study 5.4.7

According to the findings, a SHS with a PCM tank offers a 34% greater capacity for energy savings than a conventional water tank heating system. In terms of the system's energy efficiency, daytime heating is superior to full-day heating. It is recommended that the PCM storage tank's design selection parameters provide a daily heat storage capacity that covers 70–80% of the heating season. The most energy can be saved by a floor radiant system with supply and return water temperatures of 40 and 35 °C.

The real-time parameters for the entire heating season of the system with respect to the different operation modes can be obtained by solving the simulation models, and used as reference for the optimal design and operation of the actual system.

5.5 Discussion and Conclusions

Thermal energy storage is a proven technology to increase the energy efficiency of buildings in several ways, e.g., by increasing the share of renewable energy use or by increasing the efficiency of heating and cooling systems in buildings. A proper design of TES can be a challenging and sophisticated task, considering the wide range of existing and emerging technologies for TES as well as the variety of building applications requiring the integration of TES. Hence, an optimal design of TES system has increasingly attracted the attention of researchers and is a subject of many recent studies. In this context, a systematic design methodology for TES that can be adapted to a range of applications is beneficial, easing the design procedure, thus removing the barrier for deployment of TES systems in practice. However, few studies have been yet devoted to this topic. To support the establishment of a systematic design methodology, the current subtask has introduced the essential steps should be taken for optimal design of TES systems as follows.

Characterization of the thermal process is the first step should be taken in designing TES systems. Often, three parameters related to the heat transfer fluid can be used for this purpose, namely the upper temperature, the lower temperature, and the flow rate. In the next step, a detailed information on the thermal resources and thermal demands should be available. This information can identify the main

system design parameters which are the charging time, discharging time and the storage capacity. Considering the process and system boundaries, at this stage it is possible to specify the storage technology that can best suit to the application. Afterwards, in addition to the parameters related to the TES system itself, the parameters related to the integration of the system to building should also be specified in the next design step. Finally, in a smart design scheme, the aim is to optimize the system operational performance, either considering merely the TES system or the storage system in conjunction with the rest of the plant, i.e., where it is integrated. Hence, relevant application specific KPIs will be defined for performance evaluation following by defining the optimization methodology and tools employed for this purpose in the next design steps.

The introduced design steps have been applied to seven different case studies, namely design of:

- Earthbag-PCM integrated walls to maximize thermal comfort in temporary housings
- Geothermal borehole and Water tank storage systems to maximize seasonal performance factor and minimize the global lifecycle cost of solar-assisted geothermal heat pump system in a restaurant
- Thermally activated building systems (TABS) including ceiling panel with PCM material embedded with water pipe to optimize energy efficiency, thermal comfort, cost, and flexibility in a test room at a university campus
- A water tank storage in conjunction with a conventional air energy storage to minimize the levelized cost of energy while achieving maximum building self-sufficiency in integrated energy systems
- An underground water-PCM tank to optimize a heat pump cooling performance in an underground shelter
- A PCM cooling storage tank to optimize the energy performance and cost of a ground source heat pump system in an office building
- A PCM storage tank integrated with a solar heating system to optimize solar energy contribution rate, and overall heating system energy-saving in a public building

Despite the diversity among above cases studies, which include both sensible and latent TES employing in different types of buildings, it can be concluded that the design procedure in all of them can be broken down into the introduced design steps. There is discrepancy between the design cases in terms of input parameters to the proposed design methodology though. For instance, in case study 5.4.2, the upper and lower working temperatures were not considered as inputs but outputs of the design optimization. This discrepancy is due to the limitations of the existing plant before the installation of the storage system. In this regard, an important factor which plays a role is the type of the application, whether it is a retrofit application or a greenfield application. Following this work, it is recommended to include the type of the application (retrofit or greenfield) as a decisive factor in the design methodology. Moreover, thermo-chemical storage system is not among the case studies and the design process of such storage needs further investigation. While the proposed design steps can be modified according to chosen storage technology, they can be considered as a general base to develop a systematic methodology for the design of TES systems. In this study, the design process and the effectiveness of 7 steps have been clarified. By utilizing these steps, smart design becomes possible.

5.6 References

- [1] Environment, U.N., 2022. 2022 Global Status Report for Buildings and Construction [WWW Document]. UNEP - UN Environment Programme. URL <http://www.unep.org/resources/publication/2022-global-status-report-buildings-and-construction> (accessed 8.22.23).
- [2] González-Torres, M., Pérez-Lombard, L., Coronel, J.F., Maestre, I.R. and Yan, D., 2022. A review on buildings energy information: Trends, end-uses, fuels and drivers. *Energy Reports*, 8, pp.626-637.
- [3] Sharma, A., Tyagi, V.V., Chen, C.R. and Buddhi, D., 2009. Review on thermal energy storage with phase change materials and applications. *Renewable and Sustainable energy reviews*, 13(2), pp.318-345.
- [4] Violidakis, I., Atsonios, K., Iliadis, P. and Nikolopoulos, N., 2020. Dynamic modeling and energy analysis of renewable heating and electricity systems at residential buildings using phase change material based heat storage technologies. *Journal of Energy Storage*, 32, p.101942.
- [5] Dincer, I. and Rosen, M.A., 2021. *Thermal energy storage: systems and applications*. John Wiley & Sons.
- [6] Dheep, G.R. and Sreekumar, A., 2014. Influence of nanomaterials on properties of latent heat solar thermal energy storage materials—A review. *Energy Conversion and Management*, 83, pp.133-148.
- [7] Alva, G., Lin, Y. and Fang, G., 2018. An overview of thermal energy storage systems. *Energy*, 144, pp.341-378.
- [8] Navarro, L., De Gracia, A., Colclough, S., Browne, M., McCormack, S.J., Griffiths, P. and Cabeza, L.F., 2016. Thermal energy storage in building integrated thermal systems: A review. Part 1. active storage systems. *Renewable Energy*, 88, pp.526-547.
- [9] Navarro, L., De Gracia, A., Niall, D., Castell, A., Browne, M., McCormack, S.J., Griffiths, P. and Cabeza, L.F., 2016. Thermal energy storage in building integrated thermal systems: A review. Part 2. Integration as passive system. *Renewable Energy*, 85, pp.1334-1356.
- [10] Heier, J., Bales, C. and Martin, V., 2015. Combining thermal energy storage with buildings—a review. *Renewable and Sustainable Energy Reviews*, 42, pp.1305-1325.
- [11] Kuravi, S., Trahan, J., Goswami, D.Y., Rahman, M.M. and Stefanakos, E.K., 2013. Thermal energy storage technologies and systems for concentrating solar power plants. *Progress in Energy and Combustion Science*, 39(4), pp.285-319.
- [12] Gibb, D., Johnson, M., Romani, J., Gasia, J., Cabeza, L.F. and Seitz, A., 2018. Process integration of thermal energy storage systems—Evaluation methodology and case studies. *Applied energy*, 230, pp.750-760.
- [13] Zheng, N. and Wirtz, R.A., 2004. A hybrid thermal energy storage device, part 1: design methodology. *J. Electron. Packag.*, 126(1), pp.1-7.
- [14] Li, Y., Ding, Z., Shakerin, M. and Zhang, N., 2020. A multi-objective optimal design method for thermal energy storage systems with PCM: A case study for outdoor swimming pool heating application. *Journal of Energy Storage*, 29, p.101371.

- [15] Alam, M., Devapriya, S. and Sanjayan, J., 2022. Experimental investigation of the impact of design and control parameters of water-based active Phase Change Materials system on thermal energy storage. *Energy and Buildings*, p.112226.
- [16] Ručevskis, S., Akishin, P. and Korjamins, A., 2020. Parametric analysis and design optimisation of PCM thermal energy storage system for space cooling of buildings. *Energy and Buildings*, 224, p.110288.
- [17] Cui, B., Gao, D.C., Xiao, F. and Wang, S., 2017. Model-based optimal design of active cool thermal energy storage for maximal life-cycle cost saving from demand management in commercial buildings. *Applied Energy*, 201, pp.382-396.
- [18] Maleki, H., Ashrafi, M., Ilghani, N.Z., Goodarzi, M. and Muhammad, T., 2021. Pareto optimal design of a finned latent heat thermal energy storage unit using a novel hybrid technique. *Journal of Energy Storage*, 44, p.103310.
- [19] Bastien, D. and Athienitis, A.K., 2018. Passive thermal energy storage, part 1: Design concepts and metrics. *Renewable Energy*, 115, pp.1319-1327.
- [20] Bastien, D. and Athienitis, A.K., 2017. Passive thermal energy storage, part 2: Design methodology for solar and greenhouses. *Renewable Energy*, 103, pp.537-560.
- [21] Chen, Y., Galal, K.E. and Athienitis, A.K., 2014. Design and operation methodology for active building-integrated thermal energy storage systems. *Energy and buildings*, 84, pp.575-585.
- [22] Pirasaci, T., Wickramaratne, C., Moloney, F., Goswami, D.Y. and Stefanakos, E., 2018. Influence of design on performance of a latent heat storage system at high temperatures. *Applied Energy*, 224, pp.220-229.
- [23] Deng, S., Nie, C., Jiang, H. and Ye, W.B., 2019. Evaluation and optimization of thermal performance for a finned double tube latent heat thermal energy storage. *International Journal of Heat and Mass Transfer*, 130, pp.532-544.
- [24] Raul, A., Jain, M., Gaikwad, S. and Saha, S.K., 2018. Modelling and experimental study of latent heat thermal energy storage with encapsulated PCMs for solar thermal applications. *Applied Thermal Engineering*, 143, pp.415-428.
- [25] Metin, C., Hacıpaşaoğlu, S.G., Alptekin, E. and Ezan, M.A., 2019. Implementation of enhanced thermal conductivity approach to an LHTES system with in-line spherical capsules. *Energy Storage*, 1(1), p.e39.
- [26] Hübner, S., Eck, M., Stiller, C. and Seitz, M., 2016. Techno-economic heat transfer optimization of large scale latent heat energy storage systems in solar thermal power plants. *Applied Thermal Engineering*, 98, pp.483-491.
- [27] Lin, W., Ma, Z., Ren, H., Gschwander, S. and Wang, S., 2019. Multi-objective optimisation of thermal energy storage using phase change materials for solar air systems. *Renewable energy*, 130, pp.1116-1129.
- [28] Yuksel, Y.E., Ozturk, M. and Dincer, I., 2019. Performance assessment of a solar tower-based multigeneration system with thermal energy storage. *Energy Storage*, 1(4), p.e71.
- [29] Campos-Celador, Á., Diarce, G., Larrinaga, P. and García-Romero, A.M., 2020. A simple method for the design of thermal energy storage systems. *Energy Storage*, 2(6), p.e140.
- [30] IRENA (2020), Innovation Outlook: Thermal Energy Storage, International Renewable Energy

Agency, Abu Dhabi, ISBN 978-92-9260-279-6.

- [31] Giaccone, E. and Mancò, S., 2012. Energy efficiency measurement in industrial processes. *Energy*, 38(1), pp.331-345.
- [32] D. M. dos Santos and J. N. D. C. Beirão, "Generative tool to support architectural design decision of earthbag building domes," 2017, no. November, pp. 538–543. doi: 10.5151/sigradi2017-083.
- [33] GEG, "How to Build an Earthquake-Resistant Home: An Earthbag Construction Manual," Good Earth Global, 2018.
- [34] Batagarawa, "Assessing the thermal performance of phase change materials in composite hot humid / hot dry climates: An examination of office buildings in Abuja- Nigeria," 2013.
- [35] S. Ali, B. Martinson, and S. Al-Maiyah, "Evaluating neutral , preferred , and comfort range temperatures and computing adaptive equation for Kano region computing adaptive equation for Kano region," 2020.
- [36] Maria Ferrara, Enrico Fabrizio. Optimized design and integration of energy storage in Solar-Assisted Ground-Source Heat Pump systems. *Building Simulation*, 2023, under publication.
- [37] Biglia, A., Ferrara, M. and Fabrizio, E., 2021. On the real performance of groundwater heat pumps: Experimental evidence from a residential district. *Applied thermal engineering*, 192, p.116887.
- [38] Ferrara, M., Dabbene, F. and Fabrizio, E., 2017, August. Optimization algorithms supporting the cost-optimal analysis: the behavior of PSO. In *Building Simulation 2017* (Vol. 15, pp. 1418-1427). IBPSA.
- [39] D. I. Bogatu, O. B. Kazanci, and B. W. Olesen, "An experimental study of the active cooling performance of a novel radiant ceiling panel containing phase change material (PCM)," *Energy Build.*, vol. 243, p. 110981, 2021, doi: 10.1016/j.enbuild.2021.110981.
- [40] D.-I. Bogatu, J. Q. Allerhand, O. B. Kazanci, and B. W. . Olesen, "D6.3 Report on the usability of TABS panels (radiant ceiling panels with PCM)," *HybridGEOTABS*. 2019.
- [41] J. Q. Allerhand, O. B. Kazanci, and B. W. Olesen, "Investigation of the influence of operation conditions on the discharge of PCM ceiling panels," *E3S Web Conf.*, vol. 111, no. 201 9, pp. 3–9, 2019, doi: 10.1051/e3sconf/201911103021.
- [42] J. Q. Allerhand, O. B. Kazanci, and B. W. Olesen, "Energy and thermal comfort performance evaluation of PCM ceiling panels for cooling a renovated office room," *E3S Web Conf.*, vol. 111, 2019, doi: 10.1051/e3sconf/201911103020.
- [43] Zhang et al., "Resilient cooling strategies – A critical review and qualitative assessment," *Energy Build.*, vol. 251, p. 111312, 2021, doi: 10.1016/j.enbuild.2021.111312.
- [44] L. Bergia Boccardo, O. B. Kazanci, J. Quesada Allerhand, and B. W. Olesen, "Economic comparison of TABS, PCM ceiling panels and all-air systems for cooling offices," *Energy Build.*, vol. 205, p. 109527, 2019, doi: 10.1016/j.enbuild.2019.109527.
- [45] E. Bazdar, M. Sameti, F. Nasiri, F. Haghighat, Compressed air energy storage in integrated energy systems : A review, *Renew. Sustain. Energy Rev.* 167 (2022) 112701. <https://doi.org/10.1016/j.rser.2022.112701>.
- [46] Ortega-Fernández, S.A. Zavattoni, J. Rodríguez-Aseguinolaza, B. D'Aguanno, M.C. Barbato,

- Analysis of an integrated packed bed thermal energy storage system for heat recovery in compressed air energy storage technology, *Appl. Energy*. 205 (2017) 280–293. <https://doi.org/10.1016/j.apenergy.2017.07.039>.
- [47] E. Bazdar, N. Fuzhan, H. Fariborz, Effect of Low-Temperature Thermal Energy Storage on the Hybrid PV-compressed Air Energy Storage Operation, in: 2022: pp. 1609–1616. <https://doi.org/10.4229/WCPEC-82022-5DV.2.19>.
 - [48] Bazdar, E., Nasiri, F. and Haghighat, F., 2023. An improved energy management operation strategy for integrating adiabatic compressed air energy storage with renewables in decentralized applications. *Energy Conversion and Management*, 286, p.117027.
 - [49] Zeng, C., Cao, X., Haghighat, F., Yuan, Y., Klimes, L., Mankibi, M.E. and Dardir, M., 2020. Buried water-phase change material storage for load shifting: A parametric study. *Energy and Buildings*, 227, p.110428.
 - [50] Zeng, C., Yuan, Y., Cao, X., Dardir, M., Panchabikesan, K., Ji, W. and Leng, Z., 2022. Operating performance of multi-modular water-phase change material tanks for emergency cooling in an underground shelter. *International Journal of Energy Research*, 46(4), pp.4609-4629.
 - [51] Zeng, C., Yuan, Y., Haghighat, F., Panchabikesan, K., Cao, X., Yang, L. and Leng, Z., 2022. Thermo-economic analysis of geothermal heat pump system integrated with multi-modular water-phase change material tanks for underground space cooling applications. *Journal of Energy Storage*, 45, p.103726.
 - [52] Gao, X., Zhang, Z., Yuan, Y., Cao, X., Zeng, C. and Yan, D., 2018. Coupled cooling method for multiple latent heat thermal storage devices combined with pre-cooling of envelope: Model development and operation optimization. *Energy*, 159, pp.508-524.
 - [53] Han, Z., Zheng, M., Kong, F., Wang, F., Li, Z. and Bai, T., 2008. Numerical simulation of solar assisted ground-source heat pump heating system with latent heat energy storage in severely cold area. *Applied Thermal Engineering*, 28(11-12), pp.1427-1436.
 - [54] Zhu, N., Hu, P., Lei, Y., Jiang, Z. and Lei, F., 2015. Numerical study on ground source heat pump integrated with phase change material cooling storage system in office building. *Applied Thermal Engineering*, 87, pp.615-623.
 - [55] Yang, J., Xu, L., Hu, P., Zhu, N. and Chen, X., 2014. Study on intermittent operation strategies of a hybrid ground-source heat pump system with double-cooling towers for hotel buildings. *Energy and Buildings*, 76, pp.506-512.
 - [56] Zhao, J., Yuan, Y., Haghighat, F., Lu, J. and Feng, G., 2019. Investigation of energy performance and operational schemes of a Tibet-focused PCM-integrated solar heating system employing a dynamic energy simulation model. *Energy*, 172, pp.141-154.
 - [57] Ministry of housing and urban-rural development of the People's Republic of China, technical Code for solar heating system. Beijing, China: China Architecture & Building Press; 2009., n.d.
 - [58] Zhao, J., Ji, Y., Yuan, Y., Zhang, Z. and Lu, J., 2018. Energy-saving analysis of solar heating system with PCM storage tank. *Energies*, 11(1), p.237.
 - [59] Zhao, J., Ji, Y., Yuan, Y., Zhang, Z. and Lu, J., 2017. Seven operation modes and simulation models of solar heating system with PCM storage tank. *Energies*, 10(12), p.2128.

6 Subtask D - Advanced storage control applied to optimize operation of energy storage systems for building and district

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6.1 Introduction

In the context of the ongoing accelerating energy transition toward the massive use of multiple renewable energy sources, energy storages are crucial to deal with the variable dynamics of renewable energy supply that should be matched with the dynamic profiles of energy demand. Moreover, within the complex multi-source multi-energy systems that are exploited to ensure a full decarbonization of the building sector, the strategies used to control such storages may not be straightforward, as they should be set considering a large number of variables and uncertain inputs so that a multiple number of interrelated outputs are optimized.

This has been at the center of a great amount research activities in the last few years, as demonstrated by the increasing number of papers focused on energy storage and their optimal integration in the design and operation of energy systems for buildings and districts published by the most prestigious journals in the area.

One of the most comprehensive reviews on the topic of energy storage for buildings is focused on control strategies for Buildings Integrated with Thermal Energy Storage (BITES) [1]. Strengths and weaknesses of the different control techniques are discussed according to the categorization of control techniques derived from [2], shown in Figure 6.1.

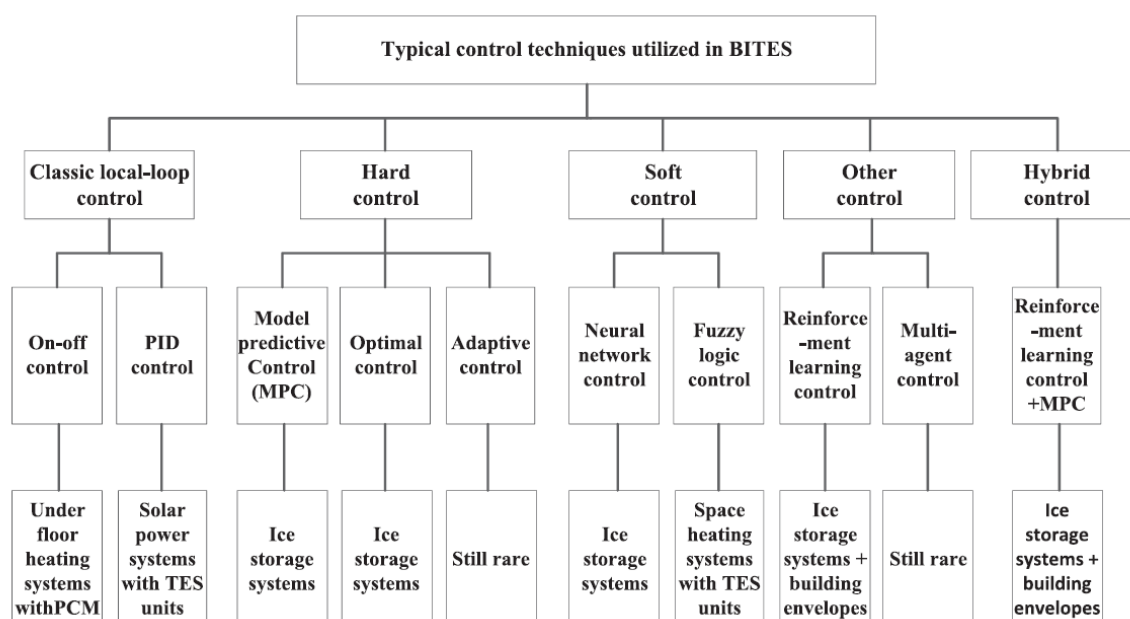


Figure 6.1: Classification and typical applications of control techniques utilized in BITES [1]

This review anticipated in 2015 the developments of the advanced control techniques that has occurred in the last few years. In particular, MPC (model predictive control) and AI-based methods are depicted as promising, but their applications were still rare and incomplete at that time.

In the following years, as a consequence of the fast development of research on the topic, several review studies dedicated to advanced control strategies based on prediction models were published. In their review published in 2017, Thiebelmont et al. [3] focus on studies related to the improvement of the storage performance due to predictive control strategies based on the weather forecast, and Tarragona et al. [4] in 2021 provide a review on studies that apply model predictive control techniques to thermal energy storages, with no reference to electrical energy storages.

In the same period, other reviews were dedicated to model predictive control applied to a specific technology for energy storage, such as PCM [5], or without a specific focus on energy storage, such as the review by Gholamzadehmir in 2021 about MPC used for HVAC system control of smart buildings [6], after the topic of integration of storages in smart building were addressed in 2018 in the review by Sanchez Ramon et al. [7]. A review dedicated to storage control in microgrids was published in 2021 [8], filling the previous gap about the control of electrical storages and enlarging the perspective from the building to the district scale.

The analysis of latest review related to the topic reveals that the current decade has been crucial for development of innovative methods for energy storage control based on advanced computational techniques, mainly based on artificial intelligence.

An updated classification of storage control techniques based on latest development is required including, but not limited to, the support of different declination of artificial intelligence to all the available control strategies, regardless of their relying on predictive models or not. In this report, the identification and review of recent studies concerning the control of energy storage integrated in systems for buildings, or group of buildings is performed. In particular, the report concentrates on papers that are not only purely theoretical or numerical studies, but where some experimental activities were carried out or where analysis are conducted based on real case-studies. This is particularly important in order to evaluate the effectiveness of the control strategies against real measurements. Thus, a systematic review process was implemented aimed at identifying the latest advancements in energy storage control, the emerging trends and the role of AI in shaping such trends, and future perspectives.

6.2 Methodology

6.2.1 The process for paper selection and inclusion in the review

Following a systematic review process based on the previously identified research question, an extensive literature research was performed through Scopus® database in June 2022. The research was carried out by considering titles, abstracts, and keywords. Thus, the TITLE-ABS-KEY (building energy storage control) AND TITLE-ABS-KEY(experimental OR real OR experiment OR case-study)) AND PUBYEAR > 2014 AND (LIMIT-TO (LANGUAGE,"English") query was introduced in the database.

This extensive literature search yielded 396 papers that were systematically selected through the process schematized in Figure 6.2, with a methodology similar to the one of Song et al. (2022) [3]. After the identification of the first set of papers (n=396), the subsequent abstract screening activities led to select 118 papers that appear to be within the scope of the paper according to the abstract and are

worth to be included in the dataset for statistical analysis in the present review (sections 2.2 and 3.2). Then, a further screening based on the whole text has led to identify a subset of 46 papers that are fully within the review scope and were analyzed more in details in sections 3.3 and 3.4, paving the way for the discussion and future perspective sections.

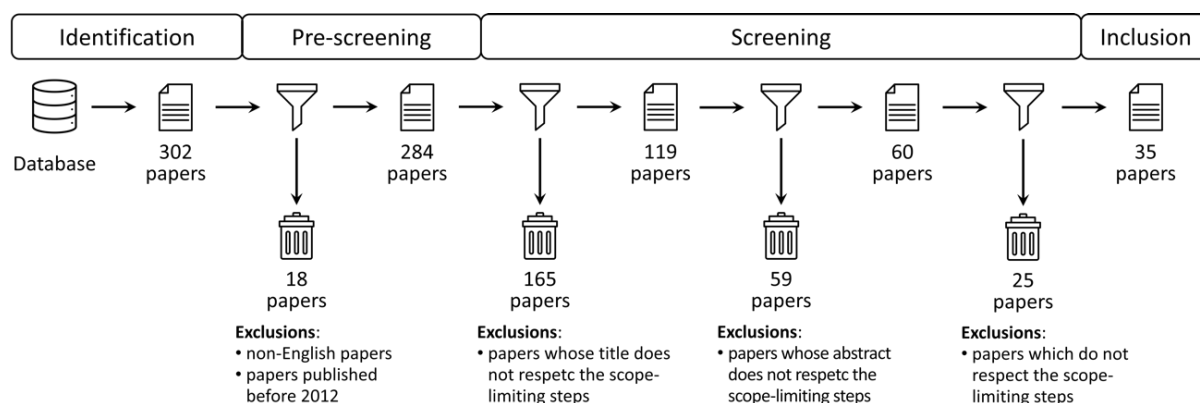
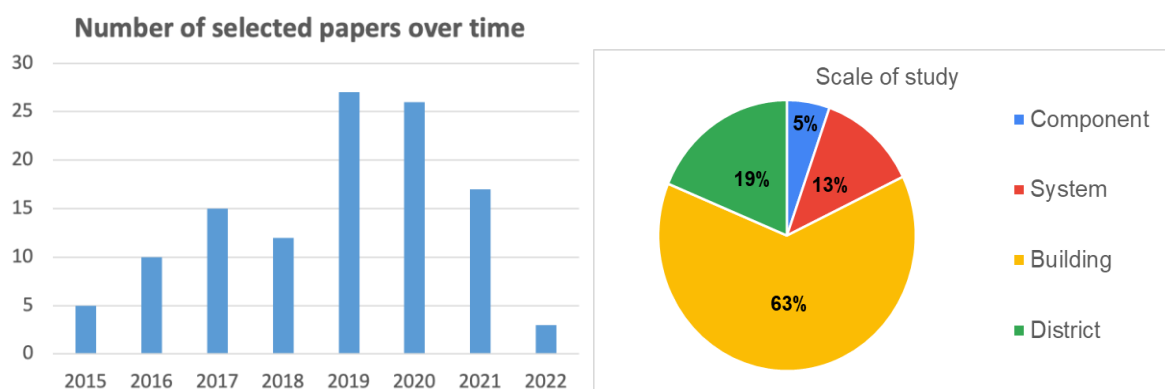


Figure 6.2: The process of creation of the dataset

6.2.2 Description of the dataset

A preliminary analysis of the literature that was analyzed is reported in Figure 6.3 where the number of papers over time and some other features are reported. It can be seen that most of the papers deal with the building scale (more than 60%) and that the remaining part are devoted to study the storage effects on districts and systems. As regards the type of the storage, active-thermal is the most common, followed by the active-electrical. As regards the type of the study, even though the initial research was done considering the “experimental” keyword, just 17% of the references are purely experimental, while 23% are based on an hardware-in-the loop approach (e.g. real storage, emulated energy use) and the vast majority concerns works that perform simulations of storages calibrated against results from experimental testbeds.



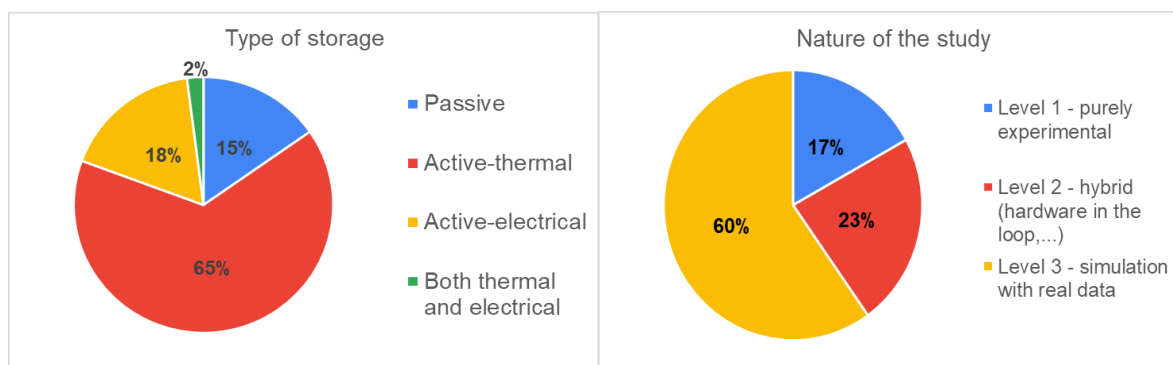


Figure 6.3. Overview of the 118 papers analysed. Year of publication, scale and nature of study, type of storage included in the study

6.3 Classification and taxonomy of control for energy storage in buildings

There are many types and categories of controls. First of all, it is necessary to divide it into two stages: the control method and the control system. Control methods are individual methods. Specifically, there are on-off control, P-control, PID control, and so on. Control systems become a more meta methodology. Control systems are classically classified into open-loop control (sequence control) and closed-loop control (feedback control). Many advanced control techniques are closed-loop controls.

This section presents an updated classification of control systems for energy storage systems based on latest literature advancement in the field. The main purpose of using the energy storage system is energy saving effect and cost saving effect by time shift of demand. That is, the control system for energy storage cannot be separated from the temporal operation of each component. In other words, the control system for energy storage is not immediate, but determines the operation from the present to the future.

The future operation can be roughly classified into non-predictive control and predictive control. For example, a thermal energy storage system that produces thermal energy at night when electricity prices are low and discharges heat during the daytime when electricity prices are high is sequential control that does not require prediction. On the other hand, predicting the next day's heat demand and determining the amount of heat production is control accompanied by prediction. Control systems for energy storage are usually either or a combination of these.

Predictive control is a type of feedback (closed-loop) control system, but not all feedback control accompanies prediction. Therefore, control systems for energy storage systems are now classified into non-predictive control and predictive control instead of the conventional open-loop control and closed-loop control classification.

Furthermore, as sub-methods of these classifications, we can classify using classical methods and Artificial Intelligence (AI). Rule-based methods that employ conditional decision branching are sometimes classified as a type of AI, but here they are classified as classical methods. These are illustrated in Figure 6.4.

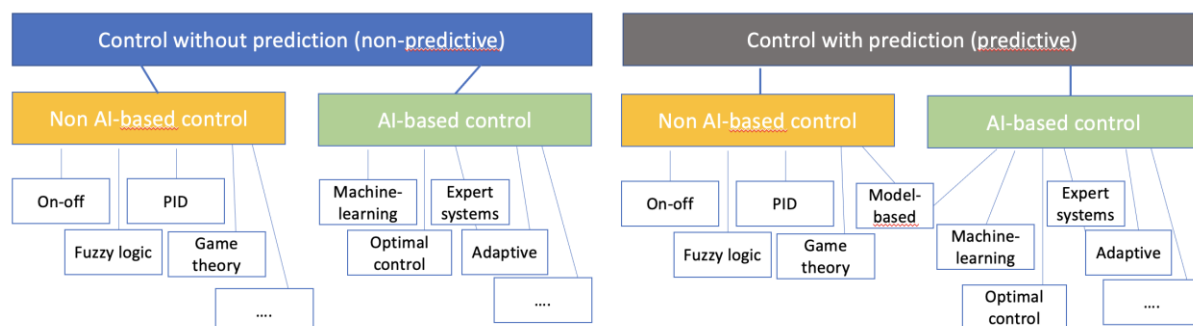


Figure 6.4: Control systems and methods for energy storage: the proposed updated classification

6.3.1 Relationships between controls and applications

It is interesting to apply the previous classification to the literature study that were considered to be analysed. As shown in Figure 6.5, regarding control without prediction, 85% of studies refer to classic control strategies. Of the 60% of papers using control with prediction, classic strategies are used in 35% of studies, while 60% refer to AI-based control strategies and the remaining 4% use hybrid methodologies.

In order to know if a rationale behind the type of control and the application appears from the studies that were analyzed, the relation between the type of storage (passive, active-thermal, active-electrical and both thermal and electrical) and the type of control (split into the two levels of analysis) was analyzed and reported in Figure 6.6: Relationship between the different levels for energy storage control. It appears that control methods based on prediction are more used for active thermal and electrical storages. Similarly, when we go from passive to active storages the use of classic control is reduced and AI or hybrid control types are preferred.

In order to study how the type of application determines the choice of control method a third representation was done matching the scale of the storage and the type of control in Figure 6.7. It can be seen that the largest the scale, the more it is necessary to use control methods with prediction and based on AI algorithms.

