Advanced Strategies for Energy Optimization: A Survey on Peak Shaving, Multi-type Energy Storage Configurations, Multiscale Neural Networks, Energy Management, Grid Stability, and Renewable Integration

www.surveyx.cn

Abstract

Modern power systems face increasing demands for energy optimization driven by energy security, cost savings, and emission reductions. The integration of renewable energy sources necessitates advanced strategies, including peak shaving, multi-type energy storage configurations, and multiscale neural networks, to ensure grid stability and efficient energy management. This survey explores these strategies, emphasizing the role of diverse energy storage solutions and sophisticated neural network models in managing energy resources across different scales. Key findings highlight the significance of peak shaving in balancing electricity demand and supply, and the pivotal role of multi-type energy storage configurations in enhancing grid stability. Multiscale neural networks offer robust solutions for optimizing energy management, addressing the stochastic nature of renewable sources. Challenges such as variability and intermittency of renewables are addressed through advanced energy management strategies and demand response systems, enhancing grid flexibility. Technological innovations, including smart grids and vehicle-to-grid technology, further support renewable integration. The survey concludes by identifying future research directions, focusing on scalable control strategies, improved battery management, and advanced optimization techniques to enhance the efficiency, reliability, and sustainability of modern energy systems. These findings underscore the critical importance of integrating advanced technologies and methodologies to navigate the complexities of contemporary power grids, promoting economic viability and environmental sustainability.

1 Introduction

1.1 The Need for Energy Optimization

The rising demand for energy optimization in modern power systems is propelled by the necessity for energy security, cost savings, and greenhouse gas emission reductions [1]. The incorporation of renewable energy sources, such as photovoltaic (PV) generators, introduces variability and intermittency, necessitating hybrid power system solutions for a reliable power supply [2]. Innovative strategies for managing distributed energy resources (DER) are essential, particularly under net energy metering (NEM) tariffs, as electrification in distribution networks increases [3].

In microgrids, optimizing energy systems is vital for minimizing operational costs and enhancing efficiency [4]. The presence of Pulse Power Loads (PPLs) in shipboard power systems highlights the need for effective energy management to meet high ramp rate demands. Additionally, the growing

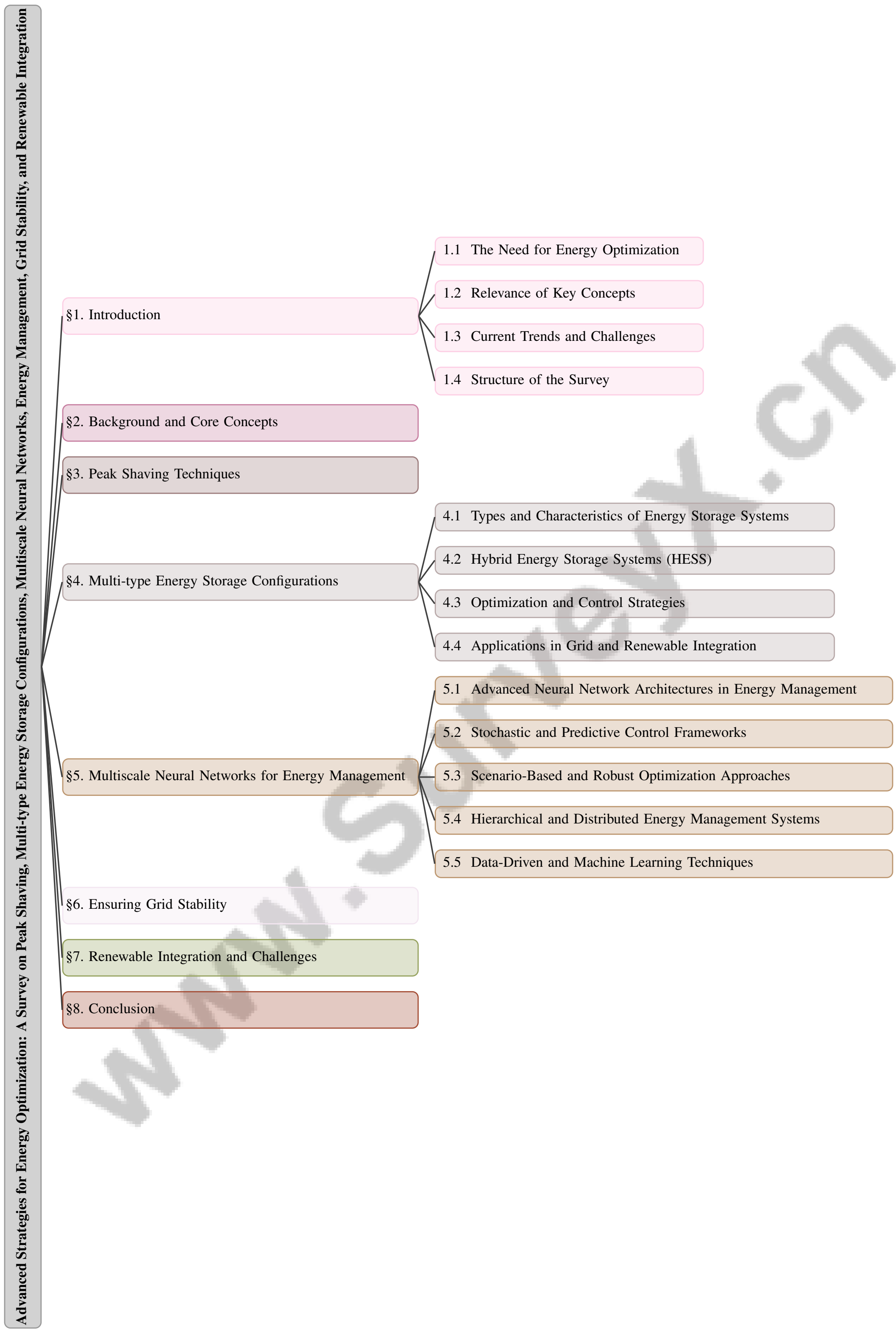


Figure 1: chapter structure

residential energy demand challenges grid reliability, underscoring the necessity for novel home energy management (HEM) strategies to maintain stability and efficiency [5].

Challenges related to energy deficiencies and high-impact low-probability (HILP) events in electrical grids further emphasize the importance of energy optimization [6]. Accurate forecasting of household power consumption is crucial for optimizing energy use and ensuring grid stability [7]. Global climate change concerns and the imperative to reduce greenhouse gas emissions also drive the demand for energy optimization [8].