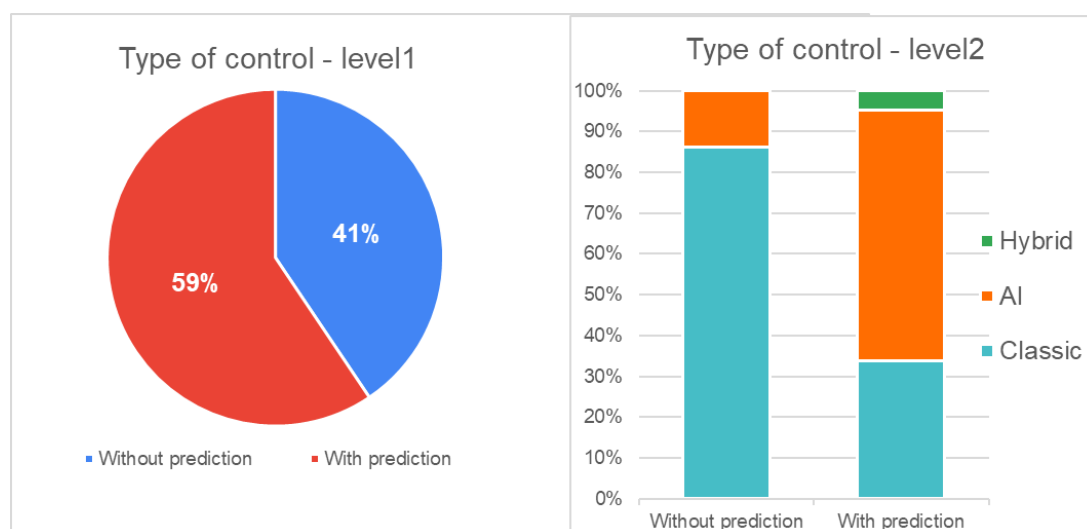


Figure 6.5: Repartition of papers according to the two levels of control types

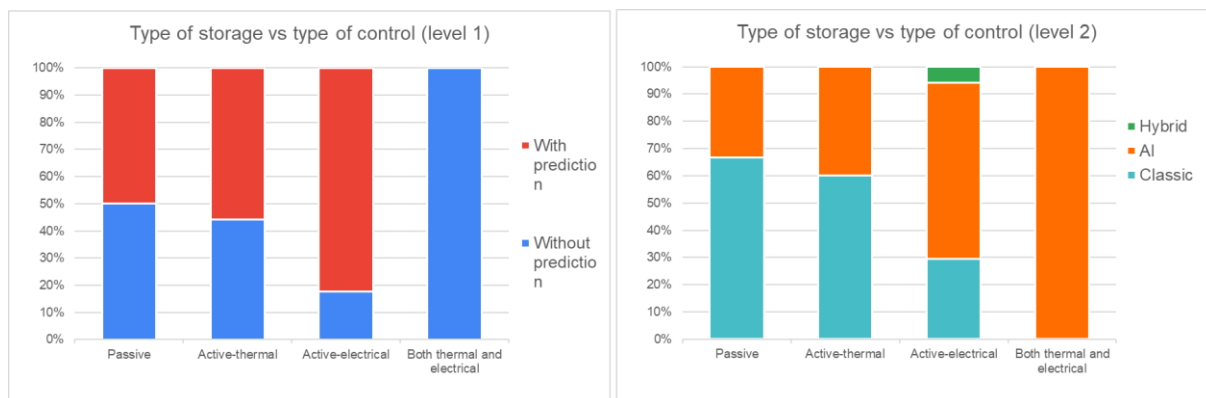


Figure 6.6: Relationship between the different levels for energy storage control

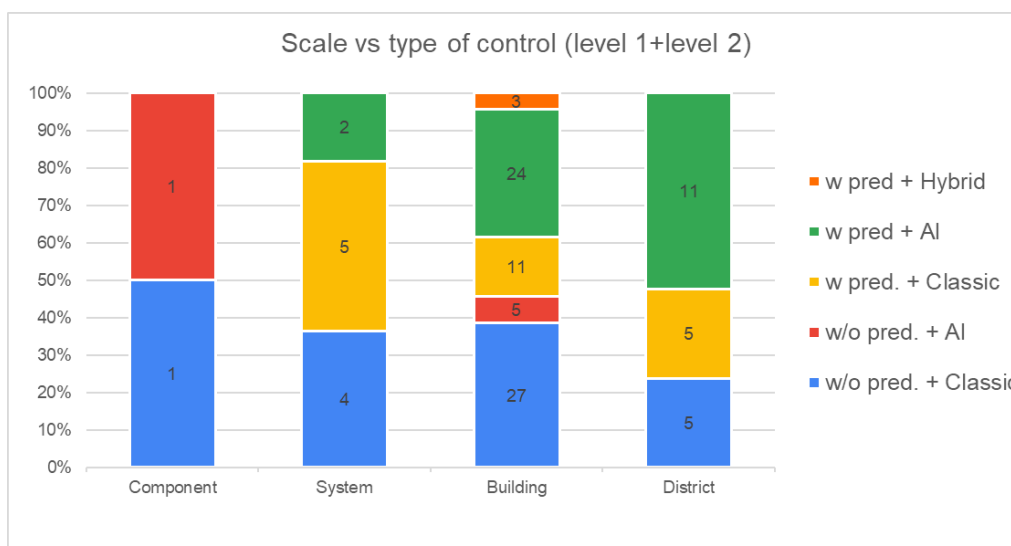


Figure 6.7: Relationship between the scale of the study and the storage control

6.3.2 Non-predictive control strategies for energy storages

6.3.2.1 Applications without the support of AI

Among the papers that were analysed, 16 papers used classic control techniques without prediction. Figure 6.8 shows the types of classic control used in the papers. Most of the studies implemented an on/off control, and two studies implemented P, PI, or PID controls (controllers using error dynamics). Some studies with on/off control adjusted their control setpoint based on criteria such as schedules [4], predefined curves [5], or energy price [6].

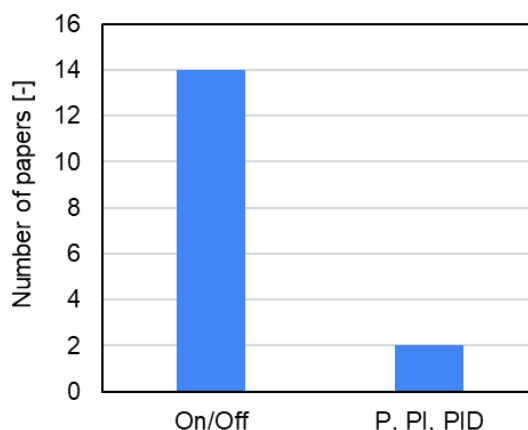


Figure 6.8: Classic control types in the selected studies

The selected studies report on the benefit of energy storage through the more efficient operation of the coupled system components, such as the reduced operating hours of the heat pump. In order to report some of the features of such applications, here are summarized some relevant studies of this approach. Meng et al. [7] conducted an experimental study of a variable air volume (VAV) air conditioning system with an air source heat pump and thermal storage tank. The heat pump was operated with an on/off control based on the return chilled water temperature. The charge/discharge of the thermal storage tank was done at fixed times. The use of heat storage reduced the on/off times of the heat pump from 43 to 7 times in a day with summer settings, and from 36 to 7 times in a day with winter settings, compared to scenarios without any storage. Zhang et al. [8] conducted an experimental study accompanied by a simulation on a hybrid solar/biomass heating system with a water storage tank. Water temperatures from the solar panels and storage tank were monitored to control the on/off behavior of the biomass boiler and the switching of the heat source (solar panels, storage tank, or boiler). The heat pump was operated with a step control of 0, 60, 80, and 100%, depending on the outdoor temperature. A simulation study of a residential building in Lvling, China showed that among the 1975 h of heating hours, 749 h was operated with just the supply water from the storage tank.

Qiang and Zhao [9] investigated the addition of a cold water storage tank to improve the operation of a gas engine heat pump (GEHP) system. The GEHP was connected to an office building for cooling purposes and domestic hot water supply. Three operation modes were assumed according to the cooling load: i) low load - energy is supplied from the energy storage when building load decreases, ii) medium load - heat pump supplies energy to the building and to the energy storage, iii) high load - heat pump and energy storage supplies energy to the building simultaneously. Adding the cold water storage tank with the current control strategy allowed the engine to run within economic mode all day, leading to a stable and efficient GEHP. The primary energy ratio improved by 68%, 9.5%, and 33%, in the low, medium, and high loads after adding the cold water storage, respectively.

Among the selected articles, energy storage in the context of demand response (DR) was commonly studied. Some studied the DR potential of the storage by its load shifting capability, while others studied price-based demand response. Chen et al. [10] conducted an experimental study to evaluate the DR potential of the building thermal mass and a thermal storage tank. The DR potential was evaluated by the cooling load reduction when pre-cooling or a setpoint offset was adopted in the system control. Within the conditions of the experimental setup, the pre-cooling (and hence the

charging of the building thermal mass) maintained comfort conditions for over 90 min without the use of active cooling. The use of a 200 L water storage tank with 9 °C chilled water was able to meet the cooling demand for over two hours for the 32 m² test facility. Romani et al. [11] conducted a simulation study with an experimentally validated numerical model of a room with a radiant wall acting as a thermal energy storage, which was coupled with a photovoltaic (PV) panel. Different control setpoint of the room for the on/off behavior of the heat pump was tested, with different priorities such as maintaining room temperature, maximizing PV energy production, and minimizing energy imported from the grid. By charging the radiant wall during off-peak hours, a maximum of 84% cost reduction compared to the baseline (on/off based on room temperature control) was achieved in the studied case. The authors identified parameters that could be further investigated, such as indoor temperature setpoint, threshold of the PV output for activating the heat pump, and the prediction of PV production, cooling load, and charging time. Cichy et al. [6] conducted a simulation case study of a large residential building with heat pumps, solar thermal collectors, hybrid collectors, PV panels, thermal storage tanks, and lithium-ion battery storages. Price-depending control was adopted to adjust the setpoint temperature of the storage tank and indoors. The most efficient heat source at the time was selected to operate the heat pump. Compared to a fixed setpoint control, the price-depending control led to an overall cost reduction of 14%. Guo et al. [12] conducted a simulation study on the demand response potential of a ventilated electric heating floor system, where the thermal mass of the floor was used as storage and the ventilation was used for discharging. Heating from the floor system was controlled by a PID controller. A fixed indoor temperature setpoint control and a control that varied the indoor temperature setpoint based on the DR status were simulated. The active discharge of the floor with ventilation reduced energy use by up to 37% with a constant setpoint control, and by 62% with a DR-based control. Chapaloglou et al. [13] used a model of a microgrid consisting of a sports center with heat pump, PV modules, and a battery to study the influence of two rule-based controls, peak shaving and price arbitrage, on the electricity cost. The peak shaving strategy made use of the stored electricity in the battery during periods with high load. In the price arbitrage, electricity could be stored in the battery during periods with electricity prices lower than the daily mean. The stored electricity could then be used in periods when the electricity prices exceeded the daily mean value. Cost reduction was obtained under both strategies, but with up to 23 percent points higher with the price arbitrage control. These values are though dependent on the on-site energy production from the PV modules. Coccia et al. [14] carried out a demand side management analysis for a water loop heat pump (WLHP) system integrated with a refrigeration system for building climate control and food preservation in a supermarket. A model was developed in TRNSYS where the role of the water loop and its thermal inertia for energy flexibility was investigated. The demand side management analysis based on the real-time electricity price showed that the setpoints that regulate the WLHP operation, namely heat recovery set point temperature, auxiliary heater set-point temperature, and dry cooler set-point temperature could be updated to reduce yearly electrical energy cost. By also optimizing the storage tank volume, a similar overall energy use was obtained but with a reduction in the yearly electricity cost of 2000 EUR.

There has also been an increasing number of studies investigating the use of phase change materials (PCM) for thermal storage. Most studies are still at the phase of developing and testing components containing PCM, and complex controls are yet to be tested. Hu et al. [15] conducted experimental and simulation studies on a newly developed, PCM enhanced ventilated window. The charging and discharging of the PCM was managed by changing the openings for ventilation, and the change in mode was determined by the time, season, and indoor temperature. Compared to the primitive control with no mode changes, the control proposed by the authors resulted in energy savings up to 62% in summer and 9.4% in winter. Stathopoulos et al. [16] investigated the load shifting potential of an air to PCM

heat exchanger. For the analysis both experimental and simulation data were used where the heat exchanger was integrated in the mechanical ventilation system which supplied air to a room. The implemented control stopped active heating from 18:00 to 20:00, when the peak winter daily electricity demand was found to occur in France. During off-peak hours, the PCM was charged by the incoming air, which was actively heated using electrical resistances. The stored heat was then released to the air being supplied to the room. The study showed that by integrating the PCM, 9 to 10% of the energy could be shifted to the off-peak period while managing to maintain a constant room temperature. Li et al. [17] investigated the development of a novel solar heat pump heating system, which used PCM as the heat storage. An air type solar collector with encased PCM was used to store thermal energy. During periods with insufficient solar radiation the energy stored in the PCM could be utilized as a heat source to the evaporator of the heat pump providing indoor heating. The control system switched operation between i) solar heating mode ii) solar-assisted heat pump heating mode iii) heat pump heating mode depending on the indoor temperature, the solar radiation intensity, and solar collector internal temperature. Experimental results showed that the solar collector could continuously supply heat for 9.5 h with an average thermal efficiency of 45%. The energy stored in the PCM could power the heat pump efficiently for 3 h. A case study over a period of 30 days during the heating period in Tongliao, China showed that the system managed to maintain the indoor temperature between 21 and 24 °C. An economic analysis showed an annual heating cost reduction of 73% when compared to an electric boiler heating system. Several studies have reported on the development of radiant ceiling panels with PCM, such as Bogatu et al. [18] and Gallardo and Berardi [19]. An early study by Bourdakos et al. [20] showed that the PCM panels could passively absorb the internal heat during the daytime, and be discharged in the night time (either by ventilation or by water cooled by night sky radiative cooling). Hence, it was shown that PCM ceiling panels have a peak shifting effect similar to that of a thermally active building system. A recent study by Gallardo and Berardi [21] conducted a simulation study to evaluate the energy flexibility potential of their PCM panels. The results showed that the panels (with a ceiling coverage of 66%) yielded an average heat storage capacity of about 430 Wh/(m²·day) and an average annual storage efficiency of 86%. Compared to the baseline all-air system, the PCM panel system was also able to shift the electric power demand by 8h.

Despite the numerous studies supporting the benefit of energy storage, there were certain limitations reported related to its design and control. One of the precautions that must be taken is reducing the parasitic loss of the storage, by means such as insulation. Le et al. [4] conducted a simulation case study of a cascade air-to-water heat pump system to be used in a retrofit of a residential building. Three heating strategies were compared: i) direct mode – the heat pump provided heat directly to the house, ii) indirect mode – the heat was first provided to the water storage tank and then to the house, and iii) combined mode – the tank was charged during the night and the heat pump provided heat directly to the house when the tank was discharged. The on/off behavior of the heating system was controlled by a room thermostat. In the studied scenario, the average room temperature of all three heating strategies were 19.6 – 19.8 °C. However, the annual electricity use was highest with the indirect mode (17,304 kWh) and lowest with the direct mode (11,777 kWh). The operating cost was highest with the indirect mode (3,028 £) and lowest with the combined mode (1,976 £). The annual system coefficient of performance (COP) of the indirect mode was 33% lower than the direct mode due to parasitic losses of the storage tank. Bengoetxea et al. [22] conducted an experimentally validated simulation study of a hybrid system for heating and domestic hot water production, comprising a micro-CHP (combined heating and power), a condensing boiler, and a thermal storage tank. The on/off and charge/discharge behavior of the components were controlled based on the setpoint of the micro-CHP return water temperature, tank temperature, and return water temperature from the consumptions (demand-side). The corresponding setpoint temperatures were determined by

an optimization function to minimize cost and to maximize exergy performance. The optimized control yielded a 7% cost reduction and 4% higher exergy efficiency compared to the baseline control from the experiments. However, the authors also pointed out that in order to benefit from the optimized control, proper insulation is necessary, keeping the transmission loss below 5% of the energy consumed.

In contrary to the studies summarized above, classic control without any prediction did not provide adequate performance in some cases. Belmonte et al. [23] conducted a simulation study of a building equipped with a water-to-water, solar-assisted heat pump system, which was coupled with a water and phase change material (PCM) tank. The charge/discharge of the heat storage components were thermostatically controlled with a dead band. The simulation results showed that the use of the PCM tank led to worse results, i.e., 30% less useful solar energy collected, 30% less solar energy transferred to the heat pump, 6% lower collector efficiency, and the reduction of heating availability from 99% to 73%. The reduced performance was associated with the longer charging/ discharging behavior of the PCM. Authors pointed out the importance of a more optimized control strategy to take full advantage of the storage capacity of the PCM tank. One method for improving a system with energy storage from a control perspective would be to refine controls of multiple components, as suggested by Borrelli et al. [5]. The authors conducted a simulation study testing different control strategies for a heating system in an existing nearly zero energy building (nZEB). In the baseline control, the boiler operation was controlled to maintain a fixed setpoint inside the water storage tank. The baseline control was compared with other strategies such as a scheduled setback of the tank temperature, or a variable temperature setpoint of the tank depending on the outdoor temperature. With the combination of a variable tank temperature setpoint and early air handling unit (AHU) operation time, primary energy use was reduced by 32 – 46% and hours within comfort range (20 – 24 °C) increased by 0.6 – 3.4% compared to baseline. The study concluded that in order to achieve energy savings and comfort, it would be necessary to optimize the control of each component within the system (i.e., AHU and boiler). Other studies also mention the necessity for more advanced control methods, such as model predictive control (MPC) and energy and demand forecast [24].

6.3.2.2 Applications supported by AI

Modern nature-inspired optimization algorithms such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) are used mostly to optimize the schedule of combined cooling, heating, and power (CCHP) systems with TES in district or building level.

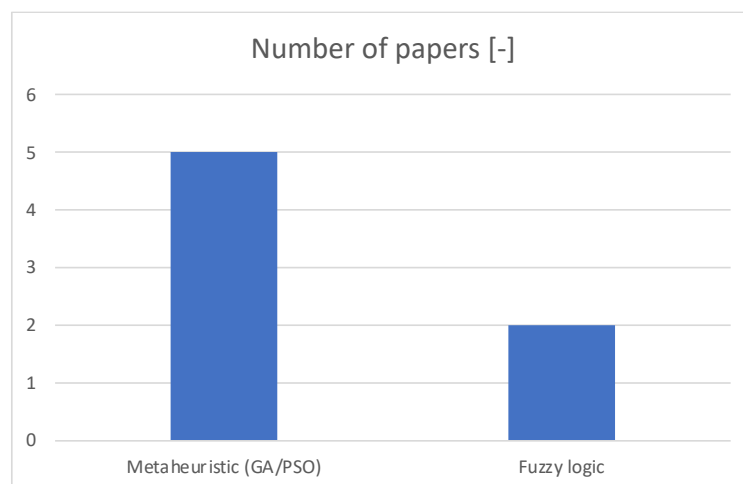


Figure 6.9: Control types in the selected studies

Li et al. [25] combine GA and dynamic programming (DP) and propose an effective hybrid optimization framework to find the optimal day-ahead scheduling as well as real-time dispatching of a CCHP system with TES. They try to minimize a multi-objective cost function including energy consumption, operation cost and environmental impacts. Their results show that the proposed scheme increases the overall performance by 1.92% in summer and by 1.91% in winter in comparison with conventional GA method.

Zhang et al. [26] in a similar work combine GA and stochastic dynamic programming (SDP) to propose a two-stage optimization scheme for an integrated energy system (IES) with demand response (DR) and TES. (IES is just another term for referring to CCHP systems). They try to minimize a multi-objective cost function including operation cost and thermal comfort. The optimization problem is divided into two sub-problems, namely demand-side and supply-side, which are solved iteratively. GA is applied in the first stage to determine the optimal electricity, cooling, and heating demand curves considering the comfort requirements of consumers. SDP then is exploited in the second stage to find the optimal schedule for storage and energy production subject to the demand curves resulted from GA. The results of the second stage are then given back to the first stage to reoptimize the demand curves. The process loops until the optimal operation schedule and demand curves are obtained. Their results show that the proposed method reduces operation cost by 3.6% in comparison with conventional GA method.

Wang et al. [27] apply a decentralized optimal control method based on multi-agent system (MAS) to minimize the operation cost of CCHP systems with TES by exploiting GA. Their results reveal that the operation cost is reduced by 10.0% on a typical summer day and by 7.7% on a typical spring day compared with a rule-based control method.

Li et al. [28] use a multi-objective seagull optimization algorithm (MOSOA) to optimize the energy consumption, operation cost and environmental impacts of CCHP systems. They propose an operation strategy called “following the state of thermal storage tank” (FST) and compare its performance with the two common strategies named “following the electric load” (FEL) and “following the thermal load” (FTL). Their results indicate that the novel proposed strategy is more economical and reduces fuel consumption effectively. It increases primary energy saving ratio by 2.53% and 2.43% in comparison with FEL and FTL strategies.

Apart from the mentioned studies regarding district level, Barthwal et al. [29] exploit multi-objective GA to optimize phase change material (PCM) and ice-based TES systems for air conditioning applications in building level. The objectives include exergy efficiency and total annual cost. Inlet and outlet temperatures of air handling unit (AHU) for discharging cycle, storage temperature, evaporator temperature and condenser temperature are five decision variables for the optimization program. They optimize the performance of the system in partial and full operating modes for two refrigerants. Their results reveal that the exergy efficiency of ice-based TES systems in full mode operation is about 33% higher than partial mode operation. However, it is achieved by compromising the total annual cost. In addition, PCM-based TES systems demonstrate higher exergy efficiency and higher total annual cost in comparison with ice-based TES systems.

Beside the metaheuristic optimization algorithms, fuzzy logic methods are also applied to improve the performance of TES systems in residential and district levels. For example, Tascioni et al. [30] suggest a smart control strategy based on a fuzzy logic approach for a latent heat TES system in a micro-scale concentrated solar power (CSP) plant linked with a combined heat and power (CHP) unit. Their results show that the proposed strategy increases electricity produced by the CHP unit by about 5% and simultaneously reduces thermal losses in the CSP plant by 30%.

Gao et al. [31] utilize a fuzzy controller to dispatch and control a TES system within an IES. They propose an optimal scheduling approach consist of two layers, one layer for day-ahead scheduling and the other one for real-time dispatching. The fuzzy logic controller is implemented in the second layer for managing the electrical and thermal storage subsystems. Their results show that the proposed method reduces the operation cost between 1%-2% in comparison with two conventional scheduling methods.

6.3.3 Predictive control techniques

6.3.3.1 Applications without the support of AI

The classic controller with prediction means that the controller schedules the control variables based on prediction from white-box models or grey-box models. It could be further classified as classic model predictive controller (MPC) or rule-based controller (RBC) based on whether or not an optimization procedure is involved to solve the optimal control signals. This review procedure found 19 existing studies on the application of such classic predictive-based controller to buildings/systems equipped with energy storage system. Among them, 18 papers focused on developing classic MPC, while 3 studies developed RBC based on the predictive result. Besides, 6 studies predicted the building/system status or performance based on grey-box models, while 14 papers developed white-box models. Moreover, most of studies evaluated the applicability of proposed controllers based on numerical study, while only 2 papers applied the classic controller in a field experiment.

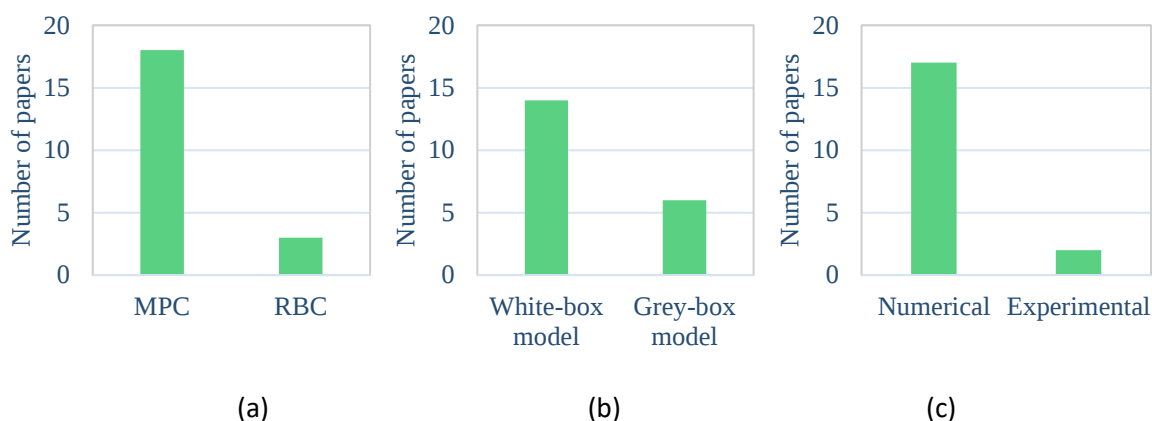


Figure 6.10: Paper distribution on (a) MPC or RBC; (b) white-box model or grey-box model; (c) numerical study or experimental study

Existing studies on the classic MPCs usually developed a white-box/black-box model for the studied systems/buildings/district to predict their status/performance, such as energy demand and indoor air temperature. Then, the predicted values would be used to form the objective function or constraints of an optimization problem to minimize the operation cost, energy cost, or peak loads, while ensuring a comfortable indoor environment and/or making sure the devices working within their rated conditions. Detailed review on classic MPC is presented as below:

Salpakari and Lund [32] developed physical realistic models for a heating system that consists of a ground-source heat pump with an electric heater, a thermal energy storage system (i.e., a water tank), a battery, and a hydronic heating system. Then, they integrated these models into the electricity cost optimization function of a MPC to get the hourly optimal compressor power, electric heater power, battery power, mass flowrate of the hydronic heating system, and number of running shiftable appliances. Besides, they applied a RBC to maximize PV self-consumption. Through a numerical case study on a Finnish low-energy house, the cost-optimal control resulted in 13-25% electricity cost saving and 8-88% decrease in the grid feed-in, compared to the inflexible reference case that did not include a battery or any shiftable appliance.

Similarly, Tang and Wang [33] predicted the power demand of chillers based on the cooling supply and coefficient of performance (COP). Meanwhile, they developed a building thermal model and simplified it as a linear discrete-time state-space model to predict the indoor air temperature. Then, an optimization problem was conducted to optimize the set-point of chiller power demand and cooling discharge rate of a cooling storage system, with the aim of minimizing the power consumption while ensuring an acceptable indoor environment. By adopting this MPC in to a TRNSYS model of a central air-conditioning system in a commercial building, the MPC was proofed to be able to achieve expected power reduction and improve indoor thermal environment.

Descamps et al. [34] assumed perfect forecast/prediction (i.e., the predicted values are the same as actual ones) for weather, heat load, and electricity cost in the MPC that is aimed at minimizing the operational cost of a district heating network, which combines a heat pump, a gas boiler, and a solar thermal productur and a thermal storage tank. The MPC reduced the operational cost by up to 5% compared to a rule-based controller (RBC).

Moreover, one type of commonly used classic MPCs is called mixed integer linear programming (MILP). For example, Martínez Ceseña and Mancarella [35] proposed an operational optimization framework based on MILP to get the optimal half-hourly time-ahead set points for all controllable devices

(including electrical energy storage and thermal energy storage systems) in a smart district with the aim of minimizing energy cost. Fratean and Dobra [36] applied a MILP controller to control the heating/cooling system, energy generation system, and storage system, with the aim of reducing the energy consumption and lifecycle cost of two buildings in Bucharest, Romania. Furthermore, Duman et al. [37] integrated MILP into a HEMS to optimize the day-ahead operation schedule of battery energy storage system and electric vehicle. In this study, the experimental house was simulated by a 1R1C model, while other devices (including refrigerator, electric vehicle, PV generation, air conditioner, etc.) were modelled by white-box models. They found that the smart HEMS decreased the daily cost by 53.2% under time-of-use (TOU) tariff of Turkey through taking advantage of self-consumption.

The classic MPCs have been used when investigating the energy storage capacity and peak shifting ability of both passive and active energy storage systems. For instance, the joint electrical-thermal model of buildings and low voltage networks (LVNs) in a district were simulated as a white-box model by Jazaeri et al. [38] with considering the thermal properties of four types of wall constructions. Their study found that high thermal inertia from inside enables the building to shift the entire cooling load from peak periods to off-peak periods. Azuatalam et al. [39] investigated the effect of the thickness of phase change materials (PCMs) on the heating cost of a building controlled by a RC model-based MPC that minimizes the heating cost and the difference between the desired indoor air temperature and the measured value.

To apply the classic MPCs to control devices/buildings in a district, Ouammi [40] proposed a white-box model based MPC to comprehensively control a smart network of residential buildings by optimally scheduling the power exchanges, charge/discharge rate of energy storage devices, the state of micro-CHP and the charging state of electric vehicles. Tang et al. [41] used the game theoretic method to minimize the electricity bill of a district through optimizing the indoor air set-point temperature and the operation of an active thermal storage system. In their study, buildings were simulated by a RC model. The result shows that the proposed game theory-based decentralized control strategy decreased the peak load by ~10%, which is over two times of the individual-level control strategy.

Due to the multiple time scale nature of energy storage systems and different dimensions between buildings and districts, developing hierarchical controllers based on the structure of MPC would be an effective solution when the control target includes several energy storage systems or consumers. For instance, Touretzky and Baldea [42] proposed a hierarchical controller for thermal energy storage systems. It consists of a fast control layer for passive storage and a slow control layer for active storage. The numerical study results show that the hierarchical controller resulted in over 59% cost saving compared to the baseline. Furthermore, Ferro et al. [43] proposed a bi-level controller to minimize the electricity cost of interconnected buildings in a smart grid. In the controller, the upper decision maker provides references for power exchange with the aim of minimizing cost and power losses. Following the references, the consumers manage storage systems and devices to achieve cost saving and comfort requirements.

Except of optimizing the operation of devices in buildings/districts with thermal storage systems, classic MPCs have also been used in design stage. For instance, Sharifi et al. [44] proposed an optimal load splitting algorithm (OLSA) to optimize the hourly load splitting between a thermally activated building system (TABS) and a secondary system over a year based on a RC model of the TABS and the building. Accordingly, the design parameters (such as supply water temperature and water flow rate) of TABS could be defined based on the optimal heat flow rate calculated by OLSA.

Furthermore, most of existing studies investigated the applicability MPCs based on the numerical study instead of the field experiment. Here, studies based on experiments would be summarized. Bürger et

al. [45] designed a one-day experiment to successfully implement a mixed-integer nonlinear MPC with the aim of economic optimization to control the operation of a solar-driven climate system, which consists of two solar thermal collectors, a hot water storage system, a cold-water storage system, and an adsorption cooling machine. Kuboth et al. [46] compared a white-box model based MPC with a reference PI-based standard controller by using them to control heat pumps in two test rigs, which include an air source heat pump and a hot water tank. The experimental result indicates that the economic MPC reduced the heat pump operation cost by 34.0%, through averagely increasing the heat pump coefficient of performance (COP) by 22.2% and the photovoltaic energy self-consumption by 234.8%.

Although the classic MPCs could reduce the peak loads and electricity cost substantially, improving its computation speed for solving the optimization problem should be concerned. For instance, Meinrenken and Mehmani [47] pointed out that solving the optimal one-day-ahead set-point temperature for an official building and battery dispatch took around 1.5h when using a standard computer with Intel Core i5 CPU and 8GB memory. To reduce the computation time, several solutions could be considered, such as using faster processor, parallel computing for different zones, or simplifying the predictive model/objective function. For example, Ostadijafari et al. [48] constructed a nonlinear economic model predictive controller (NL-EMPC), in which the predicted energy consumption was multiplied by the electricity price to form the objective function and the predicted indoor air temperature were used to set the thermal comfort constraints. Note that the indoor air temperature prediction was predicted by a bilinear model derived from a RC network model, while the energy consumption of the HVAC system and battery storage system was formulated by the state-space equations. They then mimic the behaviour of NL-EMPC by a linearized economic model predictive controller (L-EMPC) that approximate the non-linear equations by feedback linearization, constraint mapping, or piecewise linearization. The L-EMPC shows comparable cost saving ability with NL-EMPC, but much faster computation speed.

Another concern for classic MPCs is that they do not always show better control performance than traditional control strategies. For example, Oliveira et al. [49] found that a simple control policy for a water heater tank could show comparable cost reduction ability than a classic MPCs. Improving the accuracy and simplicity of predictive models may improve the applicability of MPCs [50].

Except the MPCs, the predictive results from classic models have also been integrated into RBCs to schedule preheating/precooling of the HVAC system to take advantages of thermal storage capacity of thermal mass [51]. Parejo et al. [52] proposed a homeostatic control strategy to control the PV generation, energy storage, and air conditioning of a building in a micro-grid. The proposed controller includes two different parts: predictive branch and reactive branch. The former part is aimed at maintaining a thermal comfortable indoor environment, while the later part controls the charging state of batteries to maintain the microgrid running.

6.3.3.2 Applications supported by AI

Combining model predictive control (MPC) and AI to enhance the performance of heating systems with TES in building and district levels has absorbed much attention among researchers during recent years. Usually, artificial neural networks (ANN) are exploited as the predictive model within MPC approaches and/or metaheuristic algorithms are applied to solve the optimization problem.

Cox et al. [53] exploit ANN for modelling a large district cooling system with ice storage within an MPC framework. GA was linked with MPC to solve the optimization problem. Their results show that the

proposed method is capable of reducing operation costs between 13% to 16% comparing with a fixed schedule case.

Reynolds et al. [54] exploit ANN to predict several variables including indoor temperature, building demand and solar photovoltaic generation and then use them within an MPC framework combined with GA to optimize the operation schedules of an IES system with TES. Their results show that the suggested method increase the profit by 44.88% in comparison with a to an RBC approach.

Finck et al. [55] exploit ANN to predict solar radiation, space heating demand and electricity consumption of a heat pump for a building heating system including TES and then apply an economic MPC framework to minimize the total costs of electricity consumed by the heat pump. Set points for the temperature of domestic hot water tank and space heating tank are considered as control variables and a direct search method is applied to solve the optimization program. Their results indicate that the suggested method reduces operation cost by around 10% in comparison with an RBC method. In addition, the proposed method improves demand flexibility significantly.

Lee et al. [56] examine the optimal control of charging and discharging rates of a chilled water TES tank to minimize the operation cost. They use ANN as their prediction models and then apply a metaheuristic algorithm called “ ϵ DE-RJ” to solve the optimization problem. ANN models predict a few system variables including the temperatures of the bottom, middle, and top TES tank layers. Their results show that the proposed AI-based MPC strategy reduces the operation cost by 9.1–14.6% in comparison with conventional rule-based control (RBC) approaches.

Apart from the studies which combine MPC with AI, some papers use AI as prediction model in combination with conventional control methods to optimize the operation of TES systems. For instance, Meng et al. utilize an Elman ANN for load forecasting as well as TES modeling. The ANN is coupled with PSO to optimize load prediction. Their results indicate that the proposed method is capable of reducing the operation costs effectively while keeping thermal comfort at a desired level.

6.4 Emerging trends and perspectives

6.4.1 The role of AI

Energy storage technology stabilizes the fluctuating energy supply and demand by storing and reallocating thermal and electrical energy. Environmental and economic benefits from its application are considerable and it can be applied widely at the system, building, and district levels. However, as reported in the earlier section, the potentials and advantages of energy storage technologies are very dependent on how they are controlled.

In general, the energy storage system needs to be operated from a comprehensive perspective by considering the demand load that is dynamic and easy to be influenced by external disturbances such as meteorological or building parameters [57]. Especially, the energy storage system has a strong cooperative effect with renewable energy sources, but renewable energy sources have drawbacks in that they are unstable with volatility and intermittency [58].

When it comes to classic control strategies such as feedback control or rule-based control, they only focus on the current status of the external conditions and thus easily fail to lead the energy storage system to maximize environmental and/or economic profits. Therefore, to enhance the overall efficiency of the energy storage system, an advanced control strategy that considers the thermal and/or electrical behaviors of the energy storage system under dynamic operational conditions [59].

Contrary to the classic control strategies, AI-based control can help to draw up the intelligent

management of the energy storage system by solving two main following challenges.

1. Prediction of key influencing factors of the energy storage system such as energy storage performance, meteorological parameters, and demand loads.
2. Optimization to search for best solutions of control variables for the energy storage systems to consider single or multiple objectives to maximize environmental and/or economic benefits with upper and lower capacity constraints.

For instance, Rehman et al. [60] employed an AI-based control method to optimize a photovoltaic-based energy system integrated with onsite battery and electric vehicles (EV). Based on the gradient tree boosting ensemble method, profiles of the photovoltaic energy production were estimated, and the battery charging/discharging and EV charging was optimally manipulated by linear and mixed integer programming to minimize the annual cost of the purchased electricity. In their case study, the cost was reduced by 6%–36% depending on the photovoltaic capacity.

In another previous research by Lee et al. [56], a metaheuristic algorithm was adopted to optimize the charging and discharging time and amount of sensible thermal energy storage system for minimizing the total operating cost. During the control phase, the usage temperature of the thermal energy storage tank and the energy consumption were predicted by artificial neural networks and the optimization solver referred to the predicted results in the estimation of cost-function. In their experimental validation, the AI-based control method showed operation cost savings of up to 14% compared to the classic rule-based control method.

Also, Svetozarevic et al. [61] utilized a deep reinforcement learning algorithm to optimally control the EV battery system. By adopting the deep reinforcement learning algorithm in the controller, the valve opening of the water loop for the floor heating system and charging/discharging of the EV battery was optimized to minimize the electricity cost by maintaining indoor thermal comfort. In order to determine the optimal control variables, the room temperature and the state of the EV battery were predicted by recurrent neural networks and linear models constructed based on historical data. They compared the performance of the deep reinforcement learning control policy with the classic rule-based control, and it was found that it could achieve 17% energy savings and 19% better comfort satisfaction on average.

6.4.2 How storage increase building flexibility and resilience

As stated in the previous section, energy storage technology contributes in balancing energy supply and demand. This contributes in increasing the resilience of buildings and districts during disruptive and hazardous events. A report from the IPCC defines resilience as “the ability of a system and its component parts to anticipate, absorb, accommodate, or recover from the effects of a hazardous event in a timely and efficient manner.” [62]. Zhang et al. [63] further adapted this definition for evaluating building cooling strategies in the event of heatwaves and power outages, and defined four characteristics for resilient cooling, i.e., absorptive, adaptive, and restorative capacity and recovery speed. This outlines the different stages of how a resilient building performs, where it would maintain design conditions under extreme events (absorptive capacity), endure at minimum desirable conditions in more extreme events (adaptive capacity), and recover quickly in the event of a failure (restorative capacity, recovery speed). Thermal energy storage technology is expected to contribute to the absorptive capacity. Active control of energy storage (both thermal and electrical) enables the

system to be adaptive. The restorative capacity and recovery speed are technology-dependent.

In the event of a heatwave, thermal storage such as building mass can help reduce the risk of indoor overheating, when coupled with discharging methods such as nighttime ventilation [64] or active water circulation [65]. Thermal storage at the source side and electrical storage can also help reduce the electricity use during a heatwave, when the electricity peak demands on the grid tend to increase [63], which could potentially result in a power outage. The use of predictive control with weather forecasts would enable buildings and storage systems to prepare for disruptions through efficient load management while maintaining indoor thermal conditions. When a power outage or grid failure occurs, thermal storage in the building mass will allow buildings to be habitable for a certain time before failure, especially if the thermal mass is activated (e.g., by water circulation prior to the power outage) [65]. Electrical storage will directly contribute to the resilience of buildings during a power outage or grid failure. An experimental case study conducted by Amada et al. [66] showed that a net-zero energy house with on-site photovoltaic panels and batteries was able to maintain thermal comfort in the summer of Japan with the partial operation of air conditioning units. In cases where the electrical storage is insufficient to operate active cooling systems for a building, the use of low power personalized cooling devices (e.g., fans) may be an option to make higher indoor temperatures acceptable for the occupants [67]. Existing studies suggest energy storage systems to be a resilient solution, but they are limited to classic, rule-based controls. Advanced control of such systems is worth investigating, e.g., predictive control in the context of heatwaves.

6.5 Conclusions

In the quest for a sustainable energy future, energy storage technology has emerged as a crucial component, playing a pivotal role in bridging the gap between fluctuating energy supply and demand. By effectively storing and reallocating thermal and electrical energy, this technology offers a promising solution to stabilize the power grid, enhance energy efficiency, and improve the resilience of buildings and districts during disruptive events.

The utilization of energy storage technology extends across various scales, from large-scale power systems to individual buildings. At the system level, energy storage can mitigate the intermittency of renewable energy sources, such as solar and wind power, enabling a seamless integration of these clean energy sources into the grid. By storing excess energy generated during periods of high production and releasing it during peak demand periods, energy storage technology can smooth out the fluctuations in energy supply, ensuring a more stable and reliable power grid.

On a smaller scale, energy storage systems can be implemented in buildings to optimize energy consumption and reduce reliance on the grid. By storing energy during off-peak hours and utilizing it during peak hours, buildings can significantly lower their electricity bills and contribute to overall grid stability. Additionally, energy storage systems can enhance the resilience of buildings during power outages, ensuring uninterrupted operation of critical systems and maintaining occupant comfort.

The advent of artificial intelligence (AI) has revolutionized the field of energy storage technology, enabling more intelligent and efficient management of energy storage systems. AI-based control systems can effectively predict key influencing factors such as energy storage performance, meteorological parameters, and demand loads. This predictive capability allows for proactive optimization of energy storage operations, maximizing environmental and economic benefits while ensuring system stability.

AI-based control also plays a crucial role in enhancing the resilience of buildings and districts during disruptive events. By analyzing weather forecasts and predicting potential disruptions, these intelligent systems can enable buildings and storage systems to prepare through efficient load management strategies. During disruptions, AI can optimize energy use to maintain comfortable indoor temperatures and minimize the impact of power outages.

In conclusion, energy storage technology, coupled with AI-based control, offers a transformative approach to sustainable energy management. By stabilizing the power grid, optimizing energy consumption, and enhancing resilience, this technology holds immense potential for shaping a cleaner, more sustainable, and resilient energy future.

6.6 Nomenclature

BITES	Building integrated Thermal Energy Storage
HVAC	Heating, Ventilation and Air Conditioning
MPC	Model predictive control
TES	Thermal Energy Storage

6.7 References

- [1] Z. Yu, G. Huang, F. Haghighat, H. Li, G. Zhang, Control strategies for integration of thermal energy storage into buildings: State-of-the-art review, *Energy Build* 106 (2015) 203–215. <https://doi.org/10.1016/j.enbuild.2015.05.038>.
- [2] A. Afram, F. Janabi-Sharifi, Theory and applications of HVAC control systems – A review of model predictive control (MPC), *Build Environ* 72 (2014) 343–355. <https://doi.org/10.1016/j.buildenv.2013.11.016>.
- [3] W. Song, Z. Zhang, Z. Chen, F. Wang, B. Yang, Thermal comfort and energy performance of personal comfort systems (PCS): A systematic review and meta-analysis, *Energy Build* 256 (2022) 111747. <https://doi.org/https://doi.org/10.1016/j.enbuild.2021.111747>.
- [4] K.X. Le, M.J. Huang, N.N. Shah, C. Wilson, P. mac Artain, R. Byrne, N.J. Hewitt, Techno-economic assessment of cascade air-to-water heat pump retrofitted into residential buildings using experimentally validated simulations, *Appl Energy* 250 (2019) 633–652. <https://doi.org/10.1016/J.APENERGY.2019.05.041>.
- [5] M. Borrelli, B. Merema, F. Ascione, R. Francesca De Masi, G. Peter Vanoli, H. Breesch, Evaluation and optimization of the performance of the heating system in a nZEB educational building by monitoring and simulation, *Energy Build* 231 (2021) 110616. <https://doi.org/10.1016/J.ENBUILD.2020.110616>.
- [6] M. Cichy, B. Beigelböck, K. Eder, F. Judex, Demand response of large residential buildings - A case study from “Seestadt Aspern,” *IECON Proceedings (Industrial Electronics Conference)* (2016) 3936–3941. <https://doi.org/10.1109/IECON.2016.7793518>.

- [7] Q. Meng, X. Ren, W. Wang, C. Xiong, Y. Li, Y. Xi, L. Yang, Reduction in on-off operations of an air source heat pump with active thermal storage and demand response: An experimental case study, *J Energy Storage* 36 (2021). <https://doi.org/10.1016/j.est.2021.102401>.
- [8] X. Zhang, J. Yang, Y. Fan, X. Zhao, R. Yan, J. Zhao, S. Myers, Experimental and analytic study of a hybrid solar/biomass rural heating system, *Energy* 190 (2020) 116392. <https://doi.org/10.1016/J.ENERGY.2019.116392>.
- [9] Z. Qiang, Y. Zhao, The Research on Operating Characteristic of Gas Engine Heat Pump System with Energy Storage (ESGEHP) System, *Energy Procedia* 142 (2017) 1213–1221. <https://doi.org/10.1016/J.EGYPRO.2017.12.509>.
- [10] Y. Chen, P. Xu, Z. Chen, H. Wang, H. Sha, Y. Ji, Y. Zhang, Q. Dou, S. Wang, Experimental investigation of demand response potential of buildings: Combined passive thermal mass and active storage, *Appl Energy* 280 (2020) 115956. <https://doi.org/10.1016/J.APENERGY.2020.115956>.
- [11] J. Romani, M. Belusko, A. Alemu, L.F. Cabeza, A. de Gracia, F. Bruno, Control concepts of a radiant wall working as thermal energy storage for peak load shifting of a heat pump coupled to a PV array, *Renew Energy* 118 (2018) 489–501. <https://doi.org/10.1016/J.RENENE.2017.11.036>.
- [12] J. Guo, W. Zheng, Z. Tian, Y. Wang, Y. Wang, Y. Jiang, The short-term demand response potential and thermal characteristics of a ventilated floor heating system in a nearly zero energy building, *J Energy Storage* 45 (2022) 103643. <https://doi.org/10.1016/J.EST.2021.103643>.
- [13] S. Chapaloglou, A. Nesiadis, K. Atsonios, N. Nikolopoulos, P. Grammelis, A. Carrera, O. Camara, Microgrid energy management strategies assessment through coupled thermal-electric considerations, *Energy Convers Manag* 228 (2021) 113711. <https://doi.org/10.1016/J.ENCONMAN.2020.113711>.
- [14] G. Coccia, A. Arteconi, P. D'Agaro, F. Polonara, G. Cortella, Demand side management analysis of a commercial water loop heat pump system, *Modelling, Measurement and Control C* 79 (2018) 111–118. <https://doi.org/10.18280/MMC-C.790308>.
- [15] Y. Hu, R. Guo, P.K. Heiselberg, Performance and control strategy development of a PCM enhanced ventilated window system by a combined experimental and numerical study, *Renew Energy* 155 (2020) 134–152. <https://doi.org/10.1016/J.RENENE.2020.03.137>.
- [16] N. Stathopoulos, M. el Mankibi, R. Issoglio, P. Michel, F. Haghighat, Air–PCM heat exchanger for peak load management: Experimental and simulation, *Solar Energy* 132 (2016) 453–466. <https://doi.org/10.1016/J.SOLENER.2016.03.030>.
- [17] M.Y. Li, B. Li, C. Liu, S. Su, H. Xiao, C. Zhu, Design and experimental investigation of a phase change energy storage air-type solar heat pump heating system, *Appl Therm Eng* 179 (2020) 115506. <https://doi.org/10.1016/J.APPLTHERMALENG.2020.115506>.
- [18] D.-I. Bogatu, O.B. Kazanci, B.W. Olesen, An experimental study of the active cooling performance of a novel radiant ceiling panel containing phase change material (PCM), *Energy Build* 243 (2021) 110981. <https://doi.org/10.1016/j.enbuild.2021.110981>.

- [19] A. Gallardo, U. Berardi, Design and control of radiant ceiling panels incorporating phase change materials for cooling applications, *Appl Energy* 304 (2021) 117736.
<https://doi.org/10.1016/J.APENERGY.2021.117736>.
- [20] E. Bourdakis, B.W. Olesen, F. Grossule, Night time cooling by ventilation or night sky radiation combined with in-room radiant cooling panels including phase change materials, in: 2015.
- [21] A. Gallardo, U. Berardi, Evaluation of the energy flexibility potential of radiant ceiling panels with thermal energy storage, *Energy* 254 (2022) 124447.
<https://doi.org/10.1016/J.ENERGY.2022.124447>.
- [22] A. Bengoetxea, M. Fernandez, E. Perez-Iribarren, I. Gonzalez-Pino, J. Las-Heras-Casas, A. Erkoreka, Control strategy optimization of a Stirling based residential hybrid system through multi-objective optimization, *Energy Convers Manag* 208 (2020) 112549.
<https://doi.org/10.1016/J.ENCONMAN.2020.112549>.
- [23] J.F. Belmonte, M. Díaz-Heras, J.A. Almendros-Ibáñez, L.F. Cabeza, Simulated performance of a solar-assisted heat pump system including a phase-change storage tank for residential heating applications: A case study in Madrid, Spain, *J Energy Storage* 47 (2022) 103615.
<https://doi.org/10.1016/J.EST.2021.103615>.
- [24] M. Narayanan, G. Mengedoh, W. Commerell, Importance of buildings and their influence in control system: a simulation case study with different building standards from Germany, *International Journal of Energy and Environmental Engineering* 9 (2018) 413–433.
<https://doi.org/10.1007/S40095-018-0281-9/FIGURES/11>.
- [25] F. Li, B. Sun, C. Zhang, C. Liu, A hybrid optimization-based scheduling strategy for combined cooling, heating, and power system with thermal energy storage, *Energy* 188 (2019) 115948.
<https://doi.org/10.1016/j.energy.2019.115948>.
- [26] L. Zhang, J. Kuang, B. Sun, F. Li, C. Zhang, A two-stage operation optimization method of integrated energy systems with demand response and energy storage, *Energy* 208 (2020) 118423. <https://doi.org/10.1016/j.energy.2020.118423>.
- [27] Z. Wang, C. Zhang, H. Li, Y. Zhao, A multi agent-based optimal control method for combined cooling and power systems with thermal energy storage, *Build Simul* (2021).
<https://doi.org/10.1007/s12273-021-0768-9>.
- [28] L.-L. Li, S.-J. Zheng, M.-L. Tseng, Y.-W. Liu, Performance assessment of combined cooling, heating and power system operation strategy based on multi-objective seagull optimization algorithm, *Energy Convers Manag* 244 (2021) 114443.
<https://doi.org/10.1016/j.enconman.2021.114443>.
- [29] M. Barthwal, A. Dhar, S. Powar, The techno-economic and environmental analysis of genetic algorithm (GA) optimized cold thermal energy storage (CTES) for air-conditioning applications, *Appl Energy* 283 (2021) 116253. <https://doi.org/10.1016/j.apenergy.2020.116253>.
- [30] R. Tascioni, A. Arteconi, L. Del Zotto, L. Cioccolanti, Fuzzy Logic Energy Management Strategy of a Multiple Latent Heat Thermal Storage in a Small-Scale Concentrated Solar Power Plant, *Energies (Basel)* 13 (2020) 2733. <https://doi.org/10.3390/en13112733>.
- [31] Q. Gao, X. Zhang, M. Yang, X. Chen, H. Zhou, Q. Yang, Fuzzy Decision-Based Optimal Energy Dispatch for Integrated Energy Systems With Energy Storage, *Front Energy Res* 9 (2021).
<https://doi.org/10.3389/fenrg.2021.809024>.

- [32] J. Salpakari, P. Lund, Optimal and rule-based control strategies for energy flexibility in buildings with PV, *Appl Energy* 161 (2016) 425–436. <https://doi.org/10.1016/j.apenergy.2015.10.036>.
- [33] R. Tang, S. Wang, Model predictive control for thermal energy storage and thermal comfort optimization of building demand response in smart grids, *Appl Energy* 242 (2019) 873–882. <https://doi.org/10.1016/j.apenergy.2019.03.038>.
- [34] M. Descamps, N. Lamaison, M. Vallée, R. Bavière, Operational control of a multi-energy district heating system: Comparison of model-predictive control and rule-based control, in: *ECOS 2019 - Proceedings of the 32nd International Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems*, 2019: pp. 2079–2089.
- [35] E.A. Martinez Cesena, P. Mancarella, Energy Systems Integration in Smart Districts: Robust Optimisation of Multi-Energy Flows in Integrated Electricity, Heat and Gas Networks, *IEEE Trans Smart Grid* 10 (2019) 1122–1131. <https://doi.org/10.1109/TSG.2018.2828146>.
- [36] A. Fratean, P. Dobra, Control strategies for decreasing energy costs and increasing self-consumption in nearly zero-energy buildings, *Sustain Cities Soc* 39 (2018) 459–475. <https://doi.org/10.1016/j.scs.2018.03.019>.
- [37] A.C. Duman, H.S. Erden, Ö. Gönül, Ö. Güler, A home energy management system with an integrated smart thermostat for demand response in smart grids, *Sustain Cities Soc* 65 (2021). <https://doi.org/10.1016/j.scs.2020.102639>.
- [38] J. Jazaeri, T. Alpcan, R.L. Gordon, A joint electrical and thermodynamic approach to HVAC load control, *IEEE Trans Smart Grid* 11 (2020) 15–25. <https://doi.org/10.1109/TSG.2019.2916064>.
- [39] D. Azuatalam, S. Mhanna, A. Chapman, G. Verbic, Optimal HVAC scheduling using phase-change material as a demand response resource, in: *2017 IEEE Innovative Smart Grid Technologies - Asia: Smart Grid for Smart Community, ISGT-Asia 2017*, 2018: pp. 1–5. <https://doi.org/10.1109/ISGT-Asia.2017.8378315>.
- [40] A. Ouammi, Optimal Power Scheduling for a Cooperative Network of Smart Residential Buildings, *IEEE Trans Sustain Energy* 7 (2016) 1317–1326. <https://doi.org/10.1109/TSTE.2016.2525728>.
- [41] R. Tang, S. Wang, H. Wang, Optimal power demand management for cluster-level commercial buildings using the game theoretic method, in: *Energy Procedia*, 2019: pp. 186–191. <https://doi.org/10.1016/j.egypro.2018.12.049>.
- [42] C.R. Touretzky, M. Baldea, A hierarchical scheduling and control strategy for thermal energy storage systems, *Energy Build* 110 (2016) 94–107. <https://doi.org/10.1016/j.enbuild.2015.09.049>.
- [43] G. Ferro, F. Laureri, R. Minciardi, M. Robba, Optimal Integration of Interconnected Buildings in a Smart Grid: A Bi-level Approach, in: *Proceedings - 2017 UKSim-AMSS 19th International Conference on Modelling and Simulation, UKSim 2017*, 2018: pp. 155–160. <https://doi.org/10.1109/UKSim.2017.46>.
- [44] M. Sharifi, R. Mahmoud, E. Himpe, J. Laverge, A heuristic algorithm for optimal load splitting in hybrid thermally activated building systems, *Journal of Building Engineering* 50 (2022). <https://doi.org/10.1016/j.job.2022.104160>.
- [45] A. Bürger, D. Bull, P. Sawant, M. Bohlayer, A. Klotz, D. Beschütz, A. Altmann-Dieses, M. Braun, M. Diehl, Experimental operation of a solar-driven climate system with thermal energy

- storages using mixed-integer nonlinear model predictive control, *Optim Control Appl Methods* 42 (2021) 1293–1319. <https://doi.org/10.1002/oca.2728>.
- [46] S. Kuboth, F. Heberle, T. Weith, M. Welzl, A. König-Haagen, D. Brüggemann, Experimental short-term investigation of model predictive heat pump control in residential buildings, *Energy Build* 204 (2019). <https://doi.org/10.1016/j.enbuild.2019.109444>.
 - [47] C.J. Meinrenken, A. Mehmani, Concurrent optimization of thermal and electric storage in commercial buildings to reduce operating cost and demand peaks under time-of-use tariffs, *Appl Energy* 254 (2019). <https://doi.org/10.1016/j.apenergy.2019.113630>.
 - [48] M. Ostadijafari, A. Dubey, N. Yu, Linearized Price-Responsive HVAC Controller for Optimal Scheduling of Smart Building Loads, *IEEE Trans Smart Grid* 11 (2020) 3131–3145. <https://doi.org/10.1109/TSG.2020.2965559>.
 - [49] V. de Oliveira, J. Jäschke, S. Skogestad, Optimal operation of energy storage in buildings: Use of the hot water system, *J Energy Storage* 5 (2016) 102–112. <https://doi.org/10.1016/j.est.2015.11.009>.
 - [50] P. Sawant, A. Bürger, M.D. Doan, C. Felsmann, J. Pfafferott, Development and experimental evaluation of grey-box models of a microscale polygeneration system for application in optimal control, *Energy Build* 215 (2020). <https://doi.org/10.1016/j.enbuild.2019.109725>.
 - [51] L. Martirano, E. Habib, G. Parise, G. Greco, M. Manganelli, F. Massarella, L. Parise, Smart micro grids for Nearly Zero Energy Buildings, in: *IEEE Industry Application Society, 52nd Annual Meeting: IAS 2016*, 2016. <https://doi.org/10.1109/IAS.2016.7731831>.
 - [52] A. Parejo, A. Sanchez-Squella, R. Barraza, F. Yanine, A. Barrueto-Guzman, C. Leon, Design and simulation of an energy homeostaticity system for electric and thermal power management in a building with smart microgrid, *Energies (Basel)* 12 (2019). <https://doi.org/10.3390/en12091806>.
 - [53] S.J. Cox, D. Kim, H. Cho, P. Mago, Real time optimal control of district cooling system with thermal energy storage using neural networks, *Appl Energy* 238 (2019) 466–480. <https://doi.org/10.1016/j.apenergy.2019.01.093>.
 - [54] J. Reynolds, M.W. Ahmad, Y. Rezgui, J.-L. Hippolyte, Operational supply and demand optimisation of a multi-vector district energy system using artificial neural networks and a genetic algorithm, *Appl Energy* 235 (2019) 699–713. <https://doi.org/10.1016/j.apenergy.2018.11.001>.
 - [55] C. Finck, R. Li, W. Zeiler, Optimal control of demand flexibility under real-time pricing for heating systems in buildings: A real-life demonstration, *Appl Energy* 263 (2020). <https://doi.org/10.1016/j.apenergy.2020.114671>.
 - [56] D. Lee, R. Ooka, Y. Matsuda, S. Ikeda, W. Choi, Experimental analysis of artificial intelligence-based model predictive control for thermal energy storage under different cooling load conditions, *Sustain Cities Soc* 79 (2022). <https://doi.org/10.1016/j.scs.2022.103700>.
 - [57] G.P. Henze, M. Krarti, M.J. Brandemuehl, Guidelines for improved performance of ice storage systems, *Energy Build* 35 (2003) 111–127. [https://doi.org/10.1016/S0378-7788\(01\)00140-2](https://doi.org/10.1016/S0378-7788(01)00140-2).
 - [58] M. Yekini Suberu, M. Wazir Mustafa, N. Bashir, Energy storage systems for renewable energy power sector integration and mitigation of intermittency, *Renewable and Sustainable Energy Reviews* 35 (2014) 499–514. <https://doi.org/10.1016/j.rser.2014.04.009>.

- [59] F. Nasiri, R. Ooka, F. Haghighat, N. Shirzadi, M. Dotoli, R. Carli, P. Scarabaggio, A. Behzadi, S. Rahnama, A. Afshari, F. Kuznik, E. Fabrizio, R. Choudhary, S. Sadrizadeh, Data Analytics and Information Technologies for Smart Energy Storage Systems: A State-of-the-Art Review, *Sustain Cities Soc* 84 (2022). <https://doi.org/10.1016/j.scs.2022.104004>.
- [60] H.U. Rehman, T. Korvola, R. Abdurafikov, T. Laakko, A. Hasan, F. Reda, Data analysis of a monitored building using machine learning and optimization of integrated photovoltaic panel, battery and electric vehicles in a Central European climatic condition, *Energy Convers Manag* 221 (2020). <https://doi.org/10.1016/j.enconman.2020.113206>.
- [61] B. Svetozarevic, C. Baumann, S. Muntwiler, L. Di Natale, M.N. Zeilinger, P. Heer, Data-driven control of room temperature and bidirectional EV charging using deep reinforcement learning: Simulations and experiments, *Appl Energy* 307 (2022). <https://doi.org/10.1016/j.apenergy.2021.118127>.
- [62] C.B. Field, V. Barros, T.F. Stocker, Q. Dahe, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, P.M. Midgley, Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change, 2012.
- [63] C. Zhang, O.B. Kazanci, R. Levinson, P. Heiselberg, B.W. Olesen, G. Chiesa, B. Sodagar, Z. Ai, S. Selkowitz, M. Zinzi, A. Mahdavi, H. Teufl, M. Kolokotroni, A. Salvati, E. Bozonnet, F. Chtioui, P. Salagnac, R. Rahif, S. Attia, V. Lemort, E. Elnagar, H. Breesch, A. Sengupta, L.L. Wang, D. Qi, P. Stern, N. Yoon, D.I. Bogatu, R.F. Rupp, T. Arghand, S. Javed, J. Akander, A. Hayati, M. Cehlin, S. Sayadi, S. Forghani, H. Zhang, E. Arens, G. Zhang, Resilient cooling strategies – A critical review and qualitative assessment, *Energy Build* 251 (2021) 111312. <https://doi.org/10.1016/J.ENBUILD.2021.111312>.
- [64] T. Kuczyński, A. Staszczuk, Experimental study of the influence of thermal mass on thermal comfort and cooling energy demand in residential buildings, *Energy* 195 (2020) 116984. <https://doi.org/10.1016/J.ENERGY.2020.116984>.
- [65] O.B. Kazanci, J. Shinoda, B.W. Olesen, Revisiting radiant cooling systems from a resiliency perspective, *CLIMA 2022 Conference* (2022). <https://doi.org/10.34641/CLIMA.2022.241>.
- [66] K. Amada, J. Kim, M. Inaba, M. Akimoto, S. Kashiara, S. ichi Tanabe, Feasibility of staying at home in a net-zero energy house during summer power outages, *Energy Build* 273 (2022) 112352. <https://doi.org/10.1016/J.ENBUILD.2022.112352>.
- [67] J. Shinoda, D.-I. Bogatu, B.W. Olesen, O.B. Kazanci, A qualitative evaluation of the resiliency of Personalized Environmental Control Systems (PECS), in: 42nd AIVC-10th TightVent & 8th Venticool Conference, Rotterdam, 2022.

7 Subtask E Cooperative Control of Building/District/Grid

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7.1 Introduction

The energy sector is currently undergoing a significant transformation as governments worldwide strive to reduce greenhouse gas emissions and shift away from conventional fossil-based power generation to renewable energy sources (RESs) largely in the form of wind and solar [1, 2]. Even though power generation from RESs is more sustainable from an environmental point of view, the high penetration of these sources makes power systems less reliable due to their dependence on weather conditions. The intermittence of RESs requires an adequate reserve capacity to ensure the generation-load balance, this is expensive and sometimes difficult [3, 4]. Additionally, power distribution networks, which were designed for unidirectional power flows and radial, or weakly meshed, operation [5], due to the intermittent RES generation, are now massively stressed by incessant net power load fluctuations, fast ramp and deramp events, and frequent reverse of power flow direction.

The increasing impact of distributed energy resources (DERs), as well as controllable loads and electric vehicles (EVs) in power distribution networks, is further worsening these problems, and thus new solutions should be considered in the planning and operation of modern power systems.

Traditional solutions, such as demand management controls and interconnection with other grids have been used to increase the flexibility of power networks. However, as penetration of RES increases, the employment of energy storage systems (ESSs) to counteract these problems and facilitate the full integration of RESs and DERs into power distribution grids, is unavoidable. Energy storage can support renewable energy by providing voltage support, smoothing power output fluctuations, balancing power flow in the network, matching supply and demand, and helping transmission and distribution companies (network operators and energy retailers) to meet demand reliably and sustainably [6, 7]. Indeed, ESS paired with both small and large-scale RES facilities has become a common practice in recent years, as prices of storage continue to decrease. ESSs are increasingly being embedded in power distribution networks to offer technical, economic, and environmental advantages [8]. These advantages include the above-mentioned power quality improvement, such as mitigation of voltage deviation, frequency regulation support, load shifting, load leveling, and peak shaving, facilitation of RESs integration, network expansion, and overall cost reduction and operating reserves [9, 10, 11], with a great potential for applications at both utility and end-users level. Unfortunately, misusing or mislocating ESSs in distribution networks can degrade power quality and reduce reliability, affecting voltage and frequency regulation capabilities. Thus, careful planning and control of ESSs are critical for ensuring an efficient and effective integration into power networks.

The interest in developing new technologies and control approaches for ESSs is increasing among researchers. To the best of the authors' knowledge, several significant survey papers considering ESSs in power systems have been published in the last ten years. As described in Table 7.1, these papers provide a comprehensive overview of the state-of-the-art technologies and research on ESSs, with a focus on their applications in power distribution grids.

A detailed description of different ESSs technologies and applications has been provided in survey papers [12, 13, 9, 14, 19, 22]. Most of these reviews papers focus on the use of ESSs to ensure the balance between RESs generation and demand improving the performance of whole power grid. For

instance, in [12] and [14] the authors analyze several energy storage technologies for wind power applications, while the importance of ESSs for large-scale integration of photovoltaics (PVs) is the focus of [10]. The main objectives of these articles are the introduction of the operating principles, as well as the presentation of the main characteristics of the different storage technologies suitable for these applications. Furthermore, in [13] different applications of ESS in power systems are presented together with the most relevant technologies. The paper puts the stress on the cooperation between the ESS and the RESs.