The interplay of factors such as increasing renewable energy integration, supply volatility, and the need for enhanced grid stability highlights the urgent requirement for sophisticated energy optimization strategies. These strategies are vital not only for improving system efficiency and lowering operational costs but also for fostering sustainable energy systems. By enabling the economic viability of renewable energy integration and mitigating environmental impacts, these advanced approaches address the challenges posed by uncertainty in power system operations and support the transition to a cleaner energy future [9, 10, 11, 12, 13].

1.2 Relevance of Key Concepts

Effective optimization of modern energy systems hinges on integrating advanced strategies such as peak shaving, diverse energy storage configurations, multiscale neural networks, comprehensive energy management, grid stability enhancements, and renewable energy incorporation. This integration addresses the unique challenges posed by the variability of renewable technologies, supporting the transition towards a decarbonized energy sector by ensuring reliable power supply and enhancing grid responsiveness through innovative demand response programs and energy storage solutions [10, 12]. These concepts collectively tackle the multifaceted challenges faced by contemporary power grids, paving pathways to enhance efficiency and sustainability.

Peak shaving is crucial in energy optimization, balancing electricity demand and supply to reduce operational costs and enhance grid reliability. Demand response strategies and the integration of dispatchable loads are essential for aligning consumer electricity consumption with supply conditions, emphasizing consumer behavior's role in energy optimization. Co-optimizing energy and ramping costs is vital for effective dispatch in systems with high renewable generation [14].

Multi-type energy storage configurations, including battery energy storage systems (ESS), are pivotal in addressing renewable energy variability and optimizing energy systems by balancing performance with profitable investment. The significance of optimal charging and discharging scheduling of batteries in hybrid PV/Battery/Load systems is particularly highlighted to address the intermittent nature of renewable sources like PV [8]. These configurations enhance grid stability and ensure reliable power supply, underscoring their importance in efficiently integrating renewable energy sources [15]. Furthermore, integrating demand response into energy management reflects the competitive dynamics between multi-community integrated energy systems (MCIES) operators and users [16].

Multiscale neural networks are integral to managing energy resources across different scales, particularly in stochastic environments. Techniques such as model and load predictive control frameworks optimize power and energy management by considering generator costs, degradation, and specific State of Charge (SOC) targets [17]. Accurate modeling in energy management systems is essential for addressing operational constraints and enhancing microgrid performance [4]. Advanced technologies, including deep learning-based algorithms, further improve energy management in modern systems by tackling the challenges posed by renewable energy integration [15].

Ensuring grid stability is fundamental to energy optimization, especially with increased renewable energy integration. Concepts such as Virtual Distribution Grids (VDG) and decentralized systems are crucial for managing resource and actor heterogeneity in the distribution grid, promoting stability and efficiency. Additionally, integrating electric vehicle (EV) charging into energy management systems (EMS) is vital for optimizing energy utilization and maintaining grid stability [1].

Renewable integration necessitates advanced energy management strategies, such as Integrated Energy Systems (IESs), which coordinate various energy flows for enhanced operational efficiency and security. Incorporating renewable energy sources like wind, solar, and hydropower into the electricity grid is essential for achieving decarbonization goals, enhancing energy reliability, and reducing overall energy costs, while promoting sustainability through innovative technologies like smart EV charging systems and decentralized energy solutions. This integration not only increases the share of renewables in energy consumption but also addresses their variability challenges, ultimately

AI-generated, for reference only.

fostering a more resilient and cost-effective power system [10, 18]. Additionally, employing federated learning for energy demand prediction and blockchain technology for secure transactions between consumers and prosumers represents innovative approaches to energy optimization.

Key concepts such as control strategies, optimization techniques, and energy storage solutions are critical for enhancing system stability in the context of renewable energy system (RES) integration. Big data analytics and dynamic energy management improve forecasting accuracy and user participation in energy savings, contributing to overall energy optimization. The proposed HEM strategy effectively coordinates flexible loads in smart homes with renewable energy sources, enhancing energy efficiency and cost-effectiveness [5]. Furthermore, energy community discovery, which identifies homogeneous, mixed, and self-sufficient energy communities, plays a significant role in optimizing energy distribution among users.

Collectively, these key concepts emphasize their relevance in addressing modern energy systems' challenges, optimizing performance, and promoting sustainability. By incorporating advanced strategies and technologies, including renewable energy sources like wind, solar, and hydropower, alongside demand response systems such as electric vehicles and smart charging, energy systems can significantly enhance their efficiency, reliability, and environmental sustainability. This approach not only addresses the challenges posed by renewable energy variability but also aligns with the evolving demands of contemporary power grids, paving the way for a more resilient and decarbonized energy landscape [10, 18].

1.3 Current Trends and Challenges

The energy optimization landscape is characterized by significant advancements and persistent challenges, particularly in integrating renewable energy sources and maintaining grid stability. A prominent trend is the increasing reliance on renewable energy, such as solar and wind, which, despite offering sustainable alternatives, introduces complexities in variability and intermittency. The integration of renewable energy sources into power systems, coupled with the uncertainties of variable energy resources, necessitates developing advanced forecasting and management strategies. These strategies must address challenges such as forecast accuracy, switching costs, and system reliability to ensure a consistent and reliable energy supply. Employing a stochastic hierarchical planning framework and optimizing battery energy storage systems can enhance decision-making processes, improve operational efficiency, and achieve economic and environmental sustainability in energy management systems [19, 20, 10, 13].

Decentralized energy systems, including peer-to-peer (P2P) energy management solutions, are gaining traction as they facilitate energy transactions between prosumers. However, these systems face challenges related to pricing mechanisms and the integration of diverse energy sources [21]. The complexity of managing electric vehicle (EV) charging and parking further underscores the need for innovative approaches to optimize energy distribution and reduce peak load demands [22].

Energy Management Systems (EMS) are pivotal in addressing challenges associated with real-time monitoring and rapid response to dynamic conditions essential for grid stability. However, the limited computational capabilities of current EMS hinder their effectiveness in optimizing energy flows [23]. The integration of energy storage systems (ESS) is crucial for mitigating the intermittency of renewable sources and managing peak electricity charges, yet their economic viability is often questioned due to uncertainties in efficiency and lifecycle costs.

In the distribution grid, existing energy management mechanisms are inadequate for the evolving dynamics of energy demand and supply, leading to potential inefficiencies and instability [24]. The management of distributed energy resources (DER) is further complicated by the need to maintain power quality and stability, especially with the increasing complexity of real-time coordination and prediction of power flows [25].

As electricity charges rise with load growth, effective cost management strategies, such as implementing energy storage solutions, become increasingly necessary [26]. The development of 100

While advancements in energy optimization reflect a movement towards more sophisticated and adaptable systems, significant challenges remain in cost, system stability, and integrating advanced technologies into existing infrastructure. Effectively addressing the challenges associated with integrating renewable energy sources, such as wind and solar power, is essential for successfully implementing energy optimization strategies in modern power systems, particularly with the growing reliance on decentralized energy generation and the need for real-time supply-demand matching in the grid. Technological solutions, including advanced energy storage systems, can play a pivotal role in overcoming these challenges, enhancing system reliability, and facilitating the transition towards a decarbonized energy sector [10, 12].