A presentation of different energy storage technologies has been provided in [9]. In this paper, the technologies have been classified into thermal energy storage and electrical energy storage while a discussion on different energy storage utilities for RESs is presented. The analyses include their properties, current state in the industry, and feasibility for future installation. Additionally, in [7], a detailed description of different ESSs has been provided and the different technologies have been classified into five categories, namely, electrical, mechanical, electromechanical, thermochemical, chemical, and thermal. A comparative analysis of these different technologies along with the different applications is mentioned, and the suitable technology for each application is provided. Nevertheless, the challenges associated with each storage technology and the required optimization and control techniques were not described extensively. An exhaustive discussion on ESS sizing methods in the microgrid (MG) application is presented in [19]. The paper reviews the technologies, configurations, classifications, and features detailing the advantages and disadvantages of ESSs in MG applications. Lastly, in [22] ESSs have been divided into four major categories, mechanical, electromechanical, chemical, and thermal. A detailed structure and application of each category are described followed by future challenges. However, a detailed discussion of ESS sizing and optimization techniques along with system constraints is absent.

Table 7.1: List of related review articles: ✓ and † indicate, respectively, major and minor contributions in the related research area.

Ref	Year	Main research focus	T1	T2	T3	T4	T5	T6	T7	T8	T9
[12]	2012	The article deals with the review of several ESSs for wind power applications.	✓			✓				†	
[13]	2013	The paper presents different applications of electrical energy storage technologies in power systems emphasizing on the collaboration of such entities with RESS	✓			✓	✓				
[9]	2014	The paper reviews the state of technology and installations of several energy storage technologies.	✓			†	†				
[14]	2015	The paper reviews the state of the art of ESS technologies for wind power integration support from different aspects.	✓			✓					
[15]	2015	The paper discusses ESS options for some high-power applications, e.g., frequency regulation, voltage control, oscillation damping, and voltage ride-through.	†				✓				
[16]	2018	The paper presents an overview of the state of the art control strategies specifically designed to coordinate distributed ESSs in microgrids.								✓	✓
[17]	2016	The paper describes the modeling and formulation of a variety of deterministic techniques for energy storage devices.								✓	
[10]	2017	The paper presents a review on the emerging high penetration of PV with an overview on the importance of ESS for large-scale integration of PVs.				✓					
[18]	2017	The paper provides a review of ESSs management and optimization tools needed for efficient energy storage operation in power grids.					†		✓	†	
[7]	2018	The paper provides an overview of optimal ESS placement, sizing, and operation.	†	✓	✓		†				
[19]	2018	The paper reviews the types of ESS technologies, and structures along with their configurations, classifications, features and evaluation process.	✓								
[20]	2019	In this paper, a literature review on optimal allocation and control of ESS is performed. Besides, different technologies and the benefits of the ESS are discussed.		✓	✓					†	
[21]	2020	The paper discuss on ESS sizing methods. The comparative study, including advantages, limitations, and outcomes, is presented.		✓	✓						
[22]	2021	The article highlights the ESSs applications along with the limitations of different technologies.	✓								
[23]	2021	The paper provides a review of battery ESSs concerning optimal sizing objectives and the system constraint.	†		†		†	†		✓	
[24]	2021	This paper provides a comprehensive review on shared ESS, in particular, the paper characterizes the design of shared ESSs and explain their potential and challenges.			†				✓	†	†
[25]	2022	The article reviews several storage technologies and their modeling and applications in power grids for grid operation, markets, stability, and control.	†				✓				

Notes: **T1:** Storage technologies, **T2:** Placement, **T3:** Sizing, **T4:** Applications at the generation, **T5:** Applications at the transmission/distribution, **T6:** Applications at the end-user side (DSM, EVs), **T7:** Frameworks (Private, Common, etc.), **T8:** Strategies (PQ, Droop, Voltage frequency), **T9:** Architectures (centralized, distributed, etc.).

To facilitate and improve the utilization of ESS, appropriate system design and operational strategies should be adopted. In fact, an unplanned and uncontrolled operation of ESS may impose a significant economic loss. An overview of the state-of-the-art control strategies has been described in manuscripts [16, 17, 18, 23, 24]. In detail, paper [16] presents an overview of control strategies specifically designed to coordinate distributed ESSs in MGs. The paper reviews the range of distributed storage services and the control challenges they introduce. Moreover, the authors in [17] recall some of the most used control techniques for ESS such as PI, H-infinity, and sliding mode control, while describing the formulation of such techniques based on a generalized ESS model. Paper [18] provides a history of ESS in power grids and an overview of different system architectures while reporting a summary of the leading applications for ESSs. However, the work does not highlight the different storage technologies and the required control strategies. The scope of the paper [23] is to cover all the possible aspects of battery ESS sizing, including optimization objectives, constraints, algorithm development, applications and recommendation based on research gaps. Regardless of the abovementioned contributions, this

work does not include any other storage technology used for the operation of power distribution networks. Many studies have suggested sharing the storage capacity to further exploit the potential of ESSs. In this context, the authors in [24] provide a comprehensive review of the papers on shared energy storage. In this review, the design of the shared ESSs is considered together with a description of their potential and related challenges.

It is evident from the literature review that the interest in ESSs has been growing in recent years. The above-listed papers show that a significant research effort has been spent in categorizing the different storage technologies and show their possible applications in power systems. These surveys have classified different energy storage technologies and highlighted their advantages and disadvantages. Some surveys have also emphasized the importance of ESSs in maintaining the balance between renewable energy generation and demand in power systems. However, it is also evident that there is a lack of focus on the system operation of ESSs. Few studies have analyzed the correlation between different storage technologies, grid applications, and relevant control techniques. Therefore, more research is needed to explore the operation of ESSs in power systems, especially in the context of their integration with RESs and of the provision of energy services to support network operation and control.

This subtask presents a comprehensive review of the existing studies regarding ESS in power distribution networks. The contributions of this work can be summarized as follows:

- This subtask discusses various issues related to the power quality of distribution networks and their mitigation scopes with ESSs. In detail, we present a systematic review of ESS studies published in journals or conference proceedings providing a comprehensive review of ESS integration in power distribution networks.
- We approach the review of relevant ESS papers through multiple angles, including technological, design, and optimization aspects. Additionally, we provide a detailed classification of the papers based on various criteria, such as the type of ESS used, the control strategy employed, and the application area. Our review categorizes the control architectures for ESSs and explains the advantages and challenges of developing practical operational strategies and solution techniques for different ESS applications.
- Differently from most of the recalled reviews, we show all the possible applications of ESS in power distribution grids such as frequency regulation, grid stability, voltage regulation, and ancillary services. Through the review, we identify the existing gaps in the literature and provide promising research directions to fill these gaps. We also highlight the correlation between articles considering all the possible ESS applications, recent advancements in storage technologies, and relevant control approaches available in the literature.
- To the best of our knowledge, this study is one of the few review papers highlighting together the correlation of articles considering all the possible ESSs applications with the recent advancement of storage technologies and the relevant control approaches available in the literature.

7.2 Research Methodology

This section presents in detail the methodology used to select the most relevant works regarding the application of control and optimization methods to ensure secure, efficient, and resilient grid service through the use of ESSs. To classify and organize the research contributions available in the literature, we developed a taxonomy that comprehends various services that ESSs can provide to power grids.

The proposed taxonomy is based on previous work in [26] and is shown in Figure 7.1. It specifically considers the power grid perspective, with a focus on identifying the storage services that primarily benefit utility companies [27]. It is important to note that the taxonomy is not exhaustive and may not cover all possible services that ESSs can provide. However, it captures the bulk of the values generated by ESSs in power grids and provides a useful framework for categorizing the research contributions available in the literature.

The next step involved searching for relevant research contributions related to each of the storage services in the taxonomy. It is worth noting that these services may have different names in various literature sources. Hence, to ensure comprehensive search coverage, we created a thesaurus, as shown in Table 7.2. This thesaurus allowed us to identify relevant contributions across a broad range of terms and keywords associated with each storage service.

Table 7.2: *Thesaurus of grid services provided by energy storage.*

Service	Keywords
Capacity or resource adequacy	Supply capacity; Capacity supply; Resource adequacy; Resource capacity; Reserve capacity; Capacity adequacy; Replacement Reserves. Energy time shift; Arbitrage; Energy market.
Energy arbitrage Spinning, NonSpinning, and Supplemental Reserves Voltage support	Spinning reserve; Synchronized reserve; Non-spinning reserve; Non-synchronized reserve; Supplemental Reserve; Operating reserve; Replacement reserve
Frequency response	Voltage support; Voltage control; Volt ampere reactive support; Volt ampere reactive control. Frequency response; Frequency regulation; Frequency containment; Frequency restoration; Virtual inertia; Inertia emulation; Synthetic inertia
Black start service Congestion relief	Black start; System restoration. Congestion relief; Congestion management; Congestion control; Congestion problem; Grid congestion; Network congestion; upgrade deferral; Grid Upgrade; Network upgrade.
Infrastructure upgrade deferral	

To standardize the research criteria while ensuring the inclusion of relevant papers, we utilized the widely recognized Scopus database with predetermined search parameters. Specifically, our focus was directed towards articles published from 2015 to the present in journals published by Elsevier and the Institute of Electrical and Electronics Engineers. The research query was defined to ensure the presence of the terms “storage” and “control” (or alternatively “management” or “operation”) within the title, abstract, or keywords of each paper. Additionally, we required that, for each storage service, at least one of the relevant keywords from Table 7.2 was found in the title, abstract, or paper keywords. During the search process, we opted for the “loose search” functionality offered by Scopus for the keywords enlisted in the thesaurus, while employing the “exact search” approach for the remaining part of the queries. The “loose phrase” option guaranteed the inclusion of the specified keywords while accounting for minor variations due to wildcards, lemmatization (including singular and plural forms), accented characters, synonymous terms, and punctuation. An example of a search string is ***TITLE-ABS-KEY(("Keyword 1" OR ... OR "Keyword N") AND {{control} OR {management} OR {operation}} AND {storage}) AND PUBYEAR > 2014 AND PUBLISHER({Institute of Electrical and Electronics Engineers Inc.} OR {Elsevier Ltd.}) AND DOCTYPE(ar).***

From the overall research, we obtained 2551 manuscripts, which have been categorized across the various services of the taxonomy. As is evident from the figure, a predominant proportion of the research contributions within the literature focus on Frequency and Voltage Regulation services. Although the initial search yielded a substantial quantity of articles, we undertook further steps to refine the selection process. We manually selected only those papers that strictly related to the services while disregarding any non-relevant papers that may have been included by mistake.³

In addition to the initial search, the review process was extended to encompass other relevant journal

papers and conference proceedings related to the investigated topic. After analyzing the contents of all the obtained results, a total of 198 papers were deemed to be the most relevant and have been examined in the current report.

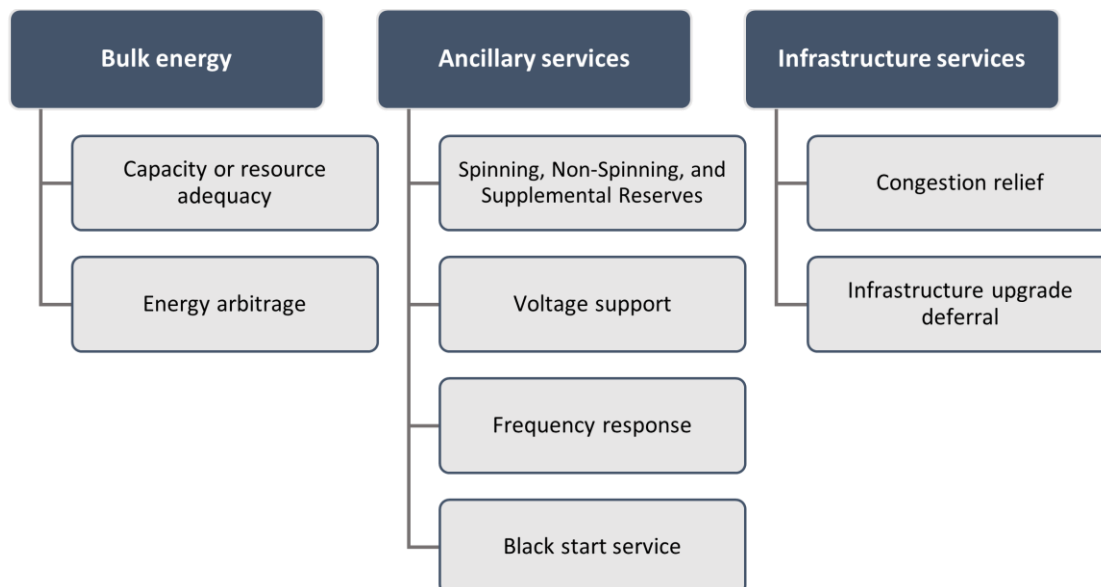


Figure 7.1: Taxonomy of grid services provided by ESSs.

7.3 Control of ESSs in power grids

As outlined in the introduction section, the control of ESSs is critical for ensuring the stability and reliability of power grids. The implementation of effective control strategies becomes imperative to manage the charging and discharging of ESS units, thereby supporting grid parameters such as frequency, voltage, and power quality. However, the selection of appropriate control techniques exceeds mere consideration regarding the technology and applications as it necessitates a comprehensive assessment of system architecture and configuration. Indeed, in contrast to the conventional power system paradigm, characterized by centralized and private-owned plants responding to the system demand, the integration of ESSs, coupled with the evolving dynamics of power systems, has led to the proposition of various configurations and architectures. These innovative approaches should be taken into account when delving into the formulation of effective control strategies for ESSs.

7.3.1 Hierarchy of control

The control system of ESSs plays a critical role in carrying out essential functions, including maintaining frequency and voltage regulation, optimizing peak shaving, facilitating load shifting, and facilitating the integration of renewable energy sources [28]. A hierarchical framework can be employed to categorize the various functions of the control system according to their response time and significance in governing ESSs. Similar to conventional control schemes in power grids, the control levels for ESS can be organized in a hierarchical system, comprising primary, secondary, and tertiary levels [16].

7.3.1.1 Primary level

The primary level, characterized by the shortest response time, plays a crucial role in delivering rapid

responses, including the regulation of grid frequency and voltage [29, 30]. Comparable to its counterpart in traditional power system control, the primary control system for ESSs for power grid support operates swiftly, even in the absence of communication. This level is often referred to as the zero level of control and is primarily utilized for active and reactive power control purposes [31].

7.3.1.2 Secondary level

The secondary level is responsible for optimizing the performance of the ESS, such as ensuring that the ESS operates at peak efficiency while meeting the specified power requirements [28]. Variations in frequency or voltage need to be kept within the acceptable range to uphold grid stability. The secondary control of ESSs in a power grid system helps to achieve this by adjusting the power output of the ESS, rather than traditional generators [32].

7.3.1.3 Tertiary level

At the highest level of control, the tertiary level encompasses long-term planning and optimization of power generation and distribution. Tertiary control in ESSs control considers factors such as demand forecasting, economic dispatch, energy market participation, and strategic decision-making [33]. Tertiary control goes beyond optimizing a single ESS and instead involves the coordination and optimization of multiple ESSs, alongside traditional power plants and renewable energy sources, in order to effectively meet the overall system requirements and objectives [34, 35].

7.3.2 Configuration frameworks

With the growing number of participants in the energy market, an additional level of classification for the ESS control approaches can be based on their ownership. It's important to note that ownership in this context doesn't solely refer to the physical ownership of the storage device, but also encompasses the level of control independence of the device. In other words, it refers to the degree of interaction between the ESS and the control infrastructure.

7.3.2.1 Private ownership

The prevailing architecture for ESSs control is commonly known as local or private. In this framework, owners have full control of the device and are driven by their individual interests. The storage capacity in this setup is not intended for resource sharing but rather functions as an energy facility supporting the exchange of energy between end-users and the power grid or infrastructure itself. Examples of such end-user applications can be found in [36], [37] where households are equipped with individual ESSs to enhance their flexibility within a liberalized energy trading market. Nevertheless, due to the high investment and maintenance cost of the ESS, equipping each end-user with an ESS is most of the time not cost-efficient. Conversely, certain promising ESS technologies, specifically designed for grid applications, are implemented by power systems operators. Often the ownership of such devices lies with the operators themselves, as they utilize these devices to optimize the overall state of the grid. These ESS technologies are deployed to serve multiple users in the energy market, allowing the operators to enhance grid stability, improve power quality, and efficiently manage energy resources.

7.3.2.2 Shared ownership

The shared ESS architecture has emerged as a novel solution to overcome the limitations of the private framework. This approach addresses the cost inefficiencies associated with individual ESS ownership by introducing cost-sharing and benefiting from economies of scale. It is particularly well-suited for

large-scale ESS implementations designed to serve multiple users. One of the real-world applications of this structure is the so-called aggregated configuration in wind farms [38] where a single ESS is used to serve a group of turbines to smooth the generation variability instead of a single ESS for each turbine. Some other examples of this framework can be found in the community energy storage, in which a common ESS is installed to serve many households in an energy community [39, 40]. There are multiple strategies to operate the common ESS systems. One of these strategies is to first determine the capacity allocated to each user and then let the users operate their block of ESS independently. [41, 42]. Another strategy involves an aggregator who assumes control over the entire system, coordinating capacity allocation and distributed energy distribution to effectively manage the shared ESS [43].

7.3.2.3 Market storage capacity

The last configuration is the so-called market storage capacity. In this scenario, the storage device is either owned by a third-party independent operator who decides the price of the storage capacity and/or energy stored in the shared ESS for the users. Unlike the aggregator in the shared ESS framework, the independent operator invests in the ESS and provides storage services to end-users or to the power system operator. A typical application of this configuration is the utilization of a large-scale ESS as a stand-alone operator, serving multiple users while optimizing options selling and energy trading in the market [44, 45]. The advantage of this approach is that the independent operator coordinates both capacity sharing and stored energy sharing for the operation of the shared ESS. However, determining the price of the capacity and energy trading is challenging. Additionally, if the independent ESS operator is a for-profit entity in the market, the design of the ESS sharing market should properly balance the conflict arising between the ESS operator and its clients.

7.3.3 Control architectures

The control of ESSs can be classified based on the coordination and communication perspective. These levels include centralized, decentralized and distributed (non)cooperative control, each with distinct characteristics as outlined in Table 7.3. Additionally, it is possible to combine these control schemes in a hybrid approach or integrate elements of autonomous and communication-based control.

7.3.3.1 Centralized control systems

In centralized control systems, the management of one or more ESSs by a single entity, such as a grid operator or a power management system. This scenario is common when private storage capacity is involved, where ESSs are privately owned and controlled by a single agent such as a user, prosumer, or system operator. The controller, whether operating locally or remotely, receives essential grid measurements, often through smart meters or remote terminal units. It then determines the control solution and communicates the set points back to the ESSs. However, when controlling a large number of ESSs in real-time this approach requires significant computational and communication resources and is sensitive to noise, communication delays, and single-point failures [46], as shown in Table 7.3. These limitations highlight the difficulties in coordinating a large number of ESSs efficiently and effectively within a centralized control framework and the necessity of different schemes.

7.3.3.2 Distributed control systems

On the other hand, in distributed control systems, ESSs are not controlled by a single entity, each ESS is controlled by an individual controller, referred to as an agent, which collaborates with other agents to reach a collective decision. This cooperation can be either cooperative or noncooperative,

depending on the goals set by the grid operator or end-users. Unlike centralized control, in a distributed approach, each controller only needs to communicate with its neighboring nodes, eliminating the need for global information about the entire state of the grid. The main objective of a distributed coordination structure is to establish a self-organized power grid that can effectively address challenges through local interactions, providing advantages such as “plug and play” capability and adaptability to system topology changes [47].

7.3.3.3 Decentralized control systems

Decentralized control represents an intermediate approach between centralized and distributed control, where control is divided between centralized and distributed components in terms of computational and communication burdens, control systems are shifting towards more distributed control architectures. Distributed and centralized control schemes offer enhanced reliability and adaptability, however, it is important to note that they require point-to-point communication, which can significantly increase computational requirements.

As outlined in Table 7.3, both distributed and decentralized control schemes offer substantial advantages in terms of robustness and flexibility for managing ESSs in power networks. These approaches are well-suited to handle limited communication capabilities, low bandwidth, and are less susceptible to communication line faults. These qualities make them highly appealing for innovative applications. Indeed, with the increasing integration of renewable resources and the need to manage computational and communication burdens, control systems are shifting towards more distributed control architectures.

Distributed and centralized control schemes offer enhanced reliability and adaptability, however, it is important to note that they require point-to-point communication, which can significantly increase computational requirements.

7.3.3.4 Hybrid control systems

Indeed, the classification of control schemes can be further expanded by considering the ownership of the storage in addition to the coordination approach as shown in Table 7.4. When an ESS is shared among multiple agents it can be controlled in a centralized manner by a single entity, often referred to as an aggregator or energy manager. Alternatively, the control of the shared ESS can be distributed among all the participating agents that collectively decide on the storage strategy, in a cooperative or noncooperative manner.

Conversely, when ESSs are involved in selling their storage capacity to the market, the control is typically carried out by a single controller. However, in this scenario, the market dynamics and the interactions between multiple market participants play a significant role in shaping the control strategy. The controller, acting as a market participant, must consider factors such as price signals, demand-supply dynamics, and market rules to determine the optimal utilization and trading of the ESS's storage capacity. The nature of the market, with multiple participants and decentralized decision-making, can lead to a distributed or decentralized noncooperative scheme. This means that the controller's strategy is influenced by the market conditions and the actions of other market participants, and the coordination of ESSs occurs through decentralized decision-making processes.

7.3.4 Control tools for ESS

This subsection explores different control techniques commonly used for controlling ESSs in power

grids.

7.3.4.1 PID-based controller

PID-based controllers are widely used as control strategies for ESS. A PID controller is designed to adjust the output of the ESS based on an error signal:

$$\frac{U(s)}{E(s)} = K_p + \frac{K_i}{s} + K_d$$

where $U(s)$ is the control signal, $E(s)$ is the error signal. The proportional gain (K_p) regulates the control action in direct proportion to the error signal. The integral gain (K_i) integrates the error over time to eliminate steady-state errors and enhance control accuracy. Lastly, the derivative gain (K_d) considers the rate of change of the error, thereby improving the controller's responsiveness and damping system oscillations.

Based on the elements present in (1), we can differentiate the so-called Proportional (P), Proportional-Integral (PI), and Proportional-Integral-Derivative (PID) controllers. Note that, this approach is often referred to as the droop control method (see Section 4).

Table 7.3: Comparison between centralized, decentralized and distributed control of ESS.

Features	Centralized	Decentralized	Distributed
DER ownership	Single owner	Multiple owners	Multiple owners
Goals	A clear single task	Uncertain tasks	Uncertain and variable tasks
Flexibility	Less	More	High
Plug-and-play	Not possible	Possible	Possible
System Extension	Complex and Troublesome	Easy	Easy and less complex
Communication and network need	High	Low	Medium
System Failure	Single point fault	Many point faults	Many point faults

Table 7.4: ESS configuration frameworks and architectures.

	Centralized	Distributed / Decentralized (cooperative)	Distributed / Decentralized (noncooperative)
Private storage capacity	ESS owned privately by a single agent (user, prosumer, system operator etc.) and controlled locally	ESS owned by several agents (user, prosumer, system operator etc.) and controlled by all the agents that decide a strategy in a cooperative way	ESS owned by several agents (user, prosumer, system operator etc.) and controlled by all the agents that decide a strategy in a noncooperative way
Shared storage capacity	ESS owned by several agents (user, prosumer, system operator etc.) and controlled by a single entity (aggregator, manager, controller)		ESS owned by a single agent (user, prosumer, system operator etc.) and the storage capacity on the market
Marked storage capacity			

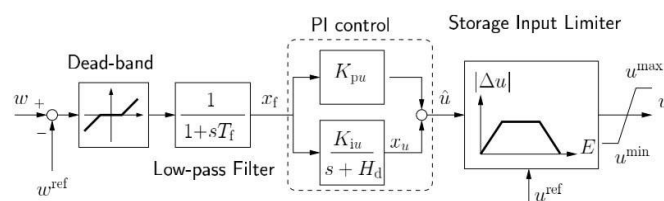


Figure 7.2: PI-based control for ESSs.

Figure 7.2 depicts a typical ESS with a PI controller scheme. This configuration consists of various components such as a dead band, a low-pass filter, and a storage input limiter. These components are designed to mitigate the effects of transients resulting from energy saturations in the ESS [48]. The parameters of the PI controller are commonly tuned using trial-and-error or pole-placement techniques. The simplicity of implementation and design, as well as the widespread utilization of this controller in industrial applications, are its main strengths. It is worth noting that the structure of the PI controller does not depend on the specific energy storage technology being employed. However, it has been demonstrated that system uncertainties and changes in the power system's topology can significantly impact the performance of the PI controller and, consequently, the overall system behavior [49]. This highlights the necessity for the development of more sophisticated and robust controllers to address these challenges.

7.3.4.2 Hysteresis Controller

The hysteresis controller is a relatively simple technique used to control the error signal by comparing it with a reference signal. It offers several advantages, including fast and adaptive response to the inverter, ease of implementation, and more. Additionally, the hysteresis controller provides an inherent current protection scheme and helps reduce the total harmonic distortion (THD) of the system. The hysteresis controller is designed to maintain the current within a predetermined range by toggling the control action when the error signal exceeds specific thresholds. The hysteresis controller's simplicity and adaptability make it a popular choice for certain applications where fast response and inherent protection are important factors. However, it's worth noting that the hysteresis controller may introduce some level of switching noise due to the abrupt changes in the control action.

7.3.4.3 H-infinity Controller

The H-infinity controller is a robust control technique designed to address disturbances and stabilize a system with fast and responsive action. Its main objective is to eliminate or minimize the effect of disturbances on the system. The H-infinity controller achieves this by formulating the control problem as an optimization task and taking appropriate control actions to achieve robust performance in the presence of uncertain parameters and disturbances. H-infinity controllers offer the advantage of a less complex implementation despite their robustness and performance capabilities.

7.3.4.4 Linear Quadratic Regulator

The Linear Quadratic Regulator (LQR) method is a widely used technique for achieving stability of ESSs, even in the presence of uncertainties and transient conditions. One of the primary advantages of employing the LQR method is its inherent stability characteristics. By formulating the control problem as an optimization task, the LQR controller is designed to minimize a quadratic cost function while satisfying system constraints. However, there are a few limitations associated with the LQR method such as potential delay in decision-making and the lag in tracking accuracy during changes in the type of load.

7.3.4.5 Fuzzy Controller

The Fuzzy Controller is a logical controller that operates based on fuzzy logic principles, which allow for the handling of linguistic variables and eliminate the need for crisp values in decision-making processes. Fuzzy logic enables the representation of uncertainty and imprecise information by assigning membership degrees to different linguistic values within a defined range, typically ranging from 0 to 1. The fuzzy logic control strategy is given by:

$$u(t) = \sum_{i=1}^n w_i u_i(t)$$

where w_i is the degree of membership of the linguistic variable to the fuzzy set, and $u_i(t)$ is the control input associated with the fuzzy set. In the context of ESS stability, the fuzzy logic controller has gained popularity due to its high robustness and user-friendly nature. It has been extensively employed in ESS control applications. One of the key advantages of the fuzzy logic controller is its ability to make decisions based on imprecise or ambiguous information. By adjusting the fuzzy rules and membership functions, the controller can optimize its response to different operating conditions and achieve desired performance objectives.

7.3.4.6 Sliding Mode Control

Sliding Mode Control (SMC) is a robust and adaptive controller that is designed to handle variations in system parameters under different operating conditions. The key characteristic of SMC is the creation of a sliding surface, which represents a desired system behavior. The controller's objective is to force the system's state trajectory to follow this sliding surface, thereby achieving the desired system performance. One limitation of sliding mode control is its lack of adaptability to uncertain changes and the dynamic behavior of nonlinear systems. To address this limitation, the controller optimizes its parameters based on the output ripple waves, aiming to minimize the impact of uncertainties and achieve improved control performance. The sliding mode controller is suitable for ESS application as it is relatively easy to implement and it exhibits low sensitivity to changes in parameter values.

7.3.4.7 Optimization-based methods

Optimization-based methods play a crucial role in achieving optimal operating conditions in ESSs control. These techniques are employed in various decision-making tasks such as storage scheduling and operation, aiming to find the best solutions while considering constraints. Mixed Integer Linear Programming (MILP) is a commonly used optimization method in ESS control. MILP formulates optimization problems with a combination of linear and integer variables. As aforementioned, ESS controls are typically categorized into primary, secondary, and tertiary controls. Tertiary controls involve decisions related to energy management and power exchange between the utility and the ESS. Several software tools such as HOMER, HYBRID 2, RETSCREEN, and GAMS are available for modeling renewable energy systems in real-time or offline. These tools utilize optimization algorithms to find optimal solutions by considering a constrained set of inputs and maximizing or minimizing an objective function. However, solving optimization problems in real-time ESS control can be computationally expensive and complex. To address these challenges, heuristic algorithms and metaheuristic methods are utilized. Heuristic algorithms employ trial-and-error techniques to solve complex problems, while metaheuristic methods are inspired by natural processes. Particle Swarm Optimization (PSO) is an example of a metaheuristic algorithm inspired by the movement of fish and bird swarms. It iteratively searches for optimal solutions within a constrained space by solving an objective function. In cases where there are a large number of components to solve, genetic algorithms provide more efficient solutions. Genetic algorithms employ the concept of "survival of the fittest" to evolve and find optimal solutions in complex and large search spaces. Another optimization algorithm, Ant Colony Optimization (ACO), mimics the behavior of ants to find optimal solutions for objective functions under constraints. This algorithm has been successfully applied to minimize losses in distribution systems and has shown advantages over genetic algorithms in certain scenarios.

7.3.4.8 Model Predictive Control

Model Predictive Control (MPC) is an advanced control strategy that utilizes a dynamic model of the ESS (and possibly of the power grid state) to predict its future behavior and solves an optimization problem to determine the control input that minimizes a predefined cost function, taking into account various constraints. The MPC control strategy is formulated as follows:

$$u(t) = \underset{u(t)}{\operatorname{argmin}} J(x(t), u(t))$$

subject to:

$$\dot{x}(t) = f(x(t), u(t))$$

and to:

$$u(t) \in \mathcal{U}, \quad x(t) \in \mathcal{X}$$

In this formulation, $u(t)$ represents the control input, $x(t)$ represents the system state, and $y(t)$ represents the system output. The cost function $J(\cdot)$ captures the desired objective of the control, while the dynamic model $f(\cdot)$ describes the system's evolution over time. The control input $u(t)$ is subject to constraints defined by the set $\mathcal{U}$, and the state $x(t)$ is subject to constraints defined by the set $\mathcal{X}$.

MPC aims to minimize the forecast error and achieve accurate tracking of the current parameter by considering future predictions of the system. One of the key advantages of MPC is its ability to handle various general and nonlinear constraints within the network, accommodating multiple inputs and outputs.

7.3.4.9 Neural Networks

A neural network-based controller is a data-driven approach that emulates the functioning of the human brain by processing input data through interconnected layers of nodes. It consists of an input layer, hidden layers with activation functions, and an output layer, where weights are adjusted to minimize the error or optimize a desired function. This closed-loop architecture allows information to flow between layers, enabling the neural network to learn and adapt to different operating conditions. The neural network controller offers adaptability, intelligence, and self-learning capabilities, making it suitable for ESS control. One of the key advantages of neural networks is their ability to process large amounts of data and extract meaningful patterns and relationships. This makes them suitable for capturing the complex dynamics and uncertainties present in power systems. By learning from historical data and real-time measurements, neural networks can make accurate predictions and control actions.

7.4 Applications of energy storage systems in power distribution networks

The use of ESS in power grids can range from large-scale applications of generation and transmission networks to reducing costs “behind the meter” to end users [50]. In this work, we employ a classification of ESS applications based on the one used in [50]. In particular, we divide the usage and benefits of the system into different categories hereafter described.

7.4.1 Bulk energy services

Bulk energy services refer to applications where ESSs are used for extended discharge or charge cycles,

typically lasting several hours or more. These applications leverage the capability of ESSs to provide a substantial amount of stored energy, enhancing the flexibility and performance of the overall system. In traditional generation systems, the sizing of power generation infrastructure is based on the forecasted peak demand, which often results in overcapacity and increased costs. Energy storage offers a solution to this challenge by providing additional supply capacity during peak demand periods [105, 106]. By storing excess energy during off-peak times and discharging it during peak periods, ESSs help meet demand without the need for installing high-capacity generation systems or purchasing additional capacity from the wholesale electricity marketplace.

Furthermore, ESSs can play a crucial role in integrating renewable energy sources, such as solar and wind, into the grid [54][72]. These renewable sources are inherently intermittent, meaning their output fluctuates based on environmental conditions [107]. By storing excess energy generated from renewables during periods of high generation and releasing it when is low, ESSs mitigate intermittency and enhance grid stability. This capability not only improves the reliability of renewable energy supply but also reduces curtailment and maximizes the utilization of clean energy resources [108].