1.4 Structure of the Survey

This survey is systematically organized to explore advanced strategies and technologies that optimize energy systems. The paper begins with an introduction that emphasizes the importance of energy optimization and the relevance of key concepts such as peak shaving, multi-type energy storage configurations, multiscale neural networks, energy management, grid stability, and renewable integration. Following this, the background and core concepts section delves into the definitions and roles of these key strategies in modern energy systems.

The survey progresses to a detailed analysis of peak shaving techniques, examining modern approaches, the role of energy storage systems, demand response strategies, and the associated challenges and solutions. This section presents an in-depth analysis of various multi-type energy storage configurations, encompassing the classification and characteristics of different energy storage systems, integration of hybrid systems, and advanced optimization and control strategies. It explores their practical applications in enhancing grid stability and facilitating the incorporation of renewable energy sources, highlighting the benefits of hybrid energy storage systems over traditional single storage solutions and assessing their performance through real-world case studies and simulations [1, 27, 18].

The analysis of multiscale neural networks in energy management encompasses a comprehensive examination of their application in various advanced frameworks, including sophisticated neural network architectures, stochastic and predictive control mechanisms such as model predictive control that optimizes dynamic power flows while accounting for forecast uncertainties, scenario-based and robust optimization techniques, as well as hierarchical and distributed energy management systems. Additionally, it explores the integration of data-driven methodologies and machine learning techniques, particularly in the context of neural network-based energy management systems for microgrids, which optimize battery state-of-charge balancing and adapt to real-time variations in photovoltaic output without the need for precise generation-load forecasting [28, 29].

The survey provides an in-depth analysis of strategies aimed at maintaining grid stability in the face of increasing renewable energy integration. It examines the implementation of advanced control systems, which are essential for managing the complexities introduced by the intermittent nature of renewable sources like solar and wind. Additionally, the survey highlights the importance of real-time monitoring and optimization techniques that enhance operational efficiency. It discusses the critical roles played by demand response mechanisms and energy management systems, which enable greater flexibility and responsiveness in the grid, thereby addressing challenges such as low power quality and generation reserve issues associated with high levels of renewable energy penetration [30, 31, 25, 12, 13].

This analysis delves into the multifaceted challenges and innovative solutions related to integrating renewable energy sources, such as wind, solar, and hydropower, into existing power systems. It specifically addresses variability and intermittency issues inherent in these renewable sources while exploring advanced energy management strategies, including demand response and grid flexibility. The study highlights the importance of technological innovations, such as energy storage systems and smart grid architectures, that facilitate the seamless integration of renewables, ultimately aiming to enhance the reliability and efficiency of power systems in the context of decarbonization efforts [30, 18, 10, 31, 32].

Finally, the conclusion summarizes the key findings and insights, highlighting potential future directions and research opportunities in optimizing energy systems through the discussed strategies and technologies. The survey aims to deliver an in-depth analysis of the current landscape and future potential of energy optimization strategies in modern power systems, particularly focusing on integrating advanced technologies such as energy storage systems (ESSs) and implementing stochastic hierarchical planning frameworks. These strategies aim to address the challenges posed by the increasing presence of intermittent renewable energy sources, enhance operational reliability and economic efficiency, and leverage demand response mechanisms to stabilize the electricity grid. By evaluating various optimization models and their applications in emerging ancillary power markets, the survey will highlight the significant benefits of innovative ESS technologies and the potential for improved system performance in a future characterized by high renewable energy integration [13, 12].The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Defining Peak Shaving and its Role in Energy Optimization

Peak shaving is a strategic approach to reducing peak electricity demand, crucial for optimizing energy systems and ensuring economic and environmental sustainability. It plays a vital role in systems with significant renewable energy generation by managing energy and ramping costs for effective load balancing [2]. In microgrids, peak shaving enhances energy management by targeting multiple objectives, including cost reduction, emissions control, and minimizing heat waste [33]. Demand response programs further augment peak demand reduction, contributing to overall system efficiency.

In shipboard power systems, peak shaving manages high ramp rate requirements of pulse power loads, ensuring stability and reliable power supply in dynamic environments [34]. For grid-connected microgrids, it reduces operational costs and optimizes energy systems through the integration of conventional and renewable generators. During high-impact low-probability (HILP) events, peak shaving manages energy shortages by prioritizing essential loads and optimizing battery systems. In residential settings, advanced Home Energy Management (HEM) strategies synchronize flexible loads for effective peak shaving, enhancing grid stability and providing economic benefits. These strategies utilize distributed load scheduling and demand-side management to optimize energy consumption at the neighborhood level, allowing households to respond to dynamic pricing while maintaining comfort and data privacy [35, 36, 37, 38].

Peak shaving significantly improves energy system efficiency by managing peak load demands, ensuring reliable power supply, and facilitating renewable energy integration through energy storage systems (ESSs) such as battery energy storage systems (BESS). These systems reduce utility costs by decreasing the need for expensive energy procurement during peak times. Various BESS technologies, including lead acid, NaS, ZnBr, and vanadium redox, are increasingly viable for peak shaving as battery prices decline. Optimizing these storage systems through innovative scrapping criteria maximizes benefits and extends operational lifespans, reinforcing the economic viability of renewable energy integration [39, 40, 26]. This approach addresses modern energy systems' challenges, promoting economic and environmental sustainability.

2.2 Multi-type Energy Storage Configurations

Multi-type energy storage configurations are essential for advancing energy optimization by enhancing the flexibility, resilience, and efficiency of modern energy systems, particularly with increasing renewable energy integration. These configurations include electrochemical batteries, thermal energy storage, and mechanical systems like pumped hydro storage, addressing challenges posed by the variability and intermittency of renewable energy sources like wind and solar power. Integrating these storage solutions enhances reliability and stability, effectively balancing supply and demand while supporting the transition to a low-carbon energy landscape [41, 10, 42, 43].

In residential contexts, integrating energy storage systems (ESS) is crucial for optimizing home energy management, reducing costs, and improving energy efficiency. Hierarchical structures of innovative methods facilitate faster-than-real-time computation and near-optimal solutions, enhancing overall system efficiency [5]. Multi-type energy storage configurations, exemplified by hybrid PV/Battery/Load systems, effectively manage energy flows and address the intermittent nature of renewable energy sources [8].

In multi-energy microgrids (MEMGs), these configurations optimize energy management amidst uncertainties in renewable energy sources (RES). Deep reinforcement learning-based approaches enhance MEMG adaptability and efficiency, ensuring reliable power supply and reducing emissions [44]. These methodologies enable optimal utilization of energy storage systems, contributing to sustainability and economic viability.

Multi-type energy storage configurations are foundational to optimizing modern energy systems, supporting a sustainable energy future. By integrating diverse storage technologies and innovative management strategies in microgrid configurations, these systems enhance the sustainability and resilience of power infrastructures. This is critical for facilities like hospitals, where reliable energy distribution is essential for uninterrupted surgical procedures and safe pharmaceutical storage. Implementing renewable energy sources, such as solar photovoltaics, alongside traditional diesel generators, improves energy resilience and optimizes economic benefits, potentially saving significant costs over operational lifespans while ensuring power supply continuity during outages [43, 45].

2.3 Multiscale Neural Networks in Energy Management

The application of multiscale neural networks in energy management systems significantly advances the optimization of energy resource allocation across various temporal and spatial dimensions. These networks process complex, high-dimensional data, addressing the stochastic nature of renewable energy sources and enhancing system resilience and efficiency. Integrating neural network-based energy management systems (NN-EMS) enables real-time balancing of state-of-charge (SoC) among batteries, utilizing outputs from optimal power flow (OPF) processes to ensure efficient energy distribution and maintain grid stability [34].

The Model Predictive Energy Management Strategy (MPEMS) is pivotal in these systems, coordinating power distribution between generators and batteries and showcasing advanced energy management techniques [34]. This strategy is enhanced by the Transfer Learning-based Temporal Fusion Transformer (TL-TFT) method, which optimizes energy management systems through improved forecasting and decision-making capabilities [7].

Additionally, the Lightweight Energy Management Method (LEMM) introduces a stochastic process for optimizing energy management in hybrid systems, highlighting the adaptability and efficiency of multiscale neural networks in dynamic environments [8]. Integrating these methodologies with robust optimization frameworks ensures reliable energy management under varying conditions, enhancing both efficiency and reliability.

Advanced neural network architectures, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), address specific power system challenges, including forecasting and real-time control. The integration of deep reinforcement learning (DRL) frameworks optimizes energy dispatching in multi-energy microgrids (MEMGs) by managing uncertainties associated with renewable energy sources (RES) and enhancing operational control. This approach ensures a reliable power supply and contributes to emissions reduction by enabling real-time energy management strategies that consider market profits, carbon emissions, and peak load demand. Employing advanced algorithms like the twin delayed deep deterministic policy gradient (TD3) and Double Dueling Deep Q Network (D3QN) allows DRL-based energy management systems to formulate optimal dispatching schemes that improve overall system efficiency and sustainability [46, 47, 44, 48]. Moreover, differentiable decision trees (DDTs) introduce novel methods in optimizing Home Energy Management Systems (HEMS), aligning with advanced neural network architectures.

Multiscale neural networks play a crucial role in optimizing energy management systems by improving resource utilization, enhancing system reliability, and increasing adaptability. This is achieved through advanced predictive modeling techniques, such as clustering-based multitasking deep neural networks, which accommodate diverse power generation patterns across customer types. These networks facilitate real-time monitoring and optimization of power systems, enabling utilities to respond swiftly to fluctuations in renewable energy outputs. Their capability to balance battery states of charge in microgrids and generate operational scenarios for renewable energy farms enhances grid stability and operational efficiency, supporting the integration of renewable energy sources into existing power infrastructures [49, 15, 50, 29]. By leveraging predictive control, robust optimization, and advanced analytics, these networks navigate the complexities of modern energy landscapes, ensuring efficient and sustainable energy distribution while addressing the multifaceted challenges of contemporary power systems.

In recent years, the importance of effective peak shaving techniques has gained significant attention due to their potential to enhance energy efficiency and reduce costs. A comprehensive understanding of these techniques requires an examination of their hierarchical structure, which categorizes modern approaches, the role of energy storage systems, demand response strategies, and the challenges that arise along with their respective solutions. Figure 2 illustrates this structure, highlighting not only the integration of advanced technologies but also the crucial importance of energy storage systems and optimization techniques. Furthermore, the figure presents innovative solutions designed to address the challenges inherent in peak shaving, thereby providing a holistic view of the current landscape in energy management. This integration of visual data serves to enhance the narrative by offering a clear representation of complex relationships and strategies within the field.

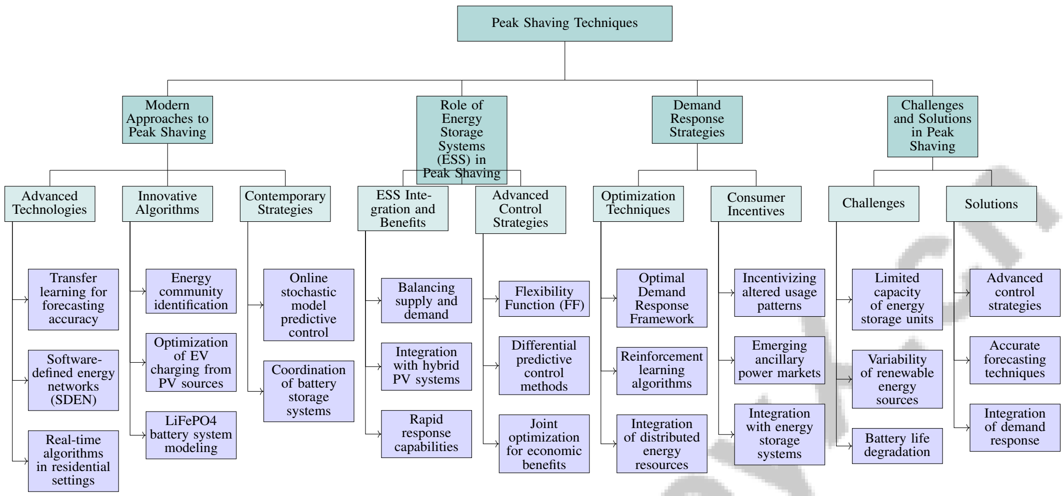


Figure 2: This figure illustrates the hierarchical structure of peak shaving techniques, categorizing modern approaches, the role of energy storage systems, demand response strategies, and challenges with solutions. It highlights the integration of advanced technologies, the importance of energy storage systems, optimization techniques, and innovative solutions to address challenges in peak shaving.