Renewable energy time shifting is closely related to energy arbitrage. Indeed, in electricity markets prices vary throughout the day, typically due to variable load patterns and RES generation. Energy arbitrage is a strategy that takes advantage of these price differences by purchasing (charging) electricity when prices are low and selling (discharging) it when prices are high [109]. ESSs enable energy arbitrage by storing bulk energy during low-price periods and utilizing it during peak demand to offset costs and achieve a more uniform load factor [110]. Although some losses occur during the charging and discharging processes, energy arbitrage can be profitable when the price differential is significant, such as during periods of abundant renewable generation [108]. It should be noted that energy arbitrage refers to wholesale buying and selling which is done by grid operators, end-users can use similar tactics, however, this is referred to as time-of-use bill management.

There is an abundance of research on the use of storage for the application of ESS for bulk energy services. Several studies have demonstrated the effectiveness of rule-based control approaches which are characterized by their simplicity and ease of implementation. Rule-based control approaches, as demonstrated in the study by [52], rely on predefined rules that govern the operation of the ESS. These rules are typically based on factors such as electricity prices, demand forecasts, and the state of charge of the battery. For example, a common rule-based strategy involves charging the ESS when electricity prices are low and discharging it when prices are high. Such approaches have shown effectiveness in specific applications, such as price-based arbitrage, and can generate significant revenue by exploiting price differences [52]. Similar to rule-based, heuristic-based control approaches as exemplified in the study by [51], rely on empirical observations and rules of thumb to determine the charging and discharging actions of the battery. These approaches are relatively simple to implement and computationally efficient. For instance, a common heuristic is to charge the battery when electricity prices are below the average price observed over a certain time window and discharge it when prices are above the average price. Heuristic-based approaches have been effective in certain scenarios, such as managing the reserve capacity of electric vehicles (EVs) for power grid support [51]. Rule-based and heuristic approaches are typically deterministic and do not require complex modeling or extensive computational resources. Despite their simplicity, these approaches have limitations. They may not be optimal in dynamic and uncertain market conditions, as they do not adapt to changing conditions in real-time while these approaches also lack the ability to capture complex interactions between different variables. While rule-based and heuristic-based approaches offer simplicity and ease of implementation, advanced control approaches have emerged to address their limitations. Advanced control strategies involve mathematical models, optimization algorithms, and real-time adaptation.

These approaches, although more complex to implement, offer the ability to adapt to dynamic and uncertain market conditions, resulting in optimized control performance. They can capture complex interactions between variables and provide a comprehensive understanding of system dynamics [53]. However, advanced control approaches require computational resources and modeling efforts, leading to higher implementation costs compared to rule-based and heuristic-based approaches.

The use of control methods in energy systems, such as PID (Proportional-Integral-Derivative) controllers and fuzzy controllers, has been extensively studied in the literature. These control methods aim to optimize the operation of ESS and improve the overall performance of the power grid. For instance, Liu et al. [51] proposed a day-ahead energy management and reserve declaration strategy for a parking lot-based ESS using electric vehicles (EVs) as a reserve resource. The strategy employed a PID controller to adjust the charging and discharging status of EVs based on the power fluctuation problem in the power grid. The results showed that the proposed strategy improved the operation profit of the parking lots by effectively utilizing the reserve capacity of EVs. Javadi et al. [54] presented a pool trading model within a local energy community that considered fuzzy control for home energy management systems (HEMSs) and other consumers. The fuzzy controller adjusted the energy consumption of the participants based on a price-based demand response program, aiming to minimize the overall bills of all participants while fulfilling their demands. The results demonstrated that the coordination among different end-users in the local energy community market led to cost reductions and increased revenues for active consumers.

Table 7.5: Bulk energy services: list of related articles.

Ref	R1	R2	R3	R4	E1	E2	E3	E4	E5	E6	E7	E8	E9	A1	A2	A3	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	G1	G2	G3
[51]														✓			✓												
[52]			✓											✓			✓								✓				
[53]					✓												✓								✓		✓		
[54]		✓																✓					✓						
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[58]					✓											✓			✓										
[59]						✓								✓	✓										✓				✓
[60]					✓											✓									✓				
[61]					✓																				✓				
[62]			✓		✓																				✓		✓		
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[65]			✓					✓																	✓			✓	
[66]		✓		✓					✓				✓												✓			✓	
[67]			✓																						✓				✓
[68]			✓	✓																					✓				
[69]			✓																						✓				
[70]																									✓				
[71]														✓													✓		
[72]	✓		✓					✓								✓													
[73]													✓			✓													
[74]					✓	✓																					✓	✓	
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[91]			✓	✓						✓																			
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[100]					✓																			✓					
[101]			✓		✓																				✓				
[102]					✓																					✓			
[103]																										✓			
[104]			✓																							✓		✓	✓

Notes

R1: Generic RES; **R2:** Photovoltaics; **R3:** Wind power; **R4:** Hydro power; **E1:** Battery energy storage systems ; **E2:** Electric vehicle V1G/V2G; **E3:** Thermal energy storage and heat pump water heaters; **E4:** Compressed-air energy storage; **E5:** Pumped storage hydropower (PSH) / PICO Hydro; **E6:** Flywheel ; **E7:** Superconducting magnetic; **E8:** Supercapacitors; **E9:** Hybrid energy storage system ; **A1:** Centralized; **A2:** Decentralized; **A3:** Distributed; **C1:** Rule based; **C2:** PID and droop control methods; **C3:** Fuzzy; **C4:** Consensus based; **C5:** Sliding Mode Control, Hysteresis, H-infinity, Feedback linearization control, Fractional Order Control Method; **C6:** Mathematical optimization; **C7:** Metaheuristic algorithms; **C8:** Optimal control, Linear Quadratic Regulator, Model predictive control; **C9:** Robust and stochastic approaches; **C10:** Machine learning based control; **G1:** Transmission; **G2:** Distribution; **G3:** Microgrid and islanded systems;

While PID controllers and fuzzy controllers offer advantages in ESS control applications, they also have certain limitations. PID controllers are based on linear models and may not be suitable for systems with nonlinear dynamics. Fuzzy controllers, although capable of handling uncertainty, can be complex to design and require extensive tuning of linguistic variables and rules.

In scenarios where market conditions are highly dynamic and uncertain, more advanced control

approaches may be more suitable. Model-based control approaches for ESSs have gained significant attention in recent years due to their ability to optimize ESS operation based on system dynamics and market data. Several studies have investigated the application of these approaches in various domains, such as electricity markets, microgrids, and renewable energy integration. Model-based approaches typically involve formulating the problem as an optimization problem and using mathematical algorithms to find the optimal solution. The cost savings from arbitrage can be estimated from market data using simple optimization techniques [111, 112] while control algorithms for arbitrage are typically based on optimal control approaches [96, 113].

One common characteristic of model-based control approaches is the utilization of mathematical models to optimize ESS operation. These models capture the relationships between system variables, such as energy prices, renewable energy generation, and load demand [98]. Several studies have also considered SoC and degradation variables [100]. For example, Zhang et al. [55] developed a MPC strategy for a battery energy storage station (BESS) in a grid with high photovoltaic power penetration. The MPC approach considered the impact of PV power on automatic generation control reserve capacity and aimed to minimize the equivalent operating cost of both the power grid and BESS.

The use of optimization algorithms is another characteristic of model-based control approaches. These algorithms, such as dynamic programming [111] and mixed-integer programming [96], are employed to find the optimal control actions that maximize revenue or minimize operating costs. For instance, Xie et al. [96] proposed a robust MPC-based bidding strategy for wind-storage systems in real-time energy and regulation markets. The strategy optimized the bidding capacities of the wind storage system to increase revenue by absorbing low-cost energy in the energy market and selling it in the energy and regulation market. Optimal dispatching strategies considering multiple services of energy storage are addressed in [57], which aims to minimize long-term operation costs. The paper shows economic operation and power balance in an uncertain environment. Additionally, [59] focuses on controlling Plug-in Electric Vehicles (PEVs) integrated with microgrids and proposes a centralized framework for co-optimizing MGs with PEVs' energy arbitrage.

Optimization-based control approaches offer a systematic and rigorous framework for managing ESS in power grids. They aim to optimize various objectives, including energy arbitrage, frequency regulation, peak shaving, and renewable integration. These approaches leverage mathematical optimization techniques to determine optimal control strategies for ESS operation.

Programming-based approaches, such as linear programming, mixed-integer programming, and convex optimization, have been widely employed in ESS control [66, 67]. For instance, in [85], a dynamic programming approach is proposed to optimize the use of battery storage for energy arbitrage and frequency regulation. The authors solve smaller subproblems at different time scales to handle the large state space and stochastic information. The advantage of programming-based approaches lies in their ability to handle complex optimization problems with well-defined objective functions and constraints. They provide reliable and efficient solutions but may suffer from computational complexity for large-scale systems. For instance, Liu et al. [51] propose an accessing guidance model for parking lots to alleviate congestion caused by electric vehicles (EVs) and present an energy management and reserve declaration strategy for parking lot operators. The study emphasizes the effective relief of congestion, enhanced reserve declaration capacity, and increased operation profit. Javadi et al. [54] introduce a pool trading model for a local energy community, demonstrating coordination among different end-users, reducing total electricity bills, and increasing revenues for active consumers.

Ding et al. [57] address optimal dispatching strategies for user-side integrated energy systems

considering multiple services of energy storage. Their two-stage coordinated scheduling method minimizes long-term operation costs, incorporating time-of-use electricity price mechanism, demand management, response, energy arbitrage, and providing reserve capacity. Saffari et al. [59] focus on controlling plug-in electric vehicles integrated with microgrids, proposing a centralized framework for co-optimizing robust/stochastic optimization with energy arbitrage. The study demonstrates the effectiveness of the framework in dealing with uncertainties and achieving improved power system performance. Kazemi et al. [60] present a method for scheduling battery storage systems participating in frequency regulation and energy markets. Their approach models the regulation market's automatic generation control signal through robust optimization and considers the impact on battery lifespan. The proposed linearized method ensures economic operation and prevents rapid depreciation. Mohsenian-Rad et al. [61] propose an optimization framework for coordinating the operation of large ESSs in nodal transmission-constrained energy markets, addressing various design factors and transforming the problem into a tractable mixed integer linear program.

Mirzaei et al. [62] present a robust-stochastic framework for evaluating the effect of a battery-based energy storage transport system in a day-ahead market-clearing model. The framework integrates the market-clearing process with a train routing problem, allowing more flexible decisions based on risk levels. Arteaga et al. [63] develop models for estimating the potential profit of a battery storage system in competitive electricity markets, considering the impact on frequency regulation service and spinning reserve.

Farahani et al. [64] propose a robust bidding strategy model for a Battery Energy Storage System (BESS) in a Joint Active and Reactive Power Market (JARPM). Their model aims to maximize the BESS owner's profit while facing price uncertainty, guaranteeing suitable profit levels for private owners. Aldaadi et al. [65] investigate a coordinated bidding model for a combined system of wind plants and compressed air energy storage systems (CAES) in the energy market. Their approach utilizes a distributionally robust optimization (DRO) approach, achieving higher realized profits with less conservative results compared to robust optimization (RO).

Pan et al. [66] propose an adaptive robust scheduling model for a hybrid energy generation system (HEGS) trading in both the day-ahead electricity and hydrogen markets. Their model maximizes total profits based on price arbitrage, considering the uncertainty of available photovoltaic (PV) power generation. Rezaei et al. [67] present a stochastic optimization framework for resilient operation scheduling of interconnected energy hubs (EHs) considering P2P energy trading and energy storage. Their framework reduces load shedding through P2P energy trading and increased energy ADMM-based control approaches have gained attention in recent years due to their ability to handle large-scale optimization problems with decentralized control. ADMM as a powerful optimization technique for distributed control problems. ADMM decomposes the optimization problem into smaller subproblems and solves them iteratively in a decentralized manner. This approach has been successfully applied in ESS control. For instance, [114] proposes an ADMM-based method for coordinating distributed ESS to minimize the overall operational cost. The ADMM framework allows for parallel computation and decentralized decision-making, which can enhance the scalability and robustness of the control system. However, the convergence of ADMM may be sensitive to problem-specific parameters and requires careful tuning.

Dynamic programming-based approaches offer a systematic approach to solving control problems by breaking them down into smaller subproblems. These approaches are particularly effective in scenarios with significant uncertainty and time-varying dynamics. In [68], a rolling stochastic optimization method is proposed for the coordinated operation of a wind farm and energy storage system. The method optimizes the bidding strategy of the wind farm and ESS union to maximize overall

profit. Dynamic programming enables a comprehensive consideration of system dynamics and uncertainties, leading to optimal control strategies. However, the curse of dimensionality limits the scalability of dynamic programming approaches for large-scale systems.

The strengths of model-based control approaches lie in their ability to adapt to changing market conditions and capture complex system dynamics. These approaches can provide more sophisticated and flexible control strategies compared to rulebased approaches. They can consider uncertainties in renewable energy generation, load demand, and electricity prices, enabling optimized decision-making in real-time. Additionally, model-based approaches can lead to improved revenue generation and cost savings compared to conventional methods. For example, Abdeltawab et al. [99] developed a model predictive control system for a hybrid wind-battery energy storage system, which aimed to achieve the maximum net profit from the electricity market. The proposed approach outperformed a conventional MPC in terms of economic profit. However, model-based control approaches also have limitations. One major challenge is obtaining accurate models of system dynamics and market data. The reliability and accuracy of these models greatly influence the performance of the control strategies. Furthermore, model-based approaches require computational resources and may have higher implementation complexity compared to rulebased approaches. The development and implementation of optimization algorithms and the integration of real-time data can pose technical and operational challenges [97].

Controlling ESS for bulk services poses a significant challenge due to the need for control actions lasting several hours or even days. This duration introduces uncertainties in system parameters, stemming from factors like fluctuating renewable energy generation, unpredictable electricity demand, and market price volatility. To tackle these uncertainties, researchers have proposed stochastic control frameworks incorporating probabilistic models or scenario-based methods. The literature extensively explores stochastic control approaches for ESSs in bulk energy services for the power grid.

A common characteristic among the reviewed papers is the consideration of uncertainty in various aspects, such as energy prices, renewable energy generation, and system demand. Managing the stochastic nature of these variables effectively necessitates robust or stochastic optimization techniques. Some papers, including [59], [62], and [65], propose robust optimization models offering conservative solutions. Others, like [64] and [67], adopt stochastic optimization approaches to handle uncertainties and achieve higher profits. Stochastic control approaches for ESS in bulk energy services offer several advantages, including enhanced power grid reliability and stability, efficient utilization of renewable energy resources, and increased profitability for ESS owners. By actively managing ESS charge and discharge, these approaches effectively balance supply and demand, mitigate power fluctuations resulting from renewable energy sources, and provide ancillary services to the grid. Revenue generation through price arbitrage and capacity provision in energy and ancillary service markets is demonstrated in [65] and [64].

However, stochastic control approaches also face challenges and limitations. Solving stochastic optimization problems, particularly for large-scale systems, entails significant computational complexity. Specific optimization algorithms or decomposition techniques proposed in papers like [53] and [60] address this challenge. Another limitation is the reliance on accurate forecasts or historical data for stochastic models, which themselves may be subject to errors and uncertainties. The robustness and performance of control strategies are affected by this issue, as discussed in [62] and [65].

Recently, data-driven control approaches have gained interest as an alternative to model-based approaches, leveraging historical data and relevant variables for optimal control actions. Data-driven

control approaches are flexible and adaptable, as they can adjust to changing market conditions based on the available data. By analyzing historical data, these approaches can identify trends, patterns, and correlations that can inform the control actions for optimal performance. Machine learning techniques, such as neural networks, support vector machines, and ensemble methods, are commonly employed in data-driven control approaches to learn from the data and make predictions.

One advantage of data-driven control approaches is their ability to handle complex systems where explicit mathematical models may be challenging to develop or inaccurate. They can capture nonlinear relationships and account for uncertainties in the system. Additionally, data-driven approaches can incorporate real-time data updates, allowing for continuous adaptation to changing conditions.

The paper [97] proposes a predictive control model for storage-based renewable power plants, optimizing profit based on electricity price prediction and trading strategies. Additionally, [102] addresses accurate battery degradation cost estimation for energy arbitrage using a model-free deep reinforcement learning method. In another study, [103] presents an agent-based transactive energy trading platform for integrating ESSs into microgrids, utilizing a reinforcement learning algorithm to develop bidding strategies. Similarly, [104] develops a decision-making framework under uncertainty for a wind and storage power plant participating in day-ahead and reserve markets, employing a two-stage convex stochastic model and data-driven approaches for generating forecasts and handling uncertainty.

These papers exemplify the application of data-driven approaches in optimizing energy storage and trading strategies, considering factors such as degradation costs, market participation, and uncertainty management. However, it's important to note that the quality and availability of historical data, as well as the selection of relevant variables, are critical for the effectiveness of data-driven approaches. Insufficient or biased data can lead to inaccurate predictions and suboptimal control actions. Furthermore, data-driven approaches may require significant computational resources for training and prediction, as they can be computationally intensive.

7.4.2 Ancillary services

The term ancillary services is used to refer to a variety of operations beyond generation and transmission that are required to maintain grid stability and security. These services generally include active power control or frequency control and reactive power control or voltage control, on various timescales.

7.4.2.1 Frequency response

The electrical grid transmits power from generators to consumers at a fixed frequency. In America, the frequency is generally 60 Hz, while in Europe and Asia, it is 50 Hz. When power generation matches power usage, the frequency remains stable. Frequency regulation is a method used to maintain the frequency within specific tolerance bounds to achieve a balance between generation and load. There are primary and secondary frequency responses, with the latter known as frequency regulation. Primary frequency response is an automatic and nearly instantaneous response by generators to frequency deviations. Frequency regulation serves as a secondary line of defense in balancing the grid, typically provided as a paid service in organized wholesale power markets.

Frequency response services play a crucial role in operating power grids. In traditional power systems, synchronous generators supply grid inertia through the kinetic energy stored in their rotating mass and adjust their production setpoint to meet new requirements. However, these services need to adapt to the challenges posed by future power systems. With the increasing integration of renewable

energy sources (RESs) into the grid, supply variability and frequency fluctuations become more frequent and severe. Additionally, the growing use of power electronics interfaced RESs reduces the grid's inertia, leading to increased frequency instability compared to traditional grids with synchronous generators.

ESSs in frequency response services often employ purely proportional controllers, commonly known as droop-based control approaches. In this approach, the ESS adjusts its power output or charging/discharging rate in response to changes in grid frequency. P-f droop control is widely used in conventional and emerging frequency response services. It ensures that the active power output of the ESS is proportional to the frequency deviation, meaning that as the frequency decreases, the ESS output increases, and vice versa. The droop rate determines the degree of power response to frequency deviation. A control algorithm monitors the rate of change of load demand and adjusts the ESS power output accordingly. Various research works highlight the importance of droop-based control approaches for effective frequency regulation and stability enhancement in ESS. In this approach, the active power output of the ESS is proportional to the frequency deviation, meaning that as the frequency decreases, the ESS output increases, and vice versa. This relation is reported as follows:

$$\Delta P_{ESS}(t) = \frac{1}{R_{ESS}} \Delta f(t)$$

where $\Delta P_{ESS}(t)$ is the response of the device to the frequency variation $\Delta f(t)$. Note that different values for the droop rates RESS provide different degrees of power in response to the frequency deviation. The drop control method is typically implemented through a control algorithm that monitors the rate of change of load demand and adjusts the power output of the ESS accordingly.

Several papers have explored the implementation and benefits of droop-based control approaches in ESS for frequency regulation and stability enhancement. For example, Charalambous et al. propose a coordinated voltage-frequency support strategy that incorporates droop-based frequency support and virtual inertia control [115]. Egido et al. test the application of ultracapacitors for frequency stability enhancement, incorporating droop control and inertia emulation in the frequency control algorithm [116]. These studies emphasize the significance of droop-based control approaches in effective frequency regulation and stability enhancement in ESS.

Furthermore, the literature review includes papers investigating the use of different control techniques and technologies in frequency regulation. Examples include voltage and frequency regulation using wind turbine-photovoltaic-battery ESSs [117], cascaded pi-fractional order PID controllers for improving frequency response in hybrid microgrid systems [118], and real-time control of battery ESSs considering voltage-dependent capability of DCAC converters [119]. These works cover various aspects of frequency regulation, including optimal scheduling, control parameter optimization, and integration of different ESSs.

Emulated inertia control is a controller that aims to mimic the behavior of traditional synchronous generators by providing virtual inertia to the system [120]. Virtual synchronous generators (VSG) and virtual inertia emulator (VIE) are commonly used techniques in emulated inertia control. VIE is a type of VSG that offers better frequency regulation by emulating the rotating mass inertia of synchronous machines. This controller can be easily implemented with a proportional strategy, the active power output is in proportion to the rate-of change-of-frequency (RoCoF) by implementing a swing equation, which effectively mitigates RoCoF.

P-f droop control is simple and easy to implement, but it may not provide precise control and may

result in over or undercompensation of frequency deviations [121]. Conversely, triggered static response services are triggered at a certain frequency level instead of using a proportional droop. A constant power or discrete step of power is generated according to the frequency level. Static providers can be useful, especially during a large loss of generation, as they are fast-acting resources. However, the static response may not be as flexible as droop control in terms of adapting to dynamic changes in frequency deviations. A recent study [122], conducted a detailed techno-economic analysis of seven novel control strategies for ESS in frequency regulation comprehend drop-based and triggered static response control approaches. The analysis offers valuable insights and establishes the minimum total capital cost required for a positive net present value change under these control strategies. The findings demonstrate a range of economically viable configurations emphasizing the significance of selecting the appropriate control strategy for maximizing technical performance and financial viability.

The above-mentioned control approaches are relatively simple and easy to implement, and they can provide fast and accurate frequency responses. However, they may not be optimal for capturing the full potential of ESS in frequency response service, as they do not consider other important factors such as state of charge (SOC) and system constraints. Advanced control approaches utilize more sophisticated techniques to optimize the performance of ESS in frequency response service. These approaches use mathematical models of the ESS, grid, and load and generation profiles to predict future grid conditions and optimize ESS power output or charging/discharging rate accordingly. Advanced control approaches can account for various factors such as SOC, grid frequency, grid stability, load and generation profiles, and system constraints, to provide optimal frequency response performance while ensuring the safe operation of ESS. However, these approaches may require more computational resources, system modeling, and real-time data, which can increase the complexity and cost of the ESS system [123].

Fuzzy logic-based techniques have been widely used to improve frequency stability and address the challenges associated with integrating renewable energy sources into power systems. These techniques utilize fuzzy logic controllers (FLCs) to design control strategies that adjust system parameters based on input signals and system conditions. One example is the virtual adaptive inertia control (VAIC) strategy, which uses fuzzy logic and virtual battery algorithms to design virtual inertia and droop parameters based on the states of energy storage battery packs (ESBPs) and bus voltage fluctuations. The VAIC strategy aims to distribute inertia and power during dynamic and steady periods, respectively, to enhance system stability [124]. Another approach is the fuzzy-based virtual synchronous generator (VSG) topology, which considers the energy level of the energy storage system. This technique incorporates a fuzzy logic controller to adjust VSG parameters based on the magnitude of perturbations while considering operational constraints. The fuzzy logic controller provides set points to an adaptive predictive controller, which, in turn, provides reference power commands to the energy storage system [125]. In addition to these examples, fuzzy logic-based control strategies have been proposed for frequency regulation in microgrids with high renewable penetration. These strategies utilize adaptive and fuzzy PI controllers, self-adaptive virtual inertia control using fuzzy logic, and intelligent control with recurrent probabilistic wavelet fuzzy neural networks [126, 127, 128]. Furthermore, fuzzy logic has been employed in the control of battery energy storage systems (BESSs) for frequency response. Hierarchical control structures have been proposed, where the aggregator layer receives information about the state of charge (SoC) of BESSs and sends commands to enable/disable the BESS control layer. The BESS controller adjusts the response of the BESSs based on the frequency deviations, prioritizing their actions according to their SoC levels [129].

Virtual inertia emulation (VIE) has also been integrated with MPC for frequency response service. A

study introduces a VIE-based controller that demonstrates robustness superior to an optimal Proportional-Integral (PI) controller, highlighting the effectiveness of MPC in VIE applications [130]. Another research work proposes an optimal coordination control strategy for a microgrid inverter and energy storage based on variable virtual inertia and damping. By dynamically configuring the virtual inertia and damping using linear quadratic optimal control, this strategy aims to improve the stability of the virtual synchronous generator (VSG), suppress oscillations of active power and frequency, and optimally configure the energy storage capacity of the VSG [131]. In a different context, a novel methodology for primary frequency response (PFR) in a microgrid is presented, combining Finite Control Set-Model Predictive Control (FCS-MPC) and droop control. The configuration involves a grid-side converter (GSC), rotor-side converter (RSC), and a BESS. The FCS-MPC adjusts the droop gain value to continuously control the frequency imbalance and determine the power required from the BESS, allowing continuous operation at the maximum power point extraction and proportional power injection for frequency control [132]. Additionally, a manuscript proposes using virtual inertia emulator-based MPC for frequency regulation in renewable energy systems. The MPC approach, compared to Proportional (P) and Proportional-Integral (PI) controllers, aims to optimize control actions by predicting future system behaviors, contributing to reducing the carbon intensity of electricity production [133]. These studies demonstrate the utilization of MPC in conjunction with VIE techniques for enhanced frequency stability and control in various power system configurations.

In addition to the previously mentioned control approaches, there are other emerging techniques that can contribute to system frequency regulation. For instance, proactive frequency control, achieved through predictive algorithms and advanced forecasting techniques, helps anticipate and mitigate frequency deviations, enhancing frequency stability and reducing the need for reactive control measures [134, 135]. Ali et al. (2021) propose a cascaded PI-FOPID controller optimized using the Gorilla Troops Optimizer (GTO) to improve the frequency response of hybrid microgrid systems, resulting in significant improvements in maximum overshoot/undershoot and settling time compared to other techniques [118]. Mohamed et al. (2022) address the coordination and enhancement of frequency stability in interconnected microgrid systems using a fractional order load frequency controller and a superconducting magnetic energy storage (SMES) virtual inertia system, optimized with the slime mold optimization algorithm (SMA) [136]. Hammad et al. (2019) propose an effective virtual inertia measure for transient stability in power systems with distributed ESSs, considering both synchronous generators and actuated ESSs [137].

The control techniques discussed above may not adequately address uncertainties and perturbations in the system, which can limit their robustness and performance under various conditions. Robust control techniques have been explored to overcome these limitations by considering system uncertainties, perturbations, and physical constraints. These techniques aim to ensure stability and performance across a wide range of dynamic systems. To address this challenge, researchers have proposed new approaches that incorporate robust control principles. For instance, a virtual inertia control based on an optimal robust controller has been introduced in [138] to enhance the frequency stability of modern power systems with renewables. The proposed robust control technique utilizes a coefficient diagram method (CDM) optimized by a metaheuristic algorithm called the chaotic crow search algorithm (CCSA). By incorporating chaotic behavior into the crow search algorithm, the proposed algorithm avoids suboptimal solutions and improves the convergence rate. These developments highlight the ongoing efforts to enhance the robustness and performance of control techniques in the presence of uncertainties and perturbations. By integrating robust control principles and considering system-specific factors, researchers aim to improve the stability and reliability of modern power systems, particularly those incorporating high levels of renewable energy sources and distributed energy resources. However, it should be noted that designing robust control structures

often relies heavily on the experience of the designer, which restricts their applicability in diverse scenarios [138].

Due to their smaller size compared to traditional generators, ESSs are often deployed in groups to provide frequency services. This necessitates effective coordination and control among the ESSs. Several control techniques have been proposed to address this challenge.

Researchers have proposed distributed control strategies for multiple BESS to deliver fast frequency response in low-inertial power systems with high penetration of renewable energy sources. A novel distributed control algorithm has been designed to optimize the operation of multiple BESS units while considering frequency-related constraints and meeting the requirements of fast frequency response. The algorithm utilizes a consensus-based alternating direction method of multipliers (ADMM) to solve the optimization problem. The control strategy also incorporates a location-dependent term to account for the impact of BESS locations on the frequency response [139]. Another approach considers a distributed ESSs-based control paradigm for transient stability of power systems. Using a multi-agent control framework, an effective virtual inertia measure is derived, encompassing both traditional synchronous generators and actuated ESSs [137]. Furthermore, a hierarchical control approach has been proposed for the control of multiple BESSs to provide frequency response. This approach involves two decision layers: the aggregator layer and the BESS control layer. The aggregator layer receives the states of charge (SoC) of BESS units and sends commands to enable/disable the BESS control layer. The BESS controller prioritizes the response of BESS units based on their SoC levels, aiming to minimize the impact on the power system and end-users during the frequency response service [129].

Furthermore, electric vehicles (EVs) can also be utilized as energy storage for frequency response service [140]. EVs can act as grid frequency regulation resources or as storage/sources in the case of vehicle-to-grid (V2G) applications. However, the charging and discharging process of EV batteries can introduce complexities in the overall system's frequency control.

ESSs are increasingly being used instead of fossil fuel plants for this application as their flexibility and up-to-millisecond fast response times make them well-suited to compensate for rapid output fluctuations by RES increasingly integrated into modern power systems [141]. Nevertheless, BESSs are susceptible to degradation and reduced lifespan due to the high cycle rates of these applications.

Hybrid energy storage systems (HESSs) are gaining popularity as an alternative to fossil fuel plants due to their flexibility and fast response times. HESSs, such as the combination of Flywheel Energy Storage Systems (FESSs) and BESSs, provide solutions to address the degradation and reduced lifespan of BESSs caused by high cycle rates. [30]. One common control approach for HESSs is the utilization of virtual synchronous generator (VSG) techniques. VSGs imitate the behavior of conventional synchronous generators and play a crucial role in maintaining frequency stability in microgrids and power systems with RES integration. The control parameters of VSGs strongly influence the frequency response of the system, and their design requires extensive analysis due to the interactions among different generation sources and loads. Particle swarm optimization (PSO) has been proposed as an effective method for designing optimal VSG parameters, considering multiple objective functions such as the integral time absolute error (ITAE) of frequency, frequency nadir, and rate of change of frequency (ROCOF) [142].

Additionally, HESSs combining supercapacitors (SCs) and batteries offer advantages for power management, with SCs handling fast-varying power and batteries compensating for longterm power fluctuations. These hybrid systems contribute to the stability and performance of virtual synchronous generators (VSGs) and can effectively mitigate power fluctuations caused by intermittent renewable energy sources [143]. Power management strategies that integrate fuzzy logic with dynamic filtering

methods have been proposed to optimize the operation of hybrid battery-SC systems, broadening the flexibility of filtering and minimizing battery degradation [144].

Furthermore, HESSs play a significant role in integrating renewable energy sources like wind power into the grid. The combination of adiabatic compressed air energy storage (ACAES) systems with wind farms (WFs) provides a solution for smoothing power fluctuations. Coordinated control frameworks and tri-level coordinated frequency control methods have been proposed in [145] to achieve frequency response and distribute frequency regulation powers among wind turbines and A-CAES units. These HESS-based solutions enhance system stability and improve frequency control during frequency events.

Table 7.6: Frequency response: list of related articles PART 1.