3 Peak Shaving Techniques

3.1 Modern Approaches to Peak Shaving

Method Name	Technological Integration	Energy Management Systems	Optimization Techniques
TL-TFT[7]	Transfer Learning	Home Energy Management	Dynamic Energy Tariffs
FL-BI[51]	Federated Learning	Decentralized Energy Management	Predict Energy Demand
HEM[5]	Genetic Algorithm	Home Energy Management	Mixed-integer Programming
MORL[33]	-	Multi-objective Framework	Borg Moea
DDT[52]	Explainable Reinforcement Learning	Home Energy Management	Gradient Descent

Table 1: This table presents a comparative analysis of various modern methods utilized for peak shaving in energy management systems. It details the technological integration, energy management systems, and optimization techniques employed by each method, highlighting their unique contributions to enhancing efficiency and reducing costs in energy distribution. The table serves as a comprehensive overview of the innovative approaches currently being explored in the field.

Modern peak shaving techniques have advanced by incorporating cutting-edge technologies to optimize energy management systems. Transfer learning significantly enhances forecasting accuracy, reducing electricity costs and refining demand management by leveraging historical data [7]. Software-defined energy networks (SDEN) facilitate virtual energy sharing among users, optimizing management and enhancing system efficiency through decentralized energy management [51].

In residential settings, real-time algorithms for energy storage management and load scheduling optimize costs and adhere to operational constraints. Home Energy Management Systems (HEMS) are pivotal, using dynamic pricing strategies and Model Predictive Control (MPC) to manage energy consumption and storage adaptively [5]. Multi-objective reinforcement learning frameworks further advance microgrid operations by enabling comprehensive energy resource management [33].

Innovative algorithms that identify energy communities optimize management and peak shaving, supported by explainable reinforcement learning models that increase user trust [52]. The optimization of electric vehicle (EV) charging from photovoltaic (PV) sources, with dynamic pricing strategies, exemplifies modern techniques that enhance frequency stability and reduce costs. This approach integrates battery storage systems for primary frequency control and peak shaving, significantly increasing profitability [53, 54].

Comprehensive modeling of LiFePO4 battery systems through mixed-integer linear programming (MILP) formulations optimizes operational strategies and sizing, enhancing peak shaving by considering variable efficiency and capacity fade. This approach reduces battery investment and operating costs, adapting to changing optimal states of charge and extending charging durations [55, 40, 56]. Myopic co-optimization algorithms simplify scheduling, streamlining modern energy management approaches.

These techniques underscore the critical role of technology in enhancing energy management systems' efficiency. As illustrated in Figure 3, the hierarchical structure of modern peak shaving approaches categorizes them into advanced forecasting methods, energy management systems, and battery and storage optimization techniques. Each category highlights key innovations and methodologies that contribute to optimizing energy management systems for enhanced efficiency and cost-effectiveness. Table 1 provides a detailed overview of the modern methods employed in peak shaving, showcasing the integration of advanced technologies and optimization techniques in energy management systems. Contemporary strategies improve power supply reliability and optimize energy distribution by integrating advanced forecasting, dynamic scheduling, and sophisticated trading mechanisms. Online stochastic model predictive control frameworks effectively manage demand charges, addressing unpredictable electricity demand and inflow. By combining multiple revenue streams, such as primary frequency control and peak shaving, battery storage systems reduce maximum consumption peaks and enhance profitability through coordinated operations [57, 53].

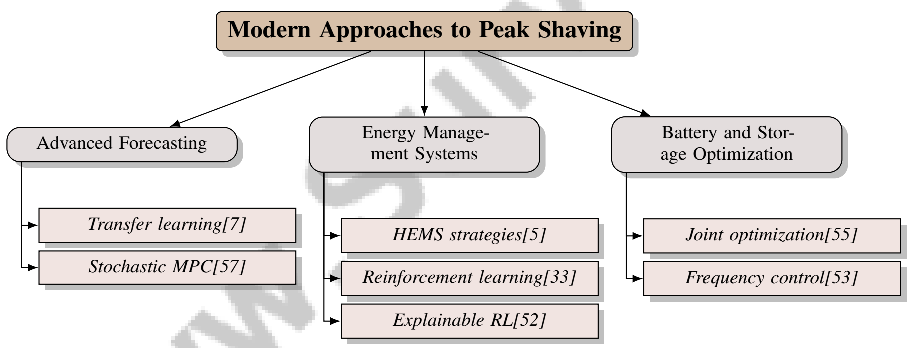


Figure 3: This figure illustrates the hierarchical structure of modern peak shaving approaches, categorizing them into advanced forecasting methods, energy management systems, and battery and storage optimization techniques. Each category highlights key innovations and methodologies that contribute to optimizing energy management systems for enhanced efficiency and cost-effectiveness.

3.2 Role of Energy Storage Systems (ESS) in Peak Shaving

Energy Storage Systems (ESS) are pivotal in enhancing peak shaving strategies by providing flexibility and resilience to modern energy systems. They balance electricity supply and demand, improving grid reliability and reducing operational costs [12]. The integration of Battery Energy Storage Systems (BESS), especially within hybrid photovoltaic (PV) systems, is crucial for managing energy during peak demand by storing excess energy generated off-peak and discharging it during peak periods [8].

Hybrid energy storage systems, combining lithium-ion and lead-acid batteries, offer rapid response capabilities and resilience during generation shortages [12]. These systems are effective in environments requiring quick adaptations to energy demand changes, ensuring reliable power supply. Shared energy storage systems optimize energy management for multiple users, maximizing profit and minimizing grid reliance.

Advanced control strategies further enhance ESS effectiveness. The Flexibility Function (FF) optimizes demand-side management by generating optimal price signals that enhance demand-

AI-generated, for reference only.

side flexibility and align consumer behavior with energy availability. This approach coordinates various appliances and energy management systems, maintaining consumer comfort while providing ancillary services for grid stability [58, 59, 36, 60]. The integration of differential predictive control methods aligns HVAC loads with local solar PV generation, smoothing net load fluctuations.

ESS are crucial for optimizing energy management and contributing to grid stability by enabling renewable energy integration and reducing reliance on less efficient generation units during peak demand. Various battery technologies, such as lead acid, NaS, ZnBr, and vanadium redox, can achieve profitability in peak shaving applications, emphasizing the importance of efficiency and energy pricing. Joint optimization of battery storage for peak shaving and frequency regulation yields greater economic benefits [53, 61, 39, 26]. By employing both local and grid-centered peak shaving techniques, these systems enhance adaptability and effectiveness.

3.3 Demand Response Strategies

Demand response strategies are essential for managing peak demand, dynamically aligning energy consumption with available supply. These strategies are effective in commercial settings, where the Optimal Demand Response Framework optimizes energy consumption while maintaining comfort levels [60]. By adjusting energy usage patterns in response to real-time price signals or grid needs, demand response programs mitigate peak loads, reduce costs, and enhance grid reliability.

In residential and commercial buildings, reinforcement learning algorithms optimize thermostatically controlled loads, contributing to peak reduction and increasing self-consumption of locally generated renewable energy [62]. These algorithms enable adaptive control of HVAC systems, aligning energy consumption with periods of lower demand or higher renewable generation.

Demand response strategies also facilitate the integration of distributed energy resources (DERs) by providing a flexible mechanism for adjusting demand. The flexibility afforded by energy storage systems and advanced control strategies is vital for maintaining grid stability, especially in systems with high renewable penetration [30, 31, 63, 64]. Demand response programs incentivize consumers to alter energy usage patterns, alleviating grid pressure during peak times and enhancing overall efficiency and sustainability.

Demand response strategies are vital for managing peak energy demand, especially in commercial buildings. By optimizing energy consumption through techniques like appliance scheduling and integrating distributed energy resources, these strategies reduce costs and enhance consumer comfort. Recent frameworks balance trade-offs between energy savings and comfort, ensuring demand response programs are viable and user-acceptable. Emerging ancillary power markets incentivize consumer participation, including energy storage systems that provide valuable services like peak shaving and regulation reserves [12, 60, 65]. By integrating advanced control algorithms and real-time data analytics, these strategies enhance modern power systems' adaptability and resilience.

3.4 Challenges and Solutions in Peak Shaving

Method Name	Control Strategies	Forecasting Accuracy	Optimization Techniques
PF-MT-CF[66]	Multi-timescale Control	Hour-ahead Robust	Predictive Modeling
MGEM[1]	Demand Response Programs	Simulation Studies	Mixed-integer Linear
TB-MPC[67]	Tube-based Mpc	Forecasting Renewable Generation	Robust Optimization
MPEMS[34]	Adaptive Energy Management	Load And Renewable	Model Predictive Control
EASS[9]	Robust Optimization	Accurate Forecasting	Robust Optimization
OUS-LiFePO4[56]	Dynamic Optimization	Not Mentioned	Milp Techniques
HSSM[16]	Stackelberg Game Framework	Data-driven Scenario	Distributed Iterative Solution

Table 2: Comparative analysis of various energy management methods detailing their control strategies, forecasting accuracy, and optimization techniques. This table highlights the diverse approaches employed to address challenges in peak shaving and energy distribution management, emphasizing the integration of predictive analytics and robust optimization frameworks.

Peak shaving, a vital aspect of energy optimization, faces numerous challenges requiring innovative solutions. A primary challenge is the limited capacity and controllability of energy storage units, complicating distribution network management [68]. This is exacerbated by the time-varying nature of reactive power compensation, which existing methods struggle to manage [66]. Advanced control strategies are needed to dynamically adapt to changing network conditions.

The variability and unpredictability of renewable energy sources (RES) present additional challenges, complicating real-time energy management and impacting peak shaving reliability [1]. Battery life degradation further complicates these issues, affecting the long-term sustainability of energy storage solutions [67]. The TB-MPC approach, incorporating battery degradation models into real-time optimization, enhances system stability [34].

Accurate forecasting of load and renewable generation is essential for effective peak shaving; however, uncertainties in these forecasts pose significant challenges [9]. The nonlinear relationship between battery operation strategies and degradation effects complicates optimization, as existing models inadequately address these interactions [56]. Advanced predictive analytics and optimization techniques are necessary to improve forecasting accuracy.

The lack of consideration for demand response and the intricate interactions among stakeholders hinder effective energy management [16]. Implementing advanced scheduling methods that incorporate demand response can address these challenges, facilitating more efficient energy distribution and peak shaving. Real-time operation optimization of microgrids must consider uncertainties in renewable generation and battery degradation, requiring robust control frameworks for reliable energy management [67].

Effectively integrating renewable energy sources into power systems requires advanced optimization techniques, innovative energy storage solutions, and sophisticated predictive analytics. These approaches enhance system reliability and facilitate efficient management of intermittent energy supplies, supporting the energy sector's decarbonization goals [19, 9, 10, 12]. Leveraging these strategies enables energy systems to achieve greater efficiency, reliability, and sustainability, aligning with modern power grids' evolving demands. Table 2 presents a comprehensive comparison of different energy management strategies, highlighting their specific control strategies, forecasting accuracy, and optimization techniques, which are crucial for addressing the challenges in peak shaving and enhancing the reliability of energy systems.

4 Multi-type Energy Storage Configurations

The exploration of multi-type energy storage configurations is pivotal for advancing energy management systems. This section evaluates various energy storage systems (ESS), emphasizing their roles in enhancing energy efficiency and reliability, crucial for contemporary applications.

4.1 Types and Characteristics of Energy Storage Systems

Energy storage systems (ESS) are essential for optimizing modern energy systems, offering technologies tailored to specific operational needs. Battery Energy Storage Systems (BESS) are particularly effective in peak shaving and frequency regulation, demonstrating versatility in energy optimization [55, 26]. Their flexibility, rapid response, and discharge efficiency make BESS a preferred choice for residential and commercial applications, influenced by capacity, discharge rates, and cycle life—factors vital for economic and operational efficiency.

Lithium-ion batteries provide economic advantages, as evidenced by systems like the 4 MW / 4 MWh lithium-ion energy storage setup, enhancing microgrid operations and ensuring grid stability [40, 69]. Beyond BESS, other storage technologies, including thermal, mechanical, and hydrogen storage, contribute uniquely to energy system efficiency [70, 71]. Thermal systems manage heating and cooling loads effectively, mechanical systems offer high-capacity storage for balancing large-scale supply and demand, and hydrogen storage, especially in salt caverns, provides a long-term solution for integrating renewable energy [72].

Integrating diverse energy resources in scheduling is vital for balanced management strategies [12]. Peer-to-peer (P2P) energy sharing enhances distribution efficiency across management domains, promoting resilience and economic viability [73, 74]. Shared energy storage solutions optimize management through collective utilization, especially in cost or space-constrained scenarios [75]. Communication technologies like Zigbee and wireless sensor networks are crucial for implementing Home Energy Management (HEM) systems, enabling real-time monitoring [76].

The diverse types of energy storage systems enhance the flexibility, reliability, and sustainability of modern energy systems. By leveraging advanced technologies such as intelligent control systems and demand response strategies, energy systems can effectively address renewable energy variability, facilitating efficient integration while supporting decarbonization goals and minimizing fossil fuel reliance [30, 43, 18, 10, 77].

As illustrated in Figure 4, the categorization of energy storage systems highlights not only the applications of battery energy storage but also various other storage technologies and energy management strategies, further emphasizing the multifaceted nature of energy storage solutions.