Ref	R1	R2	R3	R4	E1	E2	E3	E4	E5	E6	E7	E8	E9	A1	A2	A3	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	G1	G2	G3
[146]			✓		✓									✓		✓	✓						✓				✓		✓
[147]	✓				✓									✓		✓	✓												✓
[148]		✓	✓		✓									✓			✓												✓
[126]		✓	✓		✓	✓								✓			✓	✓			✓		✓						✓
[127]	✓																✓	✓	✓		✓				✓				✓
[128]																	✓	✓	✓		✓					✓			✓
[129]			✓		✓									✓	✓		✓	✓	✓		✓						✓		✓
[124]		✓			✓									✓		✓	✓	✓	✓		✓						✓		✓
[149]			✓		✓												✓	✓	✓		✓						✓		✓
[145]	✓		✓				✓	✓						✓	✓	✓	✓	✓	✓		✓			✓			✓	✓	✓
[117]		✓	✓		✓											✓	✓	✓	✓		✓						✓		✓
[118]		✓	✓		✓											✓	✓	✓	✓		✓				✓			✓	✓
[150]		✓	✓	✓			✓			✓							✓	✓	✓		✓		✓					✓	✓
[119]					✓												✓	✓	✓		✓							✓	✓
[151]																	✓	✓	✓		✓							✓	✓
[152]				✓						✓				✓			✓	✓	✓		✓		✓				✓		✓
[142]		✓			✓							✓	✓	✓			✓	✓	✓		✓		✓				✓		✓
[153]		✓			✓									✓			✓	✓	✓		✓		✓				✓		✓
[133]	✓				✓							✓		✓			✓	✓	✓		✓		✓		✓		✓		✓
[132]			✓		✓									✓			✓	✓	✓		✓		✓				✓		✓
[154]																	✓	✓	✓		✓				✓			✓	✓
[155]	✓	✓	✓		✓							✓		✓		✓	✓	✓	✓		✓			✓	✓	✓	✓	✓	✓
[156]					✓						✓						✓	✓	✓		✓				✓			✓	✓
[157]		✓			✓							✓			✓		✓	✓	✓		✓				✓			✓	✓
[158]																	✓	✓	✓		✓				✓			✓	✓
[159]			✓	✓						✓				✓			✓	✓	✓		✓						✓		✓
[160]			✓	✓				✓								✓	✓	✓	✓		✓						✓		✓
[161]			✓	✓	✓				✓				✓		✓		✓	✓	✓		✓						✓		✓
[162]			✓	✓	✓				✓								✓	✓	✓		✓					✓			✓
[163]		✓			✓												✓	✓	✓		✓						✓		✓
[164]		✓	✓		✓												✓	✓	✓		✓						✓		✓
[165]		✓			✓		✓							✓			✓	✓	✓		✓						✓		✓
[166]					✓									✓			✓	✓	✓		✓						✓		✓
[167]	✓				✓						✓			✓			✓	✓	✓		✓						✓		✓
[168]			✓								✓			✓			✓	✓	✓		✓						✓		✓
[169]												✓					✓	✓	✓		✓						✓		✓
[170]	✓		✓								✓			✓			✓	✓	✓		✓						✓		✓
[171]	✓				✓									✓			✓	✓	✓		✓						✓		✓

Notes

R1: Generic RES; **R2:** Photovoltaics; **R3:** Wind power; **R4:** Hydro power; **E1:** Battery energy storage systems ; **E2:** Electric vehicle V1G/V2G; **E3:** Thermal energy storage and heat pump water heaters; **E4:** Compressed-air energy storage; **E5:** Pumped storage hydropower (PSH) / PICO Hydro; **E6:** Flywheel ; **E7:** Superconducting magnetic; **E8:** Supercapacitors; **E9:** Hybrid energy storage system ; **A1:** Centralized; **A2:** Decentralized; **A3:** Distributed; **C1:** Rule based; **C2:** PID and droop control methods; **C3:** Fuzzy; **C4:** Consensus based; **C5:** Sliding Mode Control, Hysteresis, H-infinity, Feedback linearization control, Fractional Order Control Method; **C6:** Mathematical optimization; **C7:** Metaheuristic algorithms; **C8:** Optimal control, Linear Quadratic Regulator, Model predictive control; **C9:** Robust and stochastic approaches; **C10:** Machine learning based control; **G1:** Transmission; **G2:** Distribution; **G3:** Microgrid and islanded systems;

Table 7.7: Frequency response: list of related articles PART 2.

Ref	R1	R2	R3	R4	E1	E2	E3	E4	E5	E6	E7	E8	E9	A1	A2	A3	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	G1	G2	G3
[172]		✓	✓								✓			✓		✓	✓										✓	✓	✓
[115]					✓									✓		✓	✓										✓	✓	
[173]			✓		✓									✓			✓										✓	✓	
[174]						✓								✓	✓		✓										✓	✓	
[175]	✓				✓							✓	✓	✓			✓										✓	✓	
[176]	✓				✓					✓			✓	✓		✓	✓										✓	✓	
[28]	✓				✓							✓	✓	✓			✓										✓	✓	
[177]					✓									✓		✓	✓										✓	✓	
[178]	✓				✓									✓			✓										✓	✓	
[179]			✓		✓	✓								✓		✓	✓										✓	✓	
[180]			✓		✓									✓			✓										✓	✓	
[181]			✓		✓									✓			✓										✓	✓	
[182]					✓									✓			✓										✓	✓	
[183]												✓					✓												
[184]			✓		✓	✓											✓												
[185]		✓												✓	✓		✓												
[186]					✓								✓	✓	✓		✓												
[187]														✓			✓												
[188]		✓															✓												
[189]	✓				✓	✓						✓		✓			✓		✓			✓							
[190]	✓		✓		✓									✓					✓			✓							
[125]			✓							✓				✓				✓		✓			✓	✓					
[191]	✓				✓									✓					✓					✓					✓
[192]			✓		✓									✓					✓						✓				
[193]					✓								✓						✓								✓		✓
[194]			✓		✓									✓	✓				✓								✓		
[195]					✓							✓	✓	✓					✓								✓		
[196]			✓															✓											
[197]		✓	✓															✓											
[139]	✓				✓											✓			✓			✓		✓					
[198]																			✓			✓							
[136]											✓								✓										✓
[137]																✓				✓									
[199]					✓															✓		✓		✓	✓				
[200]			✓		✓										✓	✓						✓		✓	✓				
[201]					✓																	✓		✓	✓				
[138]		✓	✓		✓	✓								✓								✓		✓	✓				✓
[202]		✓	✓			✓								✓									✓	✓	✓				✓
[203]		✓	✓																				✓	✓	✓				✓
[204]	✓	✓	✓																				✓	✓	✓				✓
[205]	✓		✓								✓					✓							✓						✓
[206]				✓					✓															✓					✓
[131]					✓									✓									✓						✓
[207]																							✓						✓
[208]																							✓						✓
[209]					✓																		✓						✓
[210]		✓																						✓					✓
[211]		✓	✓		✓									✓										✓					✓

Notes

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7.4.2.2 Spinning, non-spinning, and supplemental reserves

A crucial requirement for electrical utilities, or groups of electrical utilities, is to keep the power on even if a generator goes offline. The system as a whole must not experience excessive variation in frequency and power flow even if the largest of the system's generators goes down. Traditionally, all generating assets in the system are deliberately run with a small percentage of reserve capacity, which adds inefficiencies, extra costs, and waste. However, fast-acting ESSs such as capacitors, flywheels, and batteries can be used instead for this application, allowing generators to be run closer to their rated

value. Reserve capacity is further split into spinning reserve (can respond within 10 seconds), supplemental reserve (can respond within 10 minutes), and backup supply (can respond within one hour).

Spinning reserve services require rapid response capabilities to regulate the frequency to the desired level [223]. High energy ESSs are suitable for providing spinning reserve services due to their fast time response. Non-spinning reserve services involve reserve capacity that can respond within 10 minutes. The main control approaches for non-spinning reserves include PID control [160, 212], optimization-based methods [213, 215, 214, 219, 51, 220, 218, 216, 217], and robust and stochastic control [213, 215, 214, 212, 222]. Supplemental reserve services require reserve capacity that can respond within one hour. Electric vehicles (EVs) have been identified as a promising reserve resource for power grids to cope with power fluctuation problems [51].

Table 7.8: Spinning, non-spinning, and supplemental reserve: list of related articles.

Ref	R1	R2	R3	R4	E1	E2	E3	E4	E5	E6	E7	E8	E9	A1	A2	A3	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	G1	G2	G3
[51]						✓								✓			✓					✓							
[212]					✓											✓		✓	✓		✓		✓		✓				✓
[160]			✓	✓				✓								✓		✓											✓
[213]		✓	✓											✓								✓		✓	✓				
[214]					✓									✓								✓			✓		✓		
[215]					✓									✓								✓			✓				
[216]	✓			✓										✓								✓							
[217]																✓						✓							✓
[218]		✓	✓											✓								✓					✓		
[219]		✓	✓				✓							✓								✓							
[220]			✓				✓							✓								✓							
[221]			✓	✓				✓						✓									✓						
[222]								✓						✓										✓	✓				

Notes

R1: Generic RES; **R2:** Photovoltaics; **R3:** Wind power; **R4:** Hydro power; **E1:** Battery energy storage systems ; **E2:** Electric vehicle V1G/V2G; **E3:** Thermal energy storage and heat pump water heaters; **E4:** Compressed-air energy storage; **E5:** Pumped storage hydropower (PSH) / PICO Hydro; **E6:** Flywheel ; **E7:** Superconducting magnetic; **E8:** Supercapacitors; **E9:** Hybrid energy storage system ; **A1:** Centralized; **A2:** Decentralized; **A3:** Distributed; **C1:** Rule based; **C2:** PID and droop control methods; **C3:** Fuzzy; **C4:** Consensus based; **C5:** Sliding Mode Control, Hysteresis, H-infinity, Feedback linearization control, Fractional Order Control Method; **C6:** Mathematical optimization; **C7:** Metaheuristic algorithms; **C8:** Optimal control, Linear Quadratic Regulator, Model predictive control; **C9:** Robust and stochastic approaches; **C10:** Machine learning based control; **G1:** Transmission; **G2:** Distribution; **G3:** Microgrid and islanded systems;

7.4.2.3 Voltage Support

In addition to frequency regulation, maintaining a stable voltage profile is a critical aspect of grid operation. Voltage stability ensures that power quality is preserved and end-user devices operate within their specified voltage limits. Voltage support, as an ancillary service, plays a crucial role in managing the reactance across the grid and mitigating voltage deviations. Historically, voltage support necessitated the addition or subtraction of reactive power-generating assets within the grid. However, challenges arose due to the limited transmission capability of reactive power over long distances. The emergence of ESS, especially distributed ones, offers a promising solution for voltage support due to their proximity to end-users and the capability to modulate both real and reactive power.

The provision of voltage support through ESS involves various control approaches that govern the real and reactive power output of the energy storage units. The ability to provide reactive power is dependent on the characteristics of the inverter employed.

The PID control strategy is a fundamental approach for voltage support. It employs proportional, integral, and derivative components to compute a control signal that adjusts the energy storage output

to maintain desired voltage levels. This control approach, commonly referred to as the droop method, adjusts the power output proportionally to the voltage deviation. Yuan et al. proposed a real-time control framework for BESSs based on the droop control approach [119]. This framework aimed to utilize the full capability of BESSs while considering the voltage-dependent capability curve of the DC-AC converter and BESS security constraints. The control system formulated the power set-points using initial droop-based control and further optimized them through a nonconvex optimization process.

MPC has gained traction for voltage support due to its ability to predict future system behavior and optimize control actions accordingly. Zhang et al. introduced a coordinated voltage and frequency control scheme for HVDC systems under pole-block fault using MPC [227]. This approach employed a two-layer controller structure with model predictive control and moving horizon estimation to calculate active and reactive power references for power sources. The simulation results validated the effectiveness of this scheme in achieving optimal voltage control and frequency regulation. Decentralized control strategies aim to distribute control actions across the network, enhancing system flexibility and response time. Kumar et al. proposed a decentralized inverter voltage control approach for solar PV and storage-based islanded microgrids [229]. This approach employed adaptive discrete proportional integral differential (ADPID) control, utilizing the peak value of the AC voltage signal as a reference. The performance of this adaptive scheme was shown to provide improved voltage stability compared to conventional PID and model reference adaptive control schemes.

Some studies have focused on hybrid approaches that combine different control methods to achieve robust voltage regulation. Charalambous et al. introduced a coordinated voltage frequency support scheme for storage systems connected to distribution grids [115]. This scheme considered the reactance-to resistance ratio of the grid impedance and developed an adaptive gain to balance voltage and frequency support. Another study proposed a real-time coordinated control strategy for a grid-voltage source converter (GVSC) and ESS in a DC distribution system [231]. This strategy utilized both proportional integral control in the GVSC and variable droop control in the ESS, optimizing power outputs based on voltage sensitivities.

Table 7.9: Voltage regulation: list of related articles.

Ref	R1	R2	R3	R4	E1	E2	E3	E4	E5	E6	E7	E8	E9	A1	A2	A3	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	G1	G2	G3
[224]													✓		✓	✓		✓	✓		✓			✓		✓			✓
[225]		✓			✓	✓										✓		✓		✓								✓	✓
[117]		✓	✓		✓											✓		✓		✓							✓	✓	✓
[226]		✓	✓		✓											✓		✓		✓							✓	✓	✓
[119]					✓												✓				✓		✓				✓	✓	✓
[227]			✓		✓												✓					✓					✓	✓	✓
[228]		✓	✓	✓													✓							✓				✓	✓
[164]		✓	✓		✓											✓		✓										✓	✓
[229]		✓												✓	✓		✓											✓	✓
[230]					✓									✓			✓											✓	✓
[115]					✓									✓			✓										✓	✓	✓
[231]																✓	✓										✓	✓	✓
[232]					✓												✓											✓	✓
[233]											✓						✓											✓	✓
[180]			✓		✓									✓			✓										✓		✓
[234]																✓	✓												✓
[235]																✓	✓												✓
[236]			✓		✓												✓												✓
[237]					✓	✓												✓				✓	✓					✓	✓
[238]													✓					✓					✓	✓		✓		✓	✓
[195]					✓							✓	✓	✓				✓								✓		✓	✓
[239]			✓															✓											✓
[240]		✓																		✓								✓	✓
[241]		✓			✓															✓								✓	✓
[242]														✓								✓	✓					✓	✓
[243]						✓										✓						✓	✓					✓	✓
[244]			✓		✓									✓	✓							✓	✓					✓	✓
[245]	✓																					✓						✓	✓
[246]														✓	✓							✓						✓	✓
[247]		✓			✓																	✓						✓	✓
[248]		✓																				✓						✓	✓
[249]					✓									✓								✓				✓			✓
[250]		✓			✓																	✓						✓	✓
[251]		✓												✓								✓						✓	✓
[252]		✓			✓																	✓						✓	✓
[253]					✓									✓	✓	✓							✓					✓	✓
[254]																							✓					✓	✓
[255]			✓																				✓					✓	✓
[256]		✓										✓											✓					✓	✓
[257]		✓			✓								✓										✓					✓	✓
[258]		✓			✓																		✓				✓	✓	✓
[259]					✓																		✓					✓	✓
[260]		✓												✓	✓	✓								✓					✓
[261]	✓				✓							✓			✓								✓					✓	✓
[262]																							✓					✓	✓
[263]																							✓					✓	✓
[264]		✓			✓									✓	✓	✓							✓				✓	✓	✓
[265]					✓																		✓				✓	✓	✓
[266]		✓			✓																		✓				✓	✓	✓
[267]					✓																				✓			✓	✓
[268]		✓			✓																					✓		✓	✓
[269]														✓	✓	✓										✓		✓	✓

Notes

R1: Generic RES; **R2:** Photovoltaics; **R3:** Wind power; **R4:** Hydro power; **E1:** Battery energy storage systems; **E2:** Electric vehicle V1G/V2G; **E3:** Thermal energy storage and heat pump water heaters; **E4:** Compressed-air energy storage; **E5:** Pumped storage hydropower (PSH) / PICO Hydro; **E6:** Flywheel; **E7:** Superconducting magnetic; **E8:** Supercapacitors; **E9:** Hybrid energy storage system; **A1:** Centralized; **A2:** Decentralized; **A3:** Distributed; **C1:** Rule based; **C2:** PID and droop control methods; **C3:** Fuzzy; **C4:** Consensus based; **C5:** Sliding Mode Control, Hysteresis, H-infinity, Feedback linearization control, Fractional Order Control Method; **C6:** Mathematical optimization; **C7:** Metaheuristic algorithms; **C8:** Optimal control, Linear Quadratic Regulator, Model predictive control; **C9:** Robust and stochastic approaches; **C10:** Machine learning based control; **G1:** Transmission; **G2:** Distribution; **G3:** Microgrid and islanded systems;

7.4.2.4 Black Start

Power system restoration has been traditionally carried out by high-power generators connected to the transmission system [280]. When the grid is affected by a power outage, these so-called “Black Start” resources are used to turn it back on. However, due to the increasing share of renewable energy sources, traditional black start resources are fading. ESSs are ideally suited to substitute traditional

power generators for black start applications because they do not require a connection to the transmission system, which makes them more flexible and adaptable in a power outage scenario [280].

Most existing control strategies for ESSs are based on the traditional droop control strategy, which is widely used in power systems for voltage and frequency regulation [164]. For black start scenarios, several control approaches have been proposed that utilize droop, voltage, and current loops to regulate the network voltage and control the output current of the ESS [230].

Despite the effectiveness of droop control strategies, they have limitations in terms of stability and controllability during blackouts. To overcome these limitations, researchers have explored alternative approaches. For instance, Delghavi and Guerrero introduced a voltage control strategy based on fractional-order sliding-mode control for islanded operation of distributed energy resource (DER) systems [270]. This strategy ensures black-start functionality, maintains output voltage quality, and protects the power-electronic interface against faults. Similarly, Yang et al. proposed a fractional-order sliding-mode control framework for system restoration under power grid faults [273].

Optimization-based approaches have also emerged as promising solutions for enhancing the stability and controllability of power systems during blackouts [278, 279, 276]. These approaches formulate optimization problems that minimize load shedding, reduce switching operations, and optimize the involvement of ESSs in power system restoration. They often employ mixed-integer linear programming (MILP) formulations to consider various control objectives and time-dependent load and generation profiles [278, 279]. In active distribution networks, a MILP-based service restoration method combines existing infrastructure and DERs to achieve optimal system restoration, considering switching operations, load shedding, and reactive power control [278].

Coordinating different energy resources and facilities through optimization approaches has also shown promise. Golshani et al. proposed a coordination strategy for wind farms and pumped-storage hydro units during power system restoration [34]. Their strategy utilizes a two-stage adaptive robust optimization problem to determine optimal operation sequences and modes for various resources.

Real-time operation and control scheduling can be achieved through MPC. MPC methods have been applied to control ESSs during black start operations, focusing on enhancing PV utilization and maintaining optimal state of charge [272, 271].

To cope with uncertainties and unexpected events, stochastic optimization approaches have been employed [276, 277]. These approaches aim to provide robust and stable power system restoration by considering external disturbances, parameter uncertainties, and unmodeled dynamics. They have been successful in reducing PV power fluctuations, minimizing wind power curtailment, and achieving resilient distribution systems. Uncertainty plays a crucial role in power system restoration. Control approaches must be robust to external disturbances, parameter uncertainties, and unmodeled dynamics. Sliding-mode control and stochastic optimization-based approaches have shown promise in providing robust and stable power system restoration [277]. For example, Shuai et al. presented an approximate dynamic programming (ADP) based algorithm for realtime operation of microgrids under uncertainties [277]. In reference [277], a method is presented to reduce PV power fluctuations by employing hybrid ESSs through stochastic mixed-integer nonlinear programming. Additionally, in [34], a coordination strategy is proposed for wind farms and pumped-storage hydro (PSH) units to minimize wind power curtailment during the restoration process using a twostage adaptive robust optimization approach.

Table 7.10: Black start: list of related articles.

Ref	R1	R2	R3	R4	E1	E2	E3	E4	E5	E6	E7	E8	E9	A1	A2	A3	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	G1	G2	G3
[270]														✓		✓		✓									✓		✓
[271]			✓		✓					✓				✓	✓			✓				✓		✓			✓	✓	✓
[272]		✓			✓									✓				✓				✓		✓				✓	✓
[230]					✓									✓				✓										✓	✓
[273]					✓							✓				✓					✓								✓
[34]			✓	✓					✓							✓						✓	✓		✓		✓		✓
[274]																✓						✓			✓			✓	✓
[275]	✓															✓						✓			✓			✓	✓
[276]									✓							✓						✓			✓			✓	✓
[277]					✓											✓						✓			✓			✓	✓
[278]	✓													✓		✓						✓					✓		✓
[279]			✓		✓									✓								✓							✓

Notes

R1: Generic RES; **R2:** Photovoltaics; **R3:** Wind power; **R4:** Hydro power; **E1:** Battery energy storage systems ; **E2:** Electric vehicle V1G/V2G; **E3:** Thermal energy storage and heat pump water heaters; **E4:** Compressed-air energy storage; **E5:** Pumped storage hydropower (PSH) / PICO Hydro; **E6:** Flywheel ; **E7:** Superconducting magnetic; **E8:** Supercapacitors; **E9:** Hybrid energy storage system ; **A1:** Centralized; **A2:** Decentralized; **A3:** Distributed; **C1:** Rule based; **C2:** PID and droop control methods; **C3:** Fuzzy; **C4:** Consensus based; **C5:** Sliding Mode Control, Hysteresis, H-infinity, Feedback linearization control, Fractional Order Control Method; **C6:** Mathematical optimization; **C7:** Metaheuristic algorithms; **C8:** Optimal control, Linear Quadratic Regulator, Model predictive control; **C9:** Robust and stochastic approaches; **C10:** Machine learning based control; **G1:** Transmission; **G2:** Distribution; **G3:** Microgrid and islanded systems;

7.4.2.5 Congestion relief

The increased penetration of RESs is changing the landscape of modern power system. The intermittency of RES and its reversed power flows is leading to new regulation issues in both transmission and distribution networks. Addressing congestion in the power system requires a combination of measures, such as upgrading transmission infrastructure, improving energy management techniques, and developing energy storage solutions. ESSs have emerged as a promising solution to mitigate congestion and ensure the stability and reliability of the power grid. In recent years, various control approaches for ESS to handle congestion relief have been proposed and extensively studied in the literature.

Optimization-based techniques have been proposed as effective methods to coordinate the operation of ESS units and alleviate congestion in distribution networks. For instance, In [286], the authors propose a flexible AC power flow control system based on the concept of flexible AC transmission systems for power distribution systems. The approach aims to optimize the use of RERs and BESSs to achieve congestion relief. Moreover, in [249], the authors propose a control framework for battery storage systems installed in the power grid to alleviate congestion problems caused by decentralized renewable generation. The proposed approach uses a linearized load flow model and a receding horizon charge path optimizer to accurately estimate voltage and overload problems in the grid and optimize the charging path of the battery storage system. The optimization problem is posed as a linear problem and solved using a linear programming (LP) solver.

MPC has emerged as a popular control approach for managing ESS in the context of congestion relief in power systems. MPC takes into account real-time grid conditions and forecasted renewable energy generation to optimize the scheduling and dispatch of ESS, effectively addressing the intermittency of renewable energy sources (RES) and alleviating congestion.

In [293], the authors propose a cooperative multi-area optimization strategy for transmission system operators (TSOs) to efficiently dispatch and redispatch energy in interconnected networks while reducing costs. They present a cooperative MPC algorithm that meets various requirements, such as convergence close to the global optimum, communication of state and input variables to all subsystems, adaptation of subsystem state towards the global optimum, inclusion of external generation costs in the objective function, satisfaction of model and input constraints, and lower

complexity of local optimization problems. Increasing integration of photovoltaic (PV) system in electric grids causes congestion during peak power feed-in. This issue is addressed in [292] with battery storage. The authors propose a MPC approach that aims to minimize battery degradation, grid congestion, and maximize self-consumption. They compare the performance of MPC and conventional maximizing self-consumption (MSC) control schemes and show that MPC achieves similar self-consumption while reducing grid congestion and battery degradation.

Furthermore in [282] the authors focus on automatically clearing network congestion in power networks using a disturbance compensation-based MPC strategy. The MPC technique considers realistic constraints such as output and rate limits and active power balance. The proposed controller is validated on test systems and shown to have better performance compared to existing techniques, regulating line power flow within seconds by controlling synchronous generators and BESS.

Optimization and MPC approach are usually proposed in conjunction to hierarchical schemes [84, 253]. These involve multiple levels of control, ranging from local ESS control to higher-level coordination and optimization. Local ESS control typically involves local energy management strategies, such as rule-based control, where ESS charging and discharging decisions are made based on predefined rules. Higher-level coordination and optimization can be achieved through centralized or distributed control approaches, where ESS units communicate and coordinate with each other to optimize their operations and relieve congestion. In [84] the authors introduce a hierarchical control framework for the optimal coordination of distributed storage devices through Virtual Storage Plants (VSPs) to provide frequency regulation and congestion management in multi-area power networks. The proposed approach combines distributed optimization and consensus-based control. At a lower level, consensus-based control is designed to track power setpoints and maintain a balanced state-of-charge among storage units. This enables the modeling of VSPs at a higher level, where a distributed optimization approach is applied to achieve cross-regional coordination of multiple VSPs to deliver frequency support to interconnected power systems while avoiding congested power flows over tie lines.

Power system operation faces an increasing level of uncertainties from renewable generation and demand, which may cause large-scale congestion under an ineffective operation. ESSs are typically operated by deterministic optimal models that do not consider uncertainties, and that uncertainties from flexible load, and renewable generation should be taken into account in ES operation to reduce system congestion effectively. There is a growing body of literature that focuses on uncertainty modeling for congestion relief with ESSs in power systems. Several studies have proposed different approaches and techniques to address the uncertainties associated with ESS operation for congestion management. There are two key methods for modeling power flows considering uncertainties: Monte-Carlo simulation and probability theory. While Monte-Carlo simulation has been used in some research papers, it may not be applicable to large-scale systems. The authors also discuss two approaches for optimization with uncertainties: stochastic programming and robust optimization. Stochastic programming considers uncertainties as probabilistic distributions and solves for optimal solutions accordingly, while robust optimization considers uncertainties as bounded sets and aims to minimize worst-case scenarios. In [283] the authors apply energy storage (ES) to reduce system peak and the congestion by the robust optimization, considering the uncertainties from the ES state-of-charge (SoC), flexible load, and renewable energy. First, a deterministic operation model for the ES, as a benchmark, is designed to reduce the variance of the branch power flow based on the least-squares concept. Then, a robust model is built to optimize the ES operation with the uncertainties in the severest case from the load, renewable energy.

Table 7.11: Congestion relief services: list of related articles.

Ref	R1	R2	R3	R4	E1	E2	E3	E4	E5	E6	E7	E8	E9	A1	A2	A3	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	G1	G2	G3
[281]																													
[282]					✓									✓	✓	✓				✓		✓		✓			✓	✓	
[283]		✓			✓									✓								✓			✓				
[284]				✓		✓	✓															✓						✓	
[285]				✓																		✓					✓		
[249]					✓									✓								✓					✓		
[286]	✓	✓			✓									✓		✓						✓					✓	✓	✓
[287]																✓						✓						✓	
[288]	✓	✓	✓			✓		✓								✓						✓						✓	
[289]	✓		✓													✓						✓						✓	
[290]		✓		✓																			✓				✓		
[291]				✓				✓															✓				✓		
[253]					✓									✓	✓	✓							✓				✓		
[292]		✓			✓									✓										✓				✓	
[293]	✓														✓	✓								✓			✓		

Notes

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7.5 Conclusion and future outlook

The ongoing transformation within the energy sector is being driven by the pressing need to curtail greenhouse gas emissions, prompting governments across the globe to shift from conventional fossil-fuel-based power generation to more environmentally sustainable alternatives. Within this context, this subtask has undertaken an exhaustive analysis of diverse control approaches applicable to ESSs in the context of power distribution grid services. Looking ahead, several key directions for further advancement in ESS control have been identified. The stochastic nature of renewable energy resources, along with load variability, necessitates optimization approaches that consider multiple cost functions and constraints. Developing fast-acting protection devices, particularly for stable microgrids during islanded operation, presents a challenge that requires attention. As power systems evolve towards smarter and more efficient grids, real-time control, mitigation, and protection mechanisms are imperative. Furthermore, the subtask emphasizes the importance of identifying vulnerabilities and implementing robust detection and mitigation plans to prevent monetary and proprietary losses. By addressing these aspects and leveraging tightly coupled and fast-processing communication systems, a more efficient and interactive power grid framework can be realized. To conclude, the exploration of control approaches for ESS in power distribution grid services is essential for enhancing power grid stability, efficiency, and reliability. While existing approaches have their merits and challenges, ongoing research and development are necessary to address the identified limitations and explore innovative solutions. By considering the stochastic nature of renewable resources, developing efficient protection mechanisms, ensuring real-time control and accounting for diverse constraints, the power grid can evolve into a more optimized and sustainable system. These advancements will facilitate the integration of ESS into modern power systems and contribute to a resilient and sustainable energy future.

7.6 References

- [1] D. B. K. Md Abu, H. Najmul, M. Soumya, P. T. Kumar, Raihan, A techno-economic feasibility of a stand-alone hybrid power generation for remote area application in Bangladesh, *Energy* 134 (2017) 775–788.
- [2] F. A. Abdul Ghani, Olabi, Renewable energy technology developments, trends and policy implications that can underpin the drive for global climate change, 2017.
- [3] E. A. Tim J, S. Vladimir, Evans, Assessment of utility energy storage options for increased renewable energy penetration, *Renew. Sustain. Energy Rev.* 16 (2012) 4141–4147.
- [4] M. B. Narayana Prasad, G. Ramachandran, Padhy, Challenges with renewable energy sources and storage in practical distribution systems, *Renew. Sustain. Energy Rev.* 73 (2017) 125–134.
- [5] B. S. Joao PS, A. M. Hadi, S.-K. Miadreza, Catalao, A Decentralized Renewable Generation Management and Demand Response in Power Distribution Networks, *IEEE Trans. Sustain. Energy* 9 (2018) 1783–1797.
- [6] W. N. S. PR, T. PC, L. PD, Jones, Evaluating the benefits of an electrical energy storage system in a future smart grid, *Energy Policy* 38 (2010) 7180–7188.
- [7] D. C. K. Daryoush, B. Octavian, K. Ganesh, M. T. S, Habibi, Overview of energy storage systems in distribution networks: Placement, sizing, operation, and power quality, *Renew. Sustain. Energy Rev.* 91 (2018) 1205–1230.
- [8] M. R. Sheibani, G. R. Yousefi, M. A. Latify, S. H. Dolatabadi, Energy storage system expansion planning in power systems: A review, *IET Renew. Power Gener.* 12 (2018) 1203–1221.
- [9] Kousksou, Tarik and Bruel, Pascal and Jamil, Abdelmajid and El Rhafiki, T and Zeraouli, Youssef, Energy storage: Applications and challenges, *Sol. Energy Mater. Sol. Cells* 120 (2014) 59–80.
- [10] L. C. S. Kit Po, J. Youwei, L. L. Lei, X. Zhao, M. M. D, Wong, A comprehensive review on large-scale photovoltaic system with applications of electrical energy storage, *Renew. Sustain. Energy Rev.* 78 (2017) 439–451.
- [11] C. A. RP, Saini, A review on Integrated Renewable Energy System based power generation for stand-alone applications: Configurations, storage options, sizing methodologies and control, *Renew. Sustain. Energy Rev.* 38 (2014) 99–120.
- [12] F. D´iaz-González, A. Sumper, O. Gomis-Bellmunt, R. VillafañilaRobles, A review of energy storage technologies for wind power applications, *Renew. Sustain. Energy Rev.* 16 (2012) 2154–2171.
- [13] K.-K. S. H, T. VV, R. NA, P. NL, Mokhlis, Emergence of energy storage technologies as the solution for reliable operation of smart power systems: A review, *Renew. Sustain. Energy Rev.* 25 (2013) 135–165.
- [14] H. Zhao, Q. Wu, S. Hu, H. Xu, C. N. Rasmussen, Review of energy storage system for wind power integration support, *Appl. Energy* 137 (2015) 545–553.
- [15] F. M. Osama, Mohammed, Energy Storage Technologies for HighPower Applications, *IEEE Trans. Ind. Appl.* 52 (2016) 1953–1962.
- [16] T. Morstyn, B. Hredzak, V. G. Agelidis, Control Strategies for Microgrids with Distributed Energy Storage Systems: An Overview, *IEEE Trans. Smart Grid* 9 (2018) 3652–3666.

- [17] A. Ortega, F. Milano, Modeling, simulation, and comparison of control techniques for energy storage systems, *IEEE Trans. Power Syst.* 32 (2017) 2445–2454.
- [18] R. H. Byrne, T. A. Nguyen, D. A. Copp, B. R. Chalamala, I. Gyuk, Energy Management and Optimization Methods for Grid Energy Storage Systems, *IEEE Access* 6 (2017) 13231–13260.
- [19] H. A. Khan, M. Zuhair, M. Rihan, A. Kumar, Review of energy storage system technologies in microgrid applications: Characteristics, issues and challenges, *Energy Convers. Methods, Technol. Futur. Dir.* 6 (2022) 291–312.
- [20] L. A. Wong, V. K. Ramachandramurthy, P. Taylor, J. B. Ekanayake, S. L. Walker, S. Padmanaban, Review on the optimal placement, sizing and control of an energy storage system in the distribution network, *J. Energy Storage* 21 (2019) 489–504.
- [21] H. M. C, F. M, K. P. Jern, B. RA, D. ZY, Zhang, Review of optimal methods and algorithms for sizing energy storage systems to achieve decarbonization in microgrid applications, *Renew. Sustain. Energy Rev.* 131 (2020) 110022. A. G. Olabi, C. Onumaegbu, T. Wilberforce, M. Ramadan, M. A. Abdelkareem, A. H. Al – Alami, Critical review of energy storage systems, *Energy* 214 (2021) 118987.
- [22] M. A. Hannan, S. B. Wali, P. J. Ker, M. S. Rahman, M. Mansor, V. K. Ramachandramurthy, K. M. Muttaqi, T. M. Mahlia, Z. Y. Dong, Battery energy-storage system: A review of technologies, optimization objectives, constraints, approaches, and outstanding issues, *J. Energy Storage* 42 (2021) 103023.
- [23] D. R. Hadi, E. Rasul, Charkhgard, The Utilization of Shared Energy Storage in Energy Systems: A Comprehensive Review, *IEEE Trans. Smart Grid* 12 (2021) 3163–3174.
- [24] Dario, C. F. others, C. C. A, B. Kankar, A. Chioma, C. Ivan, de Souza Matheus F Zambroni, F. Mostafa, G. N. Sofia, M. William, Peralta, A Review of Modeling and Applications of Energy Storage Systems in Power Grids, *Proc. IEEE* (2022) 1–26.
- [25] A. A. A. William D., H. Georgianne, C. A. B., K. B. C, R. D. M., C. S. Bingqing, C. A. L., B. D. T., Gauntlett, DOE/EPRI 2013 Electricity Storage Handbook in Collaboration with NRECA, 2013.
- [26] B. P. J. Di, A. M. J. E, H. T. D, Wu, Assigning value to energy storage systems at multiple points in an electrical grid, *Energy Environ. Sci.* 11 (2018) 1926–1944.
- [27] M. Guan, Scheduled Power Control and Autonomous Energy Control of Grid-Connected Energy Storage System (ESS) with Virtual Synchronous Generator and Primary Frequency Regulation Capabilities, *IEEE Trans. Power Syst.* 37 (2022) 942–954.
- [28] R. Khalilisenobari, M. Wu, Optimal participation of price-maker battery energy storage systems in energy and ancillary services markets considering degradation cost, *Int. J. Electr. Power Energy Syst.* 138 (2022) 107924. arXiv:2006.05659.
- [29] D. I. Stroe, V. Knap, M. Swierczynski, A. I. Stroe, R. Teodorescu, Operation of a grid-connected lithium-ion battery energy storage system for primary frequency regulation: A battery lifetime perspective, *IEEE Trans. Ind. Appl.* 53 (2017) 430–438.
- [30] D. Zhu, Y. J. A. Zhang, Optimal Online Control of Multiple Battery Energy Storage Systems for Primary Frequency Control, *IEEE Power Energy Soc. Gen. Meet. 2018-Augus* (2018) 555–565.
- [31] I. Bekker, L. Hofmann, A. Mertens, Secondary control with gridforming inverters for an island grid restoration approach without communication, *Electr. Power Syst. Res.* 213 (2022).