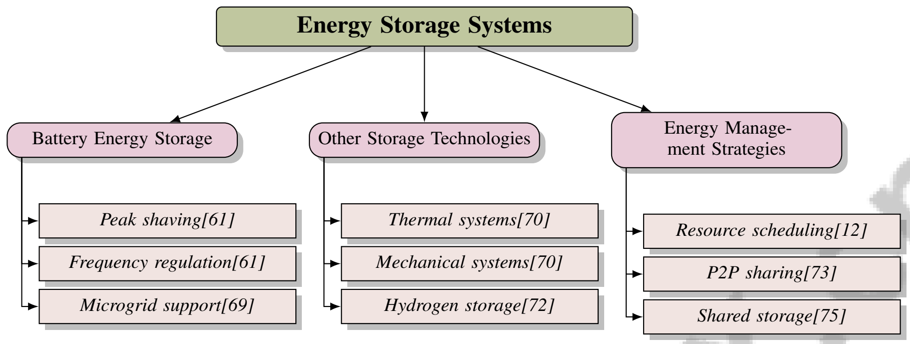


Figure 4: This figure illustrates the categorization of energy storage systems, highlighting the applications of battery energy storage, various other storage technologies, and energy management strategies.

4.2 Hybrid Energy Storage Systems (HESS)

Hybrid Energy Storage Systems (HESS) are crucial for modern energy management, combining multiple storage technologies to leverage their strengths and mitigate limitations. This integration enhances system flexibility, resilience, and efficiency, particularly with the increasing adoption of renewable energy sources. By strategically utilizing various storage technologies, such as batteries and pumped hydro, HESS effectively manage energy supply and demand fluctuations, optimizing overall performance [78].

In residential contexts, HESS optimize energy management by integrating battery systems with photovoltaic (PV) systems, reducing grid reliance and enhancing renewable self-consumption. The application of transfer learning with the Proximal Policy Optimization (PPO) algorithm exemplifies a hybrid approach to improve peak reduction and self-consumption [62]. Different pricing schemes, including Time of Use (ToU), Real Time Pricing (RTP), and Critical Peak Pricing (CPP), further enhance HEM efficiency, underscoring HESS benefits in residential settings [76].

Future research should focus on integrating on-site energy storage solutions to boost reliability and efficiency in microgrid systems [22]. Shared energy storage systems illustrate HESS's innovative potential, allowing multiple users to share resources and significantly reduce individual investments. This approach is particularly advantageous in developing regions, where federated learning combined with blockchain technology can enhance energy management and address electricity shortages [51].

HESS provide substantial advantages in energy management by optimizing network capacity and enabling corrective actions in response to outages, potentially leading to cost savings of up to 2.4 billion euros annually in high renewable energy integration systems. They also enhance reliability by addressing complexities introduced by high renewable penetration, employing advanced control strategies and optimization techniques. By mitigating variability associated with renewables, HESS support the transition to a sustainable energy landscape [30, 63, 43]. Leveraging synergies between different technologies, HESS contribute to the economic and environmental sustainability of modern energy systems, addressing contemporary power grid challenges.

4.3 Optimization and Control Strategies

Optimization and control strategies are vital for managing multi-type energy storage systems, ensuring efficient and sustainable use of energy resources. Advanced methodologies like the Seq2Seq method enhance energy management system adaptability by handling variable-length input-output

Benchmark	Size	Domain	Task Format	Metric
HESS[27]	7	Energy Storage	Classification	Power Transient Frequency, Peak Power Utilization
DL-EMB[79]	2,704	Waste Management	Energy Demand Forecasting	MAPE
EMSx[80]	70	Energy Management Systems	Optimization	Score, Management Cost
BESS-Peak[39]	1,000	Energy Storage Systems	Profitability Analysis	Net Present Value, Break-even Costs
GAN-ESP[50]	490,752	Renewable Energy	Power Distribution Modeling	KLD, Wasserstein Distance
SDDP[81]	2,000	Energy Management	Optimization	Electricity bill
BESS[26]	1,000	Energy Management	Cost-Benefit Analysis	Cost Savings, Efficiency Improvement
MSA[82]	1,440	Energy Management	Optimization	Optimization Value

Table 3: This table presents a comprehensive overview of benchmarks used in the evaluation of energy management and optimization strategies across various domains. It includes details on benchmark size, domain focus, task format, and the metrics employed for performance evaluation. These benchmarks serve as critical references for assessing the efficacy and adaptability of advanced energy management methodologies.

relationships in energy consumption data, particularly in residential settings with dynamic energy demands [83].

The RL-CES method exemplifies reinforcement learning applications for optimizing battery charging and discharging based on real-time electricity prices, maximizing economic benefits while maintaining reliability [84]. This highlights the importance of real-time data in informing energy management decisions for optimal storage system utilization.

Further optimization is achieved through the SMPC-DCM method, which utilizes real-time forecasts to enhance battery energy storage operations, addressing the stochastic nature of renewable generation [57]. Stochastic optimization approaches, such as those in [85], consider uncertainties in renewable generation and storage system degradation, ensuring robust and sustainable energy management strategies. The MDP formulation minimizes long-term battery operation costs under uncertain load conditions, enhancing economic viability [86].

High-fidelity simulations within Energy Management Systems (EMS) iteratively determine optimal BESS sizes, minimizing the levelized cost of hydrogen (LCOH) while ensuring stability [71]. Decentralized approaches, like the EnergAIze system, utilize multi-agent reinforcement learning (MARL) frameworks for dynamic energy consumption and production management, aligning with individual prosumer goals and real-time data [87].

Combining Federated Learning with a multi-agent Consensus + Innovations framework facilitates optimized energy transactions in Transactive Energy Communities (TECs), promoting efficient distribution and utilization [88]. The decentralized scheduling framework in [59] optimizes appliance usage, contributing to effective peak shaving strategies and enhancing overall system efficiency.

The compositional modeling framework allows for models that account for controllable and uncontrollable components in district networks, facilitating optimal energy management [89]. Complementary algorithms achieve optimal scheduling and secure operation under dynamic uncertainty [90].

Forecasting future energy loads and prices to minimize costs while adhering to operational constraints is demonstrated in [91]. The PF-constrained multi-timescale control framework offers optimization strategies for multi-stack power-to-hydrogen loads, balancing production efficiency and compliance [66].

The multi-objective reinforcement learning framework employs a Borg Multi-Objective Evolutionary Algorithm to optimize energy management across various microgrid objectives [33]. Training a global model on extensive household data and fine-tuning it on specific household data serves as an optimization strategy for energy storage systems [7].