- [32] M. Guo, J. Zheng, F. Mei, H. Sha, A. Gao, Y. Xie, Double-layer AGC frequency regulation control method considering operating economic cost and energy storage SOC consistency, *Int. J. Electr. Power Energy Syst.* 145 (2023).
- [33] A. Golshani, W. Sun, Q. Zhou, Q. P. Zheng, J. Wang, F. Qiu, Coordination of Wind Farm and Pumped-Storage Hydro for a Self-Healing Power Grid, *IEEE Trans. Sustain. Energy* 9 (2018) 1910–1920.
- [34] M. Bagheri-Sanjareh, M. H. Nazari, Coordination of energy storage system, PVs and smart lighting loads to reduce required battery size for improving frequency response of islanded microgrid, *Sustain. Energy, Grids Networks* 22 (2020).
- [35] T. Morstyn, M. D. McCulloch, Multiclass Energy Management for Peerto-Peer Energy Trading Driven by Prosumer Preferences, *IEEE Trans. Power Syst.* 34 (2019) 4005–4014.
- [36] S. Nguyen, W. Peng, P. Sokolowski, D. Alahakoon, X. Yu, Optimizing rooftop photovoltaic distributed generation with battery storage for peerto-peer energy trading, *Appl. Energy* 228 (2018) 2567–2580.
- [37] W. Li, G. Joo's, Performance comparison of aggregated and distributed energy storage systems in a wind farm for wind power fluctuation suppression, in: 2007 IEEE Power Eng. Soc. Gen. Meet. PES, IEEE, 2007, pp. 1–6.
- [38] Terlouw, Tom and AlSkaif, Tarek and Bauer, Christian and van Sark, Wilfried, Multi-objective optimization of energy arbitrage in community energy storage systems using different battery technologies, *Applied energy* 239 (2019) 356–372.
- [39] H. Zhu, K. Ouahada, A distributed real-time control algorithm for energy storage sharing, *Energy Build.* 230 (2021) 110478.
- [40] X. Yan, C. Gu, H. Wyman-Pain, F. Li, Capacity Share Optimization for Multiservice Energy Storage Management Under Portfolio Theory, *IEEE Trans. Ind. Electron.* 66 (2019) 1598–1607.
- [41] M. Calefati, S. Proia, P. Scarabaggio, R. Carli, M. Dotoli, A Decentralized Noncooperative Control Approach for Sharing Energy Storage Systems in Energy Communities, in: *Conf. Proc. IEEE Int. Conf. Syst. Man Cybern., IEEE*, 2021, pp. 1430–1435.
- [42] D. Kalathil, C. Wu, K. Poolla, P. Varaiya, The Sharing Economy for the Electricity Storage, *IEEE Trans. Smart Grid* 10 (2019) 556–567.
- [43] D. Z. Szabo', P. Duck, P. Johnson, Optimal trading of imbalance options for power systems using an energy storage device, *Eur. J. Oper. Res.* 285 (2020) 3–22.
- [44] Z. Zhao, K. Nakayama, R. Sharma, Decentralized Transactive Energy Auctions with Bandit Learning, in: 2019 IEEE PES Trans. Energy Syst. Conf. TESC 2019, IEEE, 2019, pp. 1–5.
- [45] T. Zhao, Z. Ding, Distributed agent consensus-based optimal resource management for microgrids, *IEEE Trans. Sustain. Energy* 9 (2018) 443– 452.
- [46] R. Wang, H. Tang, Y. Xu, Distributed cooperative optimal control of Energy Storage Systems in a microgrid, *IEEE Power Energy Soc. Gen. Meet.* 2016-Novem (2016) 238–248.
- [47] A. Ortega, F. Milano, Design of a control limiter to improve the dynamic response of energy storage systems, in: *IEEE Power Energy Soc. Gen. Meet., volume 2015-Septe*, IEEE, 2015, pp. 1–5.

- [48] A. Etxeberria, I. Vechiu, H. Camblong, J. M. Vinassa, Comparison of sliding mode and PI control of a hybrid energy storage system in a microgrid application, *Energy Procedia* 12 (2011) 966–974.
- [49] X. Xu, M. Bishop, O. Donna G, H. Chen, Application and modeling of battery energy storage in power systems, *CSEE J. Power Energy Syst.* 2 (2016) 82–90.
- [50] Z. Liu, P. Li, J. Liu, X. He, J. Han, C. Zi, N. Liang, A day-ahead energy management and reserve declaration strategy for parking lot based on electric vehicle accessing guidance, *Int. J. Electr. Power Energy Syst.* 136 (2022).
- [51] G. Edwards, S. Sheehy, C. J. Dent, M. C. Troffaes, Assessing the contribution of nightly rechargeable grid-scale storage to generation capacity adequacy, *Sustain. Energy, Grids Networks* 12 (2017) 69–81.
- [52] P. A. Dratsas, G. N. Psarros, S. A. Papathanassiou, A Real-time Redispatch Method to Evaluate the Contribution of Storage to Capacity Adequacy, *IEEE Trans. Power Syst.* (2023) 1–13.
- [53] M. S. Javadi, M. Gough, A. E. Nezhad, S. F. Santos, M. Shafie-khah, J. P. Catala~o, Pool trading model within a local energy community considering flexible loads, photovoltaic generation and energy storage systems, *Sustain. Cities Soc.* 79 (2022).
- [54] F. Zhang, A. Fu, L. Ding, Q. Wu, MPC based control strategy for battery energy storage station in a grid with high photovoltaic power penetration, *Int. J. Electr. Power Energy Syst.* 115 (2020).
- [55] E. I. Batzelis, S. A. Papathanassiou, B. C. Pal, PV System Control to Provide Active Power Reserves under Partial Shading Conditions, *IEEE Trans. Power Electron.* 33 (2018) 9163–9175.
- [56] Y. Ding, Q. Xu, Y. Xia, J. Zhao, X. Yuan, J. Yin, Optimal dispatching strategy for user-side integrated energy system considering multiservice of energy storage, *Int. J. Electr. Power Energy Syst.* 129 (2021).
- [57] C. Brivio, S. Mandelli, M. Merlo, Battery energy storage system for primary control reserve and energy arbitrage, *Sustain. Energy, Grids Networks* 6 (2016) 152–165.
- [58] M. Saffari, M. S. Misaghian, M. Kia, A. Heidari, D. Zhang, P. Dehghanian, J. Aghaei, Stochastic robust optimization for smart grid considering various arbitrage opportunities, *Electr. Power Syst. Res.* 174 (2019).
- [59] M. Kazemi, H. Zareipour, Long-term scheduling of battery storage systems in energy and regulation markets considering battery’s lifespan, *IEEE Trans. Smart Grid* 9 (2018) 6840–6849.
- [60] H. Mohsenian-Rad, Coordinated Price-Maker Operation of Large Energy Storage Units in Nodal Energy Markets, *IEEE Trans. Power Syst.* 31 (2016) 786–797.
- [61] M. A. Mirzaei, M. Hemmati, K. Zare, B. Mohammadi-Ivatloo, M. Abapour, M. Marzband, A. Farzamnia, Two-Stage Robust-Stochastic Electricity Market Clearing Considering Mobile Energy Storage in Rail Transportation, *IEEE Access* 8 (2020) 121780–121794.
- [62] J. Arteaga, H. Zareipour, A Price-Maker/Price-Taker Model for the Operation of Battery Storage Systems in Electricity Markets, *IEEE Trans. Smart Grid* 10 (2019) 6912–6920.
- [63] M. Farahani, A. Samimi, H. Shateri, Robust bidding strategy of battery energy storage system (BESS) in joint active and reactive power of dayahead and real-time markets, *J. Energy Storage* 59 (2023).

- [64] M. Aldaadi, F. Al-Ismael, A. T. Al-Awami, A. Muqbel, A coordinated bidding model for wind plant and compressed air energy storage systems in the energy and ancillary service markets using a distributionally robust optimization approach, *IEEE Access* 9 (2021) 148599–148610.
- [65] L. Pan, X. Xu, J. Liu, W. Hu, Adaptive robust scheduling of a hydro/photovoltaic/pumped-storage hybrid system in day-ahead electricity and hydrogen markets, *Sustain. Cities Soc.* 95 (2023).
- [66] S. Rezaei, A. Ghasemi, Stochastic scheduling of resilient interconnected energy hubs considering peer-to-peer energy trading and energy storages, *J. Energy Storage* 50 (2022).
- [67] H. Ding, Z. Hu, Y. Song, Rolling Optimization of Wind Farm and Energy Storage System in Electricity Markets, *IEEE Trans. Power Syst.* 30 (2015) 2676–2684.
- [68] G. Zhang, F. Li, C. Xie, Flexible Robust Risk-Constrained Unit Commitment of Power System Incorporating Large Scale Wind Generation and Energy Storage, *IEEE Access* 8 (2020) 209232–209241.
- [69] W. Tang, H. T. Yang, Optimal Operation and Bidding Strategy of a Virtual Power Plant Integrated with Energy Storage Systems and Elasticity Demand Response, *IEEE Access* 7 (2019) 79798–79809.
- [70] Y. Lin, J. X. Johnson, J. L. Mathieu, Emissions impacts of using energy storage for power system reserves, *Appl. Energy* 168 (2016) 444–456.
- [71] T. Liang, P. A. Webley, Y. C. Chen, X. She, Y. Li, Y. Ding, The optimal design and operation of a hybrid renewable micro-grid with the decoupled liquid air energy storage, *J. Clean. Prod.* 334 (2022).
- [72] Z. Tang, J. Liu, P. Zeng, A multi-timescale operation model for hybrid energy storage system in electricity markets, *Int. J. Electr. Power Energy Syst.* 138 (2022).
- [73] L. Argiolas, M. Stecca, L. M. Ramirez-Elizondo, T. B. Soeiro, P. Bauer, Optimal Battery Energy Storage Dispatch in Energy and Frequency Regulation Markets While Peak Shaving an EV Fast Charging Station, *IEEE Open Access J. Power Energy* 9 (2022) 374–385.
- [74] M. Merten, C. Olk, I. Schoeneberger, D. U. Sauer, Bidding strategy for battery storage systems in the secondary control reserve market, *Appl. Energy* 268 (2020).
- [75] T. Terlouw, T. AlSkaif, C. Bauer, W. van Sark, Multi-objective optimization of energy arbitrage in community energy storage systems using different battery technologies, *Appl. Energy* 239 (2019) 356–372.
- [76] S. Ali, S. A. A. Kazmi, M. M. Malik, A. H. U. Bhatti, M. Haseeb, S. M. R. Kazmi, D. R. Shin, Energy Management in High RER MultiMicrogrid System via Energy Trading and Storage Optimization, *IEEE Access* 10 (2022) 6541–6554.
- [77] Y. Bai, J. Wang, W. He, Energy arbitrage optimization of lithium-ion battery considering short-term revenue and long-term battery life loss, *Energy Reports* 8 (2022) 364–371.
- [78] K. Pandzic, K. Bruninx, H. Pandzic, Managing Risks Faced by Strategic Battery Storage in Joint Energy-Reserve Markets, *IEEE Trans. Power Syst.* 36 (2021) 4355–4365.
- [79] P. Zamani-Dehkordi, H. Chitsaz, L. Rakai, H. Zareipour, A price signal prediction method for energy arbitrage scheduling of energy storage systems, *Int. J. Electr. Power Energy Syst.* 122 (2020).

- [80] G. D'iaz, J. Go'mez-Aleixandre, J. Coto, O. Conejero, Maximum income resulting from energy arbitrage by battery systems subject to cycle aging and price uncertainty from a dynamic programming perspective, *Energy* 156 (2018) 647–660.
- [81] R. Xie, Y. Wang, S. Zhang, B. Lin, Q. Chen, F. Wang, X. Wang, Y. Chen, B. Xia, BESS frequency regulation strategy on the constraints of planned energy arbitrage using chance-constrained programming, *Energy Reports* 8 (2022) 73–80.
- [82] H. Su, D. Feng, Y. Zhao, Y. Zhou, Q. Zhou, C. Fang, U. Rahman, Optimization of Customer-Side Battery Storage for Multiple Service Provision: Arbitrage, Peak Shaving, and Regulation, *IEEE Trans. Ind. Appl.* 58 (2022) 2559–2573.
- [83] X. Wang, L. Ying, K. Wen, S. Lu, Bi-level non-convex joint optimization model of energy storage in energy and primary frequency regulation markets, *Int. J. Electr. Power Energy Syst.* 134 (2022).
- [84] B. Cheng, W. B. Powell, Co-Optimizing Battery Storage for the Frequency Regulation and Energy Arbitrage Using Multi-Scale Dynamic Programming, *IEEE Trans. Smart Grid* 9 (2018) 1997–2005.
- [85] D. Toquica, P. M. De Oliveira-De Jesus, A. I. Cadena, Power market equilibrium considering an EV storage aggregator exposed to marginal prices A bilevel optimization approach, *J. Energy Storage* 28 (2020).
- [86] Y. Li, S. Miao, S. Zhang, B. Yin, X. Luo, M. Dooner, J. Wang, A reserve capacity model of AA-CAES for power system optimal joint energy and reserve scheduling, *Int. J. Electr. Power Energy Syst.* 104 (2019) 279–290.
- [87] X. Guo, S. Lou, Z. Chen, Y. Wu, Y. Wang, Stochastic optimal scheduling considering reserve characteristics of retrofitted combined heat and power plants, *Int. J. Electr. Power Energy Syst.* 140 (2022).
- [88] R. Khatami, K. Oikonomou, M. Parvania, Look-ahead optimal participation of compressed air energy storage in day-ahead and real-time markets, *IEEE Trans. Sustain. Energy* 11 (2020) 682–692.
- [89] M. W. Tian, S. R. Yan, X. X. Tian, S. Nojavan, K. Jermsittiparsert, Risk and profit-based bidding and offering strategies for pumped hydro storage in the energy market, *J. Clean. Prod.* 256 (2020).
- [90] A. Akbari-Dibavar, B. Mohammadi-Ivatloo, K. Zare, Optimal stochastic bilevel scheduling of pumped hydro storage systems in a pay-as-bid energy market environment, *J. Energy Storage* 31 (2020).
- [91] I. L. Gomes, H. M. Pousinho, R. Mel'icio, V. M. Mendes, Stochastic coordination of joint wind and photovoltaic systems with energy storage in day-ahead market, *Energy* 124 (2017) 310–320.
- [92] K. Choopani, R. Effatnejad, M. Hedayati, Coordination of Energy Storage and Wind Power Plant considering Energy and Reserve Market for a Resilience Smart Grid, *J. Energy Storage* 30 (2020).
- [93] G. D'iaz, J. Coto, J. Go'mez-Aleixandre, Optimal operation value of combined wind power and energy storage in multi-stage electricity markets, *Appl. Energy* 235 (2019) 1153–1168.

- [94] B. Hu, Y. Tie, C. Shao, M. Shahidehpour, T. Niu, C. Li, K. Xie, A hierarchical transactive energy management framework for optimizing the reserve profile in district energy systems, *CSEE J. Power Energy Syst.* 7 (2021) 922–931.
- [95] Y. Xie, W. Guo, Q. Wu, K. Wang, Robust MPC-based bidding strategy for wind storage systems in real-time energy and regulation markets, *Int. J. Electr. Power Energy Syst.* 124 (2021) 106361.
- [96] T. Miseta, A. Fodor, A. Vathy-Fogarassy, Energy trading strategy for storage-based renewable power plants, *Energy* 250 (2022).
- [97] M. U. Hashmi, D. Deka, A. Busic, L. Pereira, S. Backhaus, Arbitrage with Power Factor Correction Using Energy Storage, *IEEE Trans. Power Syst.* 35 (2020) 2693–2703. arXiv:1903.06132.
- [98] H. H. Abdeltawab, Y. A. R. I. Mohamed, Market-oriented energy management of a hybrid wind-battery energy storage system via model predictive control with constraint optimizer, *IEEE Trans. Ind. Electron.* 62 (2015) 6658–6670.
- [99] Y. Shi, B. Xu, Y. Tan, D. Kirschen, B. Zhang, Optimal Battery Control under Cycle Aging Mechanisms in Pay for Performance Settings, *IEEE Trans. Automat. Contr.* 64 (2019) 2324–2339. arXiv:1709.05715.
- [100] E. Pusceddu, B. Zakeri, G. Castagneto Gisse, Synergies between energy arbitrage and fast frequency response for battery energy storage systems, *Appl. Energy* 283 (2021).
- [101] J. Cao, D. Harrold, Z. Fan, T. Morstyn, D. Healey, K. Li, Deep Reinforcement Learning-Based Energy Storage Arbitrage with Accurate Lithium-Ion Battery Degradation Model, *IEEE Trans. Smart Grid* 11 (2020) 4513–4521.
- [102] H. S. Nunna, A. Sesetti, A. K. Rathore, S. Doolla, Multiagent-Based Energy Trading Platform for Energy Storage Systems in Distribution Systems with Interconnected Microgrids, *IEEE Trans. Ind. Appl.* 56 (2020) 3207–3217.
- [103] J. L. Crespo-Vazquez, C. Carrillo, E. Diaz-Dorado, J. A. MartinezLorenzo, M. Noor-E-Alam, Evaluation of a data driven stochastic approach to optimize the participation of a wind and storage power plant in day-ahead and reserve markets, *Energy* 156 (2018) 278–291.
- [104] T. A. Nguyen, D. A. Copp, R. H. Byrne, Stacking Revenue from Energy Storage Providing Resilience, TD Deferral and Arbitrage, in: *IEEE Power Energy Soc. Gen. Meet.*, volume 2019-Augus, IEEE, 2019, pp. 1–5.
- [105] J. N. Baker, A. Collinson, Electrical energy storage at the turn of the Millennium, *Power Eng. J.* 13 (1999) 107–112.
- [106] S. Ould Amrouche, D. Rekioua, T. Rekioua, S. Bacha, Overview of energy storage in renewable energy systems, *Int. J. Hydrogen Energy* 41 (2016) 20914–20927.
- [107] M. Schwarz, Q. Auzepy, C. Knoeri, Can electricity pricing leverage electric vehicles and battery storage to integrate high shares of solar photovoltaics?, *Appl. Energy* 277 (2020) 115548.
- [108] A. S. Awad, J. D. Fuller, T. H. El-Fouly, M. M. Salama, Impact of energy storage systems on electricity market equilibrium, *IEEE Trans. Sustain. Energy* 5 (2014) 875–885.
- [109] H. Chen, T. N. Cong, W. Yang, C. Tan, Y. Li, Y. Ding, Progress in electrical energy storage system: A critical review, *Prog. Nat. Sci.* 19 (2009) 291–312.

- [110] K. Bradbury, L. Pratson, D. Patino-Echeverri, Economic viability of energy storage systems based on price arbitrage potential in real-time U.S. electricity markets, *Appl. Energy* 114 (2014) 512–519.
- [111] T. A. Nguyen, R. H. Byrne, R. J. Concepcion, I. Gyuk, Maximizing revenue from electrical energy storage in MISO energy & frequency regulation markets, in: *IEEE Power Energy Soc. Gen. Meet.*, volume 2018-Janua, IEEE, 2018, pp. 1–5.
- [112] J. Ellison, D. Bhatnagar, C. Black, K. Jenkins, Southern Company Energy Storage Study : A Study for the DOE Energy Storage Systems Program, Technical Report March, Sandia National Lab.(SNL-NM), Albuquerque, NM (United States); Southern . . . , 2013.
- [113] W. Wang, A. Abdolrashidi, N. Yu, D. Wong, Frequency regulation service provision in data center with computational flexibility, *Appl. Energy* 251 (2019).
- [114] A. Charalambous, L. Hadjidemetriou, E. Kyriakides, M. M. Polycarpou, A Coordinated Voltage-Frequency Support Scheme for Storage Systems Connected to Distribution Grids, *IEEE Trans. Power Electron.* 36 (2021) 8464–8475.
- [115] I. Egido, L. Sigrist, E. Lobato, L. Rouco, A. Barrado, An ultra-capacitor for frequency stability enhancement in small-isolated power systems: Models, simulation and field tests, *Appl. Energy* 137 (2015) 670–676.
- [116] L. Xiong, S. Huang, Y. Zhou, P. Li, Z. Wang, M. W. Khan, J. Wang, T. Niu, M. Ma, Voltage and Frequency Regulation With WT-PV-BESS in Remote Weak Grids Via Fixed-Time Containment Control, *IEEE Trans. Power Syst.* 38 (2022) 2719 – 2735.
- [117] M. Ali, H. Kotb, K. M. Aboras, N. H. Abbasy, Design of cascaded pifractional order PID controller for improving the frequency response of hybrid microgrid system using gorilla troops optimizer, *IEEE Access* 9 (2021) 150715–150732.
- [118] Z. Yuan, A. Zecchino, R. Cherkaoui, M. Paolone, Real-Time Control of Battery Energy Storage Systems to Provide Ancillary Services Considering Voltage-Dependent Capability of DC-AC Converters, *IEEE Trans. Smart Grid* 12 (2021) 4164–4175. arXiv:2006.12850.
- [119] D. Li, Q. Zhu, S. Lin, X. Y. Bian, A Self-Adaptive Inertia and Damping Combination Control of VSG to Support Frequency Stability, *IEEE Trans. Energy Convers.* 32 (2017) 397–398.
- [120] M. Dreidy, H. Mokhlis, S. Mekhilef, Inertia response and frequency control techniques for renewable energy sources: A review, *Renew. Sustain. Energy Rev.* 69 (2017) 144–155.
- [121] A. J. Hutchinson, D. T. Gladwin, Techno-economic assessment of novel hybrid energy storage control strategies for Dynamic Frequency Response, *J. Energy Storage* 55 (2022).
- [122] T. Kerdphol, F. S. Rahman, Y. Mitani, M. Watanabe, S. K. Ku'feog'lu, Robust virtual inertia control of an islanded microgrid considering high penetration of renewable energy, *IEEE Access* 6 (2017) 625–636.
- [123] W. Xing, H. Wang, L. Lu, X. Han, K. Sun, M. Ouyang, An adaptive virtual inertia control strategy for distributed battery energy storage system in microgrids, *Energy* 233 (2021).
- [124] A. W. Kumar, M. Ud din Mufti, M. Y. Zargar, Fuzzy based virtual inertia emulation in a multi-area wind penetrated power system using adaptive predictive control based flywheel storage, *Sustain. Energy Technol. Assessments* 53 (2022).

- [125] M. U. Jan, A. Xin, M. A. Abdelbaky, H. U. Rehman, S. Iqbal, Adaptive and Fuzzy PI Controllers Design for Frequency Regulation of Isolated Microgrid Integrated with Electric Vehicles, *IEEE Access* 8 (2020) 87621–87632.
- [126] T. Kerdphol, M. Watanabe, K. Hongesombut, Y. Mitani, Self-Adaptive Virtual Inertia Control-Based Fuzzy Logic to Improve Frequency Stability of Microgrid with High Renewable Penetration, *IEEE Access* 7 (2019) 76071–76083.
- [127] K. H. Tan, F. J. Lin, C. M. Shih, C. N. Kuo, Intelligent Control of Microgrid with Virtual Inertia Using Recurrent Probabilistic Wavelet Fuzzy Neural Network, *IEEE Trans. Power Electron.* 35 (2020) 7451–7464.
- [128] Z. A. Obaid, L. M. Cipcigan, M. T. Muhssin, S. S. Sami, Control of a population of battery energy storage systems for frequency response, *Int. J. Electr. Power Energy Syst.* 115 (2020) 105463.
- [129] T. Kerdphol, F. S. Rahman, Y. Mitani, M. Watanabe, S. Kufeoglu, Robust Virtual Inertia Control of an Islanded Microgrid Considering High Penetration of Renewable Energy, *IEEE Access* 6 (2018) 625–636.
- [130] X. Zhang, F. Mao, H. Xu, F. Liu, M. Li, An optimal coordination control strategy of micro-grid inverter and energy storage based on variable virtual inertia and damping of VSG, *Chinese J. Electr. Eng.* 3 (2017) 25–33.
- [131] L. A. Gomez, L. F. Lourenc_o, A. P. Grilo, M. B. Salles, L. Meegahapola, A. J. Sguarezi Filho, Primary frequency response of microgrid using doubly fed induction generator with finite control set model predictive control plus droop control and storage system, *IEEE Access* 8 (2020) 189298–189312.
- [132] N. Sockeel, J. Gafford, B. Papari, M. Mazzola, Virtual Inertia EmulatorBased Model Predictive Control for Grid Frequency Regulation Considering High Penetration of Inverter-Based Energy Storage System, *IEEE Trans. Sustain. Energy* 11 (2020) 2932–2939.
- [133] S. Wen, Y. Wang, Y. Tang, Y. Xu, P. Li, Proactive frequency control based on ultra-short-term power fluctuation forecasting for high renewables penetrated power systems, *IET Renew. Power Gener.* 13 (2019) 2166–2173.
- [134] K. R. Vasudevan, V. K. Ramachandaramurthy, G. Venugopal, J. M. Guerrero, J. B. Ekanayake, S. K. Tiong, Variable-Speed PICO Hydel Energy Storage with Synchronverter Control to Emulate Virtual Inertia in Autonomous Microgrids, *IEEE Syst. J.* 16 (2022) 452–463.
- [135] E. A. Mohamed, M. Aly, A. Elmelegi, E. M. Ahmed, M. Watanabe, S. M. Said, Enhancement the Frequency Stability and Protection of Interconnected Microgrid Systems Using Advanced Hybrid Fractional Order Controller, *IEEE Access* 10 (2022) 111936–111961.
- [136] E. Hammad, A. Farraj, D. Kundur, On Effective Virtual Inertia of Storage-Based Distributed Control for Transient Stability, *IEEE Trans. Smart Grid* 10 (2019) 327–336.
- [137] H. Ali, G. Magdy, D. Xu, A new optimal robust controller for frequency stability of interconnected hybrid microgrids considering noninertia sources and uncertainties, *Int. J. Electr. Power Energy Syst.* 128 (2021) 106651.

- [138] T. Zhao, A. Parisio, J. V. Milanovic, Location-dependent distributed control of battery energy storage systems for fast frequency response, *Int. J. Electr. Power Energy Syst.* 125 (2021) 106493.
- [139] K. M. Tan, V. K. Ramachandramurthy, J. Y. Yong, Integration of electric vehicles in smart grid: A review on vehicle to grid technologies and optimization techniques, *Renew. Sustain. Energy Rev.* 53 (2016) 720–732.
- [140] F. Mohamad, J. Teh, C. M. Lai, L. R. Chen, Development of energy storage systems for power network reliability: A review, *Energies* 11 (2018) 2278.
- [141] M. M. Mohamed, H. M. El Zoghby, S. M. Sharaf, M. A. Mosa, Optimal virtual synchronous generator control of battery/supercapacitor hybrid energy storage system for frequency response enhancement of photovoltaic/diesel microgrid, *J. Energy Storage* 51 (2022).
- [142] R. Masiello, R. Fioravanti, B. Chalamala, H. Passell, Electrification, Decarbonization, and the Future Carbon-Free Grid: The Role of Energy Storage in the Electric Grid Infrastructure, *Proc. IEEE* 110 (2022) 324– 333.
- [143] Y. Li, W. Yang, Z. Zhao, Y. Huang, Y. Liao, J. Yang, Ancillary service quantitative evaluation for primary frequency regulation of pumped storage units considering refined hydraulic characteristics, *J. Energy Storage* 45 (2022).
- [144] J. Han, S. Miao, Z. Chen, Z. Z. Liu, Y. Li, W. Yang, Z. Z. Liu, MultiView clustering and discrete consensus based tri-level coordinated control of wind farm and adiabatic compressed air energy storage for providing frequency regulation service, *Appl. Energy* 304 (2021).
- [145] S. A. Hosseini, M. Toulabi, A. Ashouri-Zadeh, A. M. Ranjbar, Battery energy storage systems and demand response applied to power system frequency control, *Int. J. Electr. Power Energy Syst.* 136 (2022) 107680.
- [146] T. Morstyn, B. Hredzak, V. G. Agelidis, Distributed Cooperative Control of Microgrid Storage, *IEEE Trans. Power Syst.* 30 (2015) 2780–2789.
- [147] J. Gouveia, C. L. Moreira, J. A. Lopes, Rule-based adaptive control strategy for grid-forming inverters in islanded power systems for improving frequency stability, *Electr. Power Syst. Res.* 197 (2021).
- [148] Y. Lin, X. Li, B. Zhai, Q. Yang, J. Zhou, X. Chen, J. Wen, A twolayer frequency control method for large-scale distributed energy storage clusters, *Int. J. Electr. Power Energy Syst.* 143 (2022) 108465.
- [149] Q. Zhang, J. Xie, X. Pan, L. Zhang, D. Fu, A Short-Term Optimal Scheduling Model for Wind-Solar-Hydro-Thermal Complementary Generation System Considering Dynamic Frequency Response, *IEEE Access* 9 (2021) 142768–142781.
- [150] T. Xu, W. Jang, T. Overbye, Commitment of Fast-Responding Storage Devices to Mimic Inertia for the Enhancement of Primary Frequency Response, *IEEE Trans. Power Syst.* 33 (2018) 1219–1230.
- [151] L. Shi, W. Lao, F. Wu, T. Zheng, K. Y. Lee, Frequency Regulation Control and Parameter Optimization of Doubly-Fed Induction Machine Pumped Storage Hydro Unit, *IEEE Access* 10 (2022) 102586–102598.

- [152] H. Ur Rehman, X. Yan, M. A. Abdelbaky, M. Ullah Jan, S. Iqbal, An advanced virtual synchronous generator control technique for frequency regulation of grid-connected PV system, *Int. J. Electr. Power Energy Syst.* 125 (2021) 106440.
- [153] Q. Yang, L. Yan, X. Chen, Y. Chen, J. Wen, A Distributed Dynamic Inertia-droop Control Strategy Based on Multi-Agent Deep Reinforcement Learning for Multiple Paralleled VSGs, *IEEE Trans. Power Syst.* (2022) 1–15.
- [154] K. Singh, Zaheeruddin, Enhancement of frequency regulation in tidal turbine power plant using virtual inertia from capacitive energy storage system, *J. Energy Storage* 35 (2021).
- [155] D. J. Ryan, R. Razzaghi, H. D. Torresan, A. Karimi, B. Bahrani, GridSupporting Battery Energy Storage Systems in Islanded Microgrids: A Data-Driven Control Approach, *IEEE Trans. Sustain. Energy* 12 (2021) 834–846.
- [156] X. He, S. Ge, H. Liu, Z. Xu, Y. Mi, C. Wang, Frequency regulation of multi-microgrid with shared energy storage based on deep reinforcement learning, *Electr. Power Syst. Res.* 214 (2023).
- [157] W. Qiu, K. Sun, W. Yao, S. You, H. Yin, X. Ma, Y. Liu, Time-frequency based cyber security defense of wide-area control system for fast frequency reserve, *Int. J. Electr. Power Energy Syst.* 132 (2021) 107151.
- [158] H. Garcia-Pereira, M. Blanco, G. Martinez-Lucas, J. I. Perez-Diaz, J. I. Sarasua, Comparison and Influence of Flywheels Energy Storage System Control Schemes in the Frequency Regulation of Isolated Power Systems, *IEEE Access* 10 (2022) 37892–37911.
- [159] S. I. Abouzeid, Y. Guo, H. C. Zhang, Cooperative control framework of the wind turbine generators and the compressed air energy storage system for efficient frequency regulation support, *Int. J. Electr. Power Energy Syst.* 130 (2021) 106844.
- [160] H. Yang, Q. Li, S. Zhao, W. Chen, H. Liu, A Hierarchical SelfRegulation Control for Economic Operation of AC/DC Hybrid Microgrid with Hydrogen Energy Storage System, *IEEE Access* 7 (2019) 89330–89341.
- [161] J. Bjork, K. H. Johansson, F. Dorfler, Dynamic Virtual Power Plant Design for Fast Frequency Reserves: Coordinating Hydro and Wind, *IEEE Trans. Control Netw. Syst.* (2022). arXiv:2107.03087.
- [162] S. Acharya, M. S. El Moursi, A. Al-Hinai, Coordinated frequency control strategy for an islanded microgrid with demand side management capability, *IEEE Transactions on Energy Conversion* 33 (2017) 639–651.
- [163] S. Li, Y. Li, X. Chen, T. Li, W. Zhang, A novel flexible power support control with voltage fluctuation suppression for islanded hybrid AC/DC microgrid involving distributed energy storage units, *Int. J. Electr. Power Energy Syst.* 123 (2020) 106265.
- [164] Y. J. Kim, J. Wang, Power Hardware-in-the-Loop Simulation Study on Frequency Regulation Through Direct Load Control of Thermal and Electrical Energy Storage Resources, *IEEE Trans. Smart Grid* 9 (2018) 2786–2796.
- [165] U. Bose, S. K. Chattopadhyay, C. Chakraborty, B. Pal, A novel method of frequency regulation in microgrid, *IEEE Trans. Ind. Appl.* 55 (2019) 111–121.
- [166] A. Hussain, S. Hasan, S. Patil, W. Shireen, Fast frequency regulation in islanded microgrid using model-based load estimation, *IEEE Transactions on Energy Conversion* 36 (2021) 3188–3198.

- [167] R. M. Kamel, Standalone micro grid power quality improvement using inertia and power reserves of the wind generation systems, *Renew. Energy* 97 (2016) 572–584.
- [168] I. Egido, L. Sigrist, E. Lobato, L. Rouco, A. Barrado, An ultra-capacitor for frequency stability enhancement in small-isolated power systems: Models, simulation and field tests, *Appl. Energy* 137 (2015) 670–676.
- [169] M. N. Musarrat, M. R. Islam, K. M. Muttaqi, D. Sutanto, Enhanced Frequency Support from a PMSG-Based Wind Energy Conversion System Integrated with a High Temperature SMES in Standalone Power Supply Systems, *IEEE Trans. Appl. Supercond.* 29 (2019) 1.
- [170] Y. J. Kim, G. Del-Rosario-Calaf, L. K. Norford, Analysis and Experimental Implementation of Grid Frequency Regulation Using Behind-the-Meter Batteries Compensating for Fast Load Demand Variations, *IEEE Trans. Power Syst.* 32 (2017) 484–498.
- [171] H. Peng, L. Luan, Z. Xu, W. Mo, Y. Wang, Event-triggered mechanism based control method of smes to improve microgrids stability under extreme conditions, *IEEE Transactions on Applied Superconductivity* 31 (2021) 1–4.
- [172] Y. Li, L. He, F. Liu, Y. Tan, Y. Cao, L. Luo, M. Shahidehpour, A dynamic coordinated control strategy of WTG-ES combined system for shortterm frequency support, *Renew. Energy* 119 (2018) 1–11.
- [173] S. Izadkhast, P. Garcia-Gonzalez, P. Frías, L. Ramírez-Elizondo, P. Bauer, An Aggregate Model of Plug-in Electric Vehicles Including Distribution Network Characteristics for Primary Frequency Control, *IEEE Trans. Power Syst.* 31 (2016) 2987–2998.
- [174] J. Fang, Y. Tang, H. Li, X. Li, A Battery/Ultracapacitor Hybrid Energy Storage System for Implementing the Power Management of Virtual Synchronous Generators, *IEEE Trans. Power Electron.* 33 (2018) 2820–2824.
- [175] D. Terazono, J. Liu, Y. Miura, S. Sakabe, H. Bevrani, T. Ise, Grid Frequency Regulation Support from Back-to-Back Motor Drive System with Virtual-Synchronous-Generator-Based Coordinated Control, *IEEE Trans. Power Electron.* 36 (2021) 2901–2913.
- [176] D. R. Aryani, H. Song, Y. S. Cho, Operation strategy of battery energy storage systems for stability improvement of the Korean power system, *J. Energy Storage* 56 (2022) 106091.
- [177] W. Yang, Y. Wen, H. Pandžić, W. Zhang, A multi-state control strategy for battery energy storage based on the state-of-charge and frequency disturbance conditions, *Int. J. Electr. Power Energy Syst.* 135 (2022).
- [178] S. Debbarma, R. Shrivastwa, Grid Frequency Support from V2G Aggregators and HVdc Links in Presence of Nonsynchronous Units, *IEEE Syst. J.* 13 (2019) 1757–1766.
- [179] L. Shang, X. Dong, C. Liu, Z. Gong, Fast Grid Frequency and Voltage Control of Battery Energy Storage System Based on the AmplitudePhase-Locked-Loop, *IEEE Trans. Smart Grid* 13 (2022) 941–953.
- [180] L. Miao, J. Wen, H. Xie, C. Yue, W. J. Lee, Coordinated Control Strategy of Wind Turbine Generator and Energy Storage Equipment for Frequency Support, *IEEE Trans. Ind. Appl.* 51 (2015) 2732–2742.

- [181] Y. Meng, X. Li, X. Liu, X. Cui, P. Xu, S. Li, A Control Strategy for Battery Energy Storage Systems Participating in Primary Frequency Control Considering the Disturbance Type, *IEEE Access* 9 (2021) 102004– 102018.
- [182] Y. Wang, C. Wang, L. Xu, J. Meng, Y. Hei, Adjustable Inertial Response from the Converter with Adaptive Droop Control in DC Grids, *IEEE Trans. Smart Grid* 10 (2019) 3198–3209.
- [183] J. Meng, Y. Mu, H. Jia, J. Wu, X. Yu, B. Qu, Dynamic frequency response from electric vehicles considering travelling behavior in the Great Britain power system, *Appl. Energy* 162 (2016) 966–979.
- [184] Q. Wang, J. Fang, W. Yao, D. Li, X. Ai, J. Wen, DC optimizer-based decentralized frequency support scheme of large-scale PV plants considering partial shading conditions, *Int. J. Electr. Power Energy Syst.* 142 (2022).
- [185] H. Shadabi, I. Kamwa, A decentralized non-linear dynamic droop control of a hybrid energy storage system bluefor primary frequency control in integrated AC-MTDC systems, *Int. J. Electr. Power Energy Syst.* 136 (2022).
- [186] D. Bao, X. Pan, Y. Wang, A Novel Hybrid Control Method for SinglePhase-Input Variable Frequency Speed Control System with a Small DC-Link Capacitor, *IEEE Trans. Power Electron.* 34 (2019) 9016–9032.
- [187] A. F. Hoke, M. Shirazi, S. Chakraborty, E. Muljadi, D. Maksimovic, Rapid Active Power Control of Photovoltaic Systems for Grid Frequency Support, *IEEE J. Emerg. Sel. Top. Power Electron.* 5 (2017) 1154–1163.
- [188] R. Mandal, K. Chatterjee, Design of a maiden synthetic inertia controller using super-capacitor energy storages and electric vehicles and real-time validation of the performance of the controller, *J. Energy Storage* 55 (2022).
- [189] P. Li, Z. Tan, Y. Zhou, C. Li, R. Li, X. Qi, Secondary frequency regulation strategy with fuzzy logic method and self-adaptive modification of state of charge, *IEEE Access* 6 (2018) 43575–43585.
- [190] B. Long, Y. Liao, K. T. Chong, J. Rodriguez, J. M. Guerrero, Enhancement of Frequency Regulation in AC Microgrid: A Fuzzy-MPC Controlled Virtual Synchronous Generator, *IEEE Trans. Smart Grid* 12 (2021) 3138–3149.
- [191] M. Taghvaei, M. Gilvanejad, M. Sedighizade, Cooperation of largescale wind farm and battery storage in frequency control: An optimal Fuzzy-logic based controller, *J. Energy Storage* 46 (2022).
- [192] K. R. Vasudevan, V. K. Ramachandaramurthy, G. Venugopal, J. M. Guerrero, G. David Agundis Tinajero, Synergizing pico hydel and battery energy storage with adaptive synchronverter control for frequency regulation of autonomous microgrids, *Appl. Energy* 325 (2022).
- [193] B. Peng, F. Zhang, J. Liang, L. Ding, Z. Liang, Q. Wu, Coordinated control strategy for the short-term frequency response of a DFIG-ES system based on wind speed zone classification and fuzzy logic control, *Int. J. Electr. Power Energy Syst.* 107 (2019) 363–378.
- [194] J. Li, F. Yao, Q. Yang, Z. Wei, H. He, Variable Voltage Control of a Hybrid Energy Storage System for Firm Frequency Response in the U.K., *IEEE Trans. Ind. Electron.* 69 (2022) 13394–13404.

- [195] S. Zhang, Y. Mishra, M. Shahidehpour, Fuzzy-Logic Based Frequency Controller for Wind, IEEE Power Energy Soc. 31 (2016) 1595 – 1603.
- [196] S. Zhang, Y. Mishra, M. Shahidehpour, Fuzzy-Logic Based Frequency Controller for Wind Farms Augmented with Energy Storage Systems, IEEE Trans. Power Syst. 31 (2016) 1595–1603.
- [197] Y. Wang, Y. Xu, Y. Tang, K. Liao, M. H. Syed, E. Guillo-Sansano, G. M. Burt, Aggregated Energy Storage for Power System Frequency Control: A Finite-Time Consensus Approach, IEEE Trans. Smart Grid 10 (2019) 3675–3686.
- [198] R. K. Subroto, K. L. Lian, C. C. Chu, C. J. Liao, A Fast Frequency Control Based on Model Predictive Control Taking into Account of Optimal Allocation of Power from the Energy Storage System, IEEE Trans. Power Deliv. 36 (2021) 2467–2478.
- [199] W. Bao, Q. Wu, L. Ding, S. Huang, V. Terzija, A Hierarchical Inertial Control Scheme for Multiple Wind Farms with BESSs Based on ADMM, IEEE Trans. Sustain. Energy 12 (2021) 751–760.
- [200] V. Trovato, A. Bialecki, A. Dallagi, Unit Commitment with InertiaDependent and Multispeed Allocation of Frequency Response Services, IEEE Trans. Power Syst. 34 (2019) 1537–1548.
- [201] M. H. Khooban, An Optimal Non-Integer Model Predictive Virtual Inertia Control in Inverter-Based Modern AC Power Grids-Based V2G Technology, IEEE Trans. Energy Convers. 36 (2021) 1336–1346.
- [202] G. K. Suman, J. M. Guerrero, O. P. Roy, Robust Frequency Control in Interconnected Microgrids: An H2/H-infinity Control Approach, IEEE Syst. J. 16 (2022) 2044–2055.
- [203] R. Mandal, K. Chatterjee, Virtual inertia emulation and RoCoF control of a microgrid with high renewable power penetration, Electr. Power Syst. Res. 194 (2021).
- [204] A. Elmelegi, E. A. Mohamed, M. Aly, E. M. Ahmed, A. A. A. Mohamed, O. Elbaksawi, Optimized Tilt Fractional Order Cooperative Controllers for Preserving Frequency Stability in Renewable EnergyBased Power Systems, IEEE Access 9 (2021) 8261–8277.
- [205] I. Sami, N. Ullah, S. M. Mueen, K. Techato, S. Chowdhury, J. S. Ro, Control Methods for Standalone and Grid Connected Micro-Hydro Power Plants with Synthetic Inertia Frequency Support: A Comprehensive Review, IEEE Access 8 (2020) 176313–176329.
- [206] S. Pulendran, J. E. Tate, Energy storage system control for prevention of transient under-frequency load shedding, IEEE Trans. Smart Grid 8 (2017) 927–936.
- [207] W. Liu, G. Geng, Q. Jiang, H. Fan, J. Yu, Model-Free Fast Frequency Control Support with Energy Storage System, IEEE Trans. Power Syst. 35 (2020) 3078–3086.
- [208] A. S. Mir, N. Senroy, Self-Tuning Neural Predictive Control Scheme for Ultrabattery to Emulate a Virtual Synchronous Machine in Autonomous Power Systems, IEEE Trans. Neural Networks Learn. Syst. 31 (2020) 136–147.
- [209] J. Chang, Y. Du, E. Lim, H. Wen, X. Li, J. Lin, Coordinated Frequency Regulation Using Solar Forecasting Based Virtual Inertia Control for Islanded Microgrids, IEEE Trans. Sustain. Energy 12 (2021) 2393–2403.
- [210] B. Singh, R. Sharma, S. Kewat, Robust control strategies for syrg-pv and wind-based islanded microgrid, IEEE Transactions on Industrial Electronics 68 (2020) 3137–3147.
- [211] A. Al-Hinai, H. Alyammahi, H. Haes Alhelou, Coordinated intelligent frequency control incorporating battery energy storage system, minimum variable contribution of demand

- response, and variable load damping coefficient in isolated power systems, *Energy Reports* 7 (2021) 8030–8041.
- [212] S. Zhao, Y. Fang, Z. Wei, Stochastic optimal dispatch of integrating concentrating solar power plants with wind farms, *Int. J. Electr. Power Energy Syst.* 109 (2019) 575–583.
 - [213] S. S. Parvar, H. Nazaripouya, Optimal Operation of Battery Energy Storage Under Uncertainty Using Data-Driven Distributionally Robust Optimization, *Electr. Power Syst. Res.* 211 (2022).
 - [214] M. Kazemi, H. Zareipour, N. Amjady, W. D. Rosehart, M. Ehsan, Operation Scheduling of Battery Storage Systems in Joint Energy and Ancillary Services Markets, *IEEE Trans. Sustain. Energy* 8 (2017) 1726–1735.
 - [215] A. Banshwar, N. K. Sharma, Y. R. Sood, R. Shrivastava, Market-based participation of energy storage scheme to support renewable energy sources for the procurement of energy and spinning reserve, *Renew. Energy* 135 (2019) 326–344.
 - [216] A. Cagnano, A. Caldarulo Bugliari, E. De Tuglie, A cooperative control for the reserve management of isolated microgrids, *Appl. Energy* 218 (2018) 256–265.
 - [217] S. W. Alnaser, S. Z. Althaher, C. Long, Y. Zhou, J. Wu, Residential community with PV and batteries: Reserve provision under grid constraints, *Int. J. Electr. Power Energy Syst.* 119 (2020).
 - [218] A. K. Pandey, V. K. Jadoun, J. N.S., Real-time and day-ahead risk averse multi-objective operational scheduling of virtual power plant using modified Harris Hawk’s optimization, *Electr. Power Syst. Res.* 220 (2023) 109285.
 - [219] I. Pavić, T. Capuder, I. Kuzle, Value of flexible electric vehicles in providing spinning reserve services, *Appl. Energy* 157 (2015) 60–74.
 - [220] M. E. Nazari, M. M. Ardehali, Optimal bidding strategy for a GENCO in day-ahead energy and spinning reserve markets with considerations for coordinated wind-pumped storage-thermal system and CO₂ emission, *Energy Strateg. Rev.* 26 (2019).
 - [221] H. A. Bafrani, M. Sedighzadeh, M. Dowlatshahi, M. H. Ershadi, M. M. Rezaei, Spinning reserve stochastic model of compressed air energy storage in day-ahead joint energy and reserve market using information gap decision theory method, *Int. J. Electr. Power Energy Syst.* 141 (2022).
 - [222] U. Akram, M. Nadarajah, R. Shah, F. Milano, A review on rapid responsive energy storage technologies for frequency regulation in modern power systems, *Renew. Sustain. Energy Rev.* 120 (2020) 109626.
 - [223] R. Sepehrzad, A. Mahmoodi, S. Y. Ghalebi, A. R. Moridi, A. R. Seifi, Intelligent hierarchical energy and power management to control the voltage and frequency of micro-grids based on power uncertainties and communication latency, *Electr. Power Syst. Res.* 202 (2022).
 - [224] M. Zeraati, M. E. Hamedani Golshan, J. M. Guerrero, A ConsensusBased Cooperative Control of PEV Battery and PV Active Power Curtailment for Voltage Regulation in Distribution Networks, *IEEE Trans. Smart Grid* 10 (2019) 670–680.
 - [225] M. Alrashidi, S. Rahman, A bi-level optimization method for voltage control in distribution networks using batteries and smart inverters with high wind and photovoltaic penetrations, *Int. J. Electr. Power Energy Syst.* 151 (2023).

- [226] Y. Zhang, P. Kou, L. Yu, D. Liang, Coordinated voltage and frequency control for HVDC sending end under pole-block fault: Using model predictive control, *Int. J. Electr. Power Energy Syst.* 136 (2022).
- [227] S. C. Sahoo, A. K. Barik, D. C. Das, Synchronized voltage-frequency regulation in sustainable microgrid using novel Green Leaf-hopper Flame optimization, *Sustain. Energy Technol. Assessments* 52 (2022).
- [228] M. Kumar, B. Tyagi, A Robust Adaptive Decentralized Inverter Voltage Control Approach for Solar PV and Storage-Based Islanded Microgrid, *IEEE Trans. Ind. Appl.* 57 (2021) 5356–5371.
- [229] M. Shahparasti, H. Laaksonen, K. Kauhaniemi, P. Lauttamus, S. Strandberg, J. Strandberg, Inrush Current Management During Medium Voltage Microgrid Black Start With Battery Energy Storage System, *IEEE Access* 10 (2022) 42273–42282.
- [230] D. Y. Shin, D. H. Kwon, S. I. Moon, Y. T. Yoon, Real-Time Coordinated Control of a Grid-VSC and ESSs in a DC Distribution System for Total Power Loss Reduction Considering Variable Droop Using Voltage Sensitivities, *IEEE Access* 11 (2023) 8293–8300.
- [231] W. Kang, M. Chen, Y. Guan, B. Wei, J. C. Vasquez Q., J. M. Guerrero, Event-triggered distributed voltage regulation by heterogeneous BESS in low-voltage distribution networks, *Appl. Energy* 312 (2022).
- [232] T. Penthia, A. K. Panda, S. K. Sarangi, Implementing dynamic evolution control approach for DC-link voltage regulation of superconducting magnetic energy storage system, *Int. J. Electr. Power Energy Syst.* 95 (2018) 275–286.
- [233] Z. Li, Q. Zhang, Q. Guo, S. Nojavan, Pumped hydro energy storage arbitrage in the day-ahead market in smart grid using stochastic p-robust optimization method, *Sustain. Cities Soc.* 75 (2021).
- [234] C. Yu, H. Xu, C. Liu, C. Chen, M. Sun, X. Zhang, Research on Modeling, Stability and Dynamic Characteristics of Voltage-controlled Gridconnected Energy Storage Inverters Under High Penetration, *Int. J. Electr. Power Energy Syst.* 143 (2022).
- [235] H. Luo, C. Xu, K. Dai, C. Cheng, Y. Huang, F. Pan, Balance Control of SOC for MMC-BESS With Power Fluctuation Suppression, PCC Voltage Regulation, and Harmonic Mitigation in Grid-Connected Wind Farm, *IEEE Access* 10 (2022) 117732–117744.
- [236] K. R. Reddy, S. Meikandasivam, Load Flattening and Voltage Regulation Using Plug-In Electric Vehicle's Storage Capacity with Vehicle Prioritization Using ANFIS, *IEEE Trans. Sustain. Energy* 11 (2020) 260–270.
- [237] A. Ghasemi, M. Sedighzadeh, A. Fakharian, M. R. Nasiri, Intelligent voltage and frequency control of islanded micro-grids based on power fluctuations and communication system uncertainty, *Int. J. Electr. Power Energy Syst.* 143 (2022).
- [238] C. Kim, W. Kim, Enhanced Low-Voltage Ride-Through Coordinated Control for PMSG Wind Turbines and Energy Storage Systems Considering Pitch and Inertia Response, *IEEE Access* 8 (2020) 212557–212567.
- [239] Y. Wang, K. T. Tan, X. Y. Peng, P. L. So, Coordinated Control of Distributed Energy-Storage Systems for Voltage Regulation in Distribution Networks, *IEEE Trans. Power Deliv.* 31 (2016) 1132–1141.

- [240] Z. M. J.M., H. G. M.E., Guerrero, Distributed Control of Energy-Storage Systems for Voltage Regulation in Distribution Network with High PV Penetration, 2018 UKACC 12th Int. Conf. Control. Control 2018 9 (2018) 169–173.
- [241] A. Giannitrapani, S. Paoletti, A. Vicino, D. Zarrilli, Optimal Allocation of Energy Storage Systems for Voltage Control in LV Distribution Networks, IEEE Trans. Smart Grid 8 (2017) 2859–2870.
- [242] M. H. Hemmatpour, M. H. Rezaeian Koochi, P. Dehghanian, P. Dehghanian, Voltage and energy control in distribution systems in the presence of flexible loads considering coordinated charging of electric vehicles, Energy 239 (2022).
- [243] R. Hemmati, N. Azizi, M. Shafie-khah, J. P. Catala, Decentralized frequency-voltage control and stability enhancement of standalone wind turbine-load-battery, Int. J. Electr. Power Energy Syst. 102 (2018) 1–10.
- [244] Y. Xie, L. Liu, Q. Wu, Q. Zhou, Robust model predictive control based voltage regulation method for a distribution system with renewable energy sources and energy storage systems, Int. J. Electr. Power Energy Syst. 118 (2020).
- [245] Bahramipanah, M. and Cherkaoui, R. and Paolone, M., M. Bahramipanah, R. Cherkaoui, M. Paolone, Decentralized voltage control of clustered active distribution network by means of energy storage systems, Electr. Power Syst. Res. 136 (2016) 370–382.
- [246] H. Almasalma, G. Deconinck, Simultaneous Provision of Voltage and Frequency Control by PV-Battery Systems, IEEE Access 8 (2020) 152820–152836.
- [247] S. Wang, L. Du, X. Fan, Q. Huang, Deep reinforcement scheduling of energy storage systems for real-time voltage regulation in unbalanced LV Networks with high PV penetration, IEEE Trans. Sustain. Energy 12 (2021) 2342–2352.
- [248] W. van Westering, H. Hellendoorn, Low voltage power grid congestion reduction using a community battery: Design principles, control and experimental validation, Int. J. Electr. Power Energy Syst. 114 (2020) 105349.
- [249] T. Tewari, A. Mohapatra, S. Anand, Coordinated control of OLTC and energy storage for voltage regulation in distribution network with high PV penetration, IEEE Trans. Sustain. Energy 12 (2021) 262–272.
- [250] X. Sun, J. Qiu, Y. Yi, Y. Tao, Sun, X. and Qiu, J. and Yi, Y. and Tao, Y., Cost-Effective Coordinated Voltage Control in Active Distribution Networks with Photovoltaics and Mobile Energy Storage Systems, IEEE Trans. Sustain. Energy 13 (2022) 501–513.
- [251] Y. Zhang, K. Meng, F. Luo, H. Yang, J. Zhu, Z. Y. Dong, Multi-agentbased voltage regulation scheme for high photovoltaic penetrated active distribution networks using battery energy storage systems, IEEE Access 8 (2020) 7323–7333.
- [252] K. D. Pippi, G. C. Kryonidis, A. I. Nousedilis, T. A. Papadopoulos, A unified control strategy for voltage regulation and congestion management in active distribution networks, Electr. Power Syst. Res. 212 (2022).
- [253] F. M. Camilo, R. Castro, M. E. Almeida, V. Ferra, Energy management in unbalanced low voltage distribution networks with microgeneration and storage by using a multi-objective optimization algorithm, J. Energy Storage 33 (2021).

- [254] A. K. ALAhmad, Voltage regulation and power loss mitigation by optimal allocation of energy storage systems in distribution systems considering wind power uncertainty, *J. Energy Storage* 59 (2023).
- [255] M. Aryanezhad, Management and coordination of LTC, SVR, shunt capacitor and energy storage with high PV penetration in power distribution system for voltage regulation and power loss minimization, *Int.J. Electr. Power Energy Syst.* 100 (2018) 178–192.
- [256] P. Ariyaratna, K. M. Muttaqi, D. Sutanto, A novel control strategy to mitigate slow and fast fluctuations of the voltage profile at common coupling Point of rooftop solar PV unit with an integrated hybrid energy storage system, *J. Energy Storage* 20 (2018) 409–417.
- [257] H. Nasrazadani, A. Sedighi, H. Seifi, Enhancing long-term voltage stability of a power system integrated with large-scale photovoltaic plants using a battery energy storage control scheme, *Int. J. Electr. Power Energy Syst.* 131 (2021).
- [258] H. Zuo, Y. Teng, S. Cheng, P. Sun, Z. Chen, Distributed multi-energy storage cooperative optimization control method for power grid voltage stability enhancement, *Electr. Power Syst. Res.* 216 (2023).
- [259] A. Rosini, D. Mestriner, A. Labella, A. Bonfiglio, R. Procopio, A decentralized approach for frequency and voltage regulation in islanded PV-Storage microgrids, *Electr. Power Syst. Res.* 193 (2021).
- [260] T. Morstyn, A. V. Savkin, B. Hredzak, H. D. Tuan, Scalable Energy Management for Low Voltage Microgrids Using Multi-Agent Storage System Aggregation, *IEEE Trans. Power Syst.* 33 (2018) 1614–1623.
- [261] H. Yepes-Fernández, M. Restrepo, A. Arango-Manrique, A Study on Control Strategies for Aggregated Community Energy Storage Systems in Medium Voltage Distribution Networks, *IEEE Access* 10 (2022) 119321–119332.
- [262] Y. Guo, Q. Wu, H. Gao, X. Chen, J. Ostergaard, H. Xin, MPC-Based Coordinated Voltage Regulation for Distribution Networks with Distributed Generation and Energy Storage System, *IEEE Trans. Sustain. Energy* 10 (2019) 1731–1739.
- [263] P. Balram, L. A. Tuan, O. Carlson, Comparative study of MPC based coordinated voltage control in LV distribution systems with photovoltaics and battery storage, *Int. J. Electr. Power Energy Syst.* 95 (2018) 227– 238.
- [264] O. B. Adewuyi, R. Shigenobu, K. Ooya, T. Senjyu, A. M. Howlader, Static voltage stability improvement with battery energy storage considering optimal control of active and reactive power injection, *Electr. Power Syst. Res.* 172 (2019) 303–312.
- [265] S. Moury, J. Lam, A Soft-Switched, Multiport Photovoltaic Power Optimizer with Integrated Storage Interface and Output Voltage Regulation, *IEEE Trans. Ind. Electron.* 68 (2021) 3917–3927.
- [266] N. Tshivhase, A. N. Hasan, T. Shongwe, An Average Voltage Approach to Control Energy Storage Device and Tap Changing Transformers under High Distributed Generation, *IEEE Access* 9 (2021) 108731– 108753.

- [267] P. Chen, S. Liu, X. Wang, I. Kamwa, Physics-Shielded Multi-Agent Deep Reinforcement Learning for Safe Active Voltage Control with Photovoltaic/Battery Energy Storage Systems, *IEEE Trans. Smart Grid* (2022) 1–1.
- [268] Y. Xiang, Y. Lu, J. Liu, Deep reinforcement learning based topologyaware voltage regulation of distribution networks with distributed energy storage, *Appl. Energy* 332 (2023).
- [269] M. B. Delghavi, S. Shoja-Majidabad, A. Yazdani, Fractional-Order Sliding-Mode Control of Islanded Distributed Energy Resource Systems, *IEEE Trans. Sustain. Energy* 7 (2016) 1482–1491.
- [270] W. Liu, Y. Liu, Hierarchical model predictive control of wind farm with energy storage system for frequency regulation during black-start, *Int.J. Electr. Power Energy Syst.* 119 (2020) 105893.
- [271] J. Li, H. You, J. Qi, M. Kong, S. Zhang, H. Zhang, Stratified optimization strategy used for restoration with photovoltaic-battery energy storage systems as black-start resources, *IEEE Access* 7 (2019) 127339– 127352.
- [272] B. Yang, J. Wang, Y. Sang, L. Yu, H. Shu, S. Li, T. He, L. Yang, X. Zhang, T. Yu, Applications of supercapacitor energy storage systems in microgrid with distributed generators via passive fractionalorder sliding-mode control, *Energy* 187 (2019).
- [273] M. H. Yeganehkia, M. M. Rezaei, M. Abedi, M. Dowlatshahi, Presenting a new IGDT-based scheme for risk-based developing of distribution system restoration using online islanding method, *Sustain. Energy, Grids Networks* 34 (2023).
- [274] F. Liu, C. Chen, C. Lin, G. Li, H. Xie, Z. Bie, Utilizing Aggregated Distributed Renewable Energy Sources with Control Coordination for Resilient Distribution System Restoration, *IEEE Trans. Sustain. Energy* 14 (2023) 1043 – 1056.
- [275] L. Zhang, S. Yu, B. Zhang, G. Li, Y. Cai, W. Tang, Outage management of hybrid AC/DC distribution systems: Co-optimize service restoration with repair crew and mobile energy storage system dispatch, *Appl. Energy* 335 (2023).
- [276] H. Shuai, J. Fang, X. Ai, J. Wen, H. He, Optimal Real-Time Operation Strategy for Microgrid: An ADP-Based Stochastic Nonlinear Optimization Approach, *IEEE Trans. Sustain. Energy* 10 (2019) 931–942.
- [277] M. G. Choi, J. H. Choi, S. Y. Yun, S. J. Ahn, MILP-Based Service Restoration Method Utilizing Both Existing Infrastructure and DERs in Active Distribution Networks, *IEEE Access* 10 (2022) 36477–36489.
- [278] L. Sun, W. Liu, C. Y. Chung, M. Ding, R. Bi, L. Wang, Improving the restorability of bulk power systems with the implementation of a wf-bess system, *IEEE Trans. Power Syst.* 34 (2019) 2366–2377.
- [279] A. Peña Asensio, S. Arnaltes Go´mez, J. L. Rodriguez-Amenedo, Blackstart capability of PV power plants through a grid-forming control based on reactive power synchronization, *Int. J. Electr. Power Energy Syst.* 146 (2023).
- [280] X. Wang, T. Zhao, A. Parisio, Frequency regulation and congestion management by Virtual Storage Plants, *Sustain. Energy, Grids Networks* 29 (2022).

- [281] K. Chakravarthi, P. Bhui, N. K. Sharma, B. C. Pal, Real Time Congestion Management Using Generation Re-dispatch: Modeling and Controller Design, *IEEE Trans. Power Syst.* 38 (2022) 1–14.
- [282] X. Yan, C. Gu, X. Zhang, F. Li, Robust Optimization-Based Energy Storage Operation for System Congestion Management, *IEEE Syst. J.* 14 (2020) 2694–2702.
- [283] F. H. Aghdam, M. W. Mudiyansele, B. Mohammadi-Ivatloo, M. Marzband, Optimal scheduling of multi-energy type virtual energy storage system in reconfigurable distribution networks for congestion management, *Appl. Energy* 333 (2023).
- [284] S. Gope, A. K. Goswami, P. K. Tiwari, S. Deb, Rescheduling of real power for congestion management with integration of pumped storage hydro unit using firefly algorithm, *Int. J. Electr. Power Energy Syst.* 83 (2016) 434–442.
- [285] D. Ranamuka, K. M. Muttaqi, D. Sutanto, Flexible AC Power Flow Control in Distribution Systems by Coordinated Control of Distributed Solar-PV and Battery Energy Storage Units, *IEEE Trans. Sustain. Energy* 11 (2020) 2054–2062.
- [286] R. Moreno, R. Moreira, G. Strbac, A MILP model for optimising multiservice portfolios of distributed energy storage, *Appl. Energy* 137 (2015) 554–566.
- [287] J. Salehi, A. Abdolahi, Optimal scheduling of active distribution networks with penetration of PHEV considering congestion and air pollution using DR program, *Sustain. Cities Soc.* 51 (2019).
- [288] J. Salehi, A. Namvar, F. S. Gazijahani, M. Shafie-khah, J. P. Catala~o, Effect of power-to-gas technology in energy hub optimal operation and gas network congestion reduction, *Energy* 240 (2022).
- [289] N. Lou, Y. Zhang, Y. Wang, Q. Liu, H. Li, Y. Sun, Z. Guo, Two-stage congestion management considering virtual power plant with cascade hydro-photovoltaic-pumped storage hybrid generation, *IEEE Access* 8 (2020) 186335–186347.
- [290] N. Tarashandeh, A. Karimi, Utilization of energy storage systems in congestion management of transmission networks with incentive-based approach for investors, *J. Energy Storage* 33 (2021).
- [291] U. R. Nair, M. Sandelic, A. Sangwongwanich, T. Dragicevic, R. CostaCastello, F. Blaabjerg, Grid Congestion Mitigation and Battery Degradation Minimisation Using Model Predictive Control in PV-Based Microgrid, *IEEE Trans. Energy Convers.* 36 (2021) 1500–1509.
- [292] M. Kahl, C. Freye, T. Leibfried, A Cooperative Multi-Area Optimization with Renewable Generation and Storage Devices, *IEEE Trans. Power Syst.* 30 (2015) 2386–2395.