These optimization and control strategies highlight the integration of advanced methodologies in managing multi-type energy storage systems. Utilizing real-time data analytics, predictive modeling, and decentralized frameworks significantly enhances adaptability, operational efficiency, and sustainability, effectively addressing modern power grid challenges such as optimizing energy flow, enhancing demand response, and integrating renewables while empowering consumers and micro-energy producers to participate actively in the electricity market. Robust data analytics and high-performance computing are essential for dynamic energy management in smart grids, enabling improved forecasting and resource allocation [25, 92]. Table 3 provides a detailed overview of representative benchmarks that underpin the evaluation of optimization and control strategies in energy management systems.

4.4 Applications in Grid and Renewable Integration

The integration of multi-type energy storage systems is pivotal for enhancing grid stability and facilitating renewable energy incorporation. These systems provide the flexibility and resilience necessary to address the variability and intermittency of renewable generation, ensuring reliable power supply. The GFM-L concept, for example, demonstrates significant potential in improving stability and flexibility in power systems with high renewable penetration, underscoring the critical role of advanced energy storage solutions [93].

Strategic deployment of energy storage solutions is essential for managing challenges posed by renewable intermittency, as highlighted by their role in enhancing grid stability [30]. By buffering against energy supply fluctuations, these systems maintain consistent power delivery, reducing reliance on conventional generation resources.

Advanced load scheduling frameworks facilitate the integration of renewable sources like solar PV and BESS into residential energy management, optimizing utilization and enhancing grid stability [35]. This enables more efficient use of distributed energy resources, contributing to power system resilience and sustainability.

The integration of electric vehicle (EV) charging with PV energy exemplifies the synergy between renewables and storage solutions, supporting grid stability through optimized charging schedules [54]. This approach enhances renewable utilization and alleviates grid strain during peak demand periods, promoting balanced energy distribution.

In rural and isolated communities, smart microgrids enhance grid stability and renewable integration by efficiently managing local resources and improving energy access [94]. These microgrids utilize multi-type energy storage configurations to optimize resource use, ensuring reliable supply even amid grid disruptions.

The proposed multi-microgrid formation method enhances renewable resource integration by dynamically forming microgrids to optimize resource utilization during outages [95]. This improves power system resilience and maximizes renewable energy use, reducing dependence on external sources.

Zonal Congestion Management methods integrate battery storage with renewable generation curtailment into a unified control strategy, optimizing their use under time-delay constraints [96]. This ensures efficient energy distribution and minimizes congestion, contributing to grid stability and reliability.

Reliable forecasting tools, such as LSTM-based models, improve renewable energy integration by providing accurate net load forecasts in microgrids [97]. These tools enable precise energy management and planning, ensuring effective integration of renewables into existing power systems.

The effective implementation of multi-type energy storage systems is crucial for enhancing grid stability and facilitating renewable energy integration, essential for transitioning to sustainable and resilient energy systems. These systems address challenges posed by renewable intermittency while optimizing local energy utilization. By leveraging technologies like electric vehicles for demand response and various battery configurations, energy storage solutions can significantly increase renewables' share in the energy mix, reduce excess electricity production, and improve overall grid reliability [30, 10, 18]. Advanced storage technologies and innovative management strategies effectively tackle the multifaceted challenges of modern power grids, promoting environmental sustainability and economic viability.

5 Multiscale Neural Networks for Energy Management

The adoption of multiscale neural networks represents a significant advancement in energy management, optimizing complex systems by capturing and processing data across various granularities.

This section delves into sophisticated neural network architectures that refine energy management strategies, addressing the intricate challenges of modern power grids to facilitate energy optimization.

5.1 Advanced Neural Network Architectures in Energy Management

Advanced neural network architectures are pivotal in optimizing energy management systems, employing sophisticated algorithms and data-driven methodologies to navigate modern power grid complexities. These architectures facilitate dynamic adjustments and resource allocation, enhancing energy management frameworks' adaptability and efficiency. Neural network-based energy management systems (NN-EMS) optimize inverter outputs using real-time data, maintaining state of charge (SoC) balance and optimizing power sharing among distributed generators [34].

Model Predictive Control (MPC) techniques enable real-time power management optimization in shipboard power systems (SPSs) by predicting future load demands and adjusting generation accordingly [17]. The Sliding Model Predictive Control methodology enhances energy management by managing battery usage and predicting future load demands, crucial for system resilience and longevity [6]. This is complemented by a two-stage optimization framework integrating day-ahead scheduling with real-time adjustments, optimizing energy management through advanced modeling techniques [4].

Model-free reinforcement learning exemplifies neural networks in energy management, enabling systems to learn optimal strategies through environmental interaction [33]. The integration of deep reinforcement learning (DRL) addresses nonlinear optimization problems in multi-energy microgrids (MEMGs), showcasing advanced architectures' potential to enhance system efficiency and adaptability [44].

The Multi-Community Optimization (MCO) method provides optimal solutions for real-time energy management, demonstrating significant computational efficiency improvements over traditional methods [3]. The Lightweight Energy Management Method (LEMM) employs efficient algorithms to streamline complex energy management tasks [8].

In residential energy management, a multi-objective nonlinear mixed-integer programming approach, framed as sequential model predictive control and solved via a genetic algorithm, optimizes economic and operational efficiency [5]. This is further supported by comprehensive modeling of multiple energy storage system (ESS) technologies for demand response program participation, highlighting neural network architectures' versatility in energy management [12].

As illustrated in Figure 5, the hierarchical categorization of advanced neural network architectures in energy management emphasizes the distinct roles of neural network-based systems, reinforcement learning applications, and various optimization techniques. Each category highlights specific methodologies and their contributions to enhancing energy management systems.

Advanced neural network architectures significantly enhance energy management systems' optimization by providing robust, adaptive, and intelligent solutions. Techniques such as predictive analytics and stochastic modeling improve operational efficiency, reliability, and sustainability, particularly in modern power grids integrating variable renewable energy sources. Stochastic hierarchical planning frameworks facilitate decision-making under uncertainty, addressing complexities from renewable energy variability. Data-driven robust predictive control methods enable cooperative energy management across buildings, yielding substantial energy savings and accommodating unpredictable disturbances. Collectively, these innovations align energy systems with contemporary power networks' dynamic requirements, ensuring adaptability to fluctuating demands and contributing to a sustainable energy future [20, 98, 99, 57, 13].

5.2 Stochastic and Predictive Control Frameworks

Stochastic and predictive control frameworks are essential for optimizing energy management systems by addressing uncertainties in load demand and renewable energy generation. Utilizing algorithms such as stochastic hierarchical planning and evolving graph analysis, these frameworks enhance adaptability and efficiency in energy management processes. They tackle complexities introduced by high renewable energy integration and modern power systems' dynamic nature, ensuring reliable and sustainable energy distribution while fostering collaboration among various stakeholders in the energy market [24, 13, 23].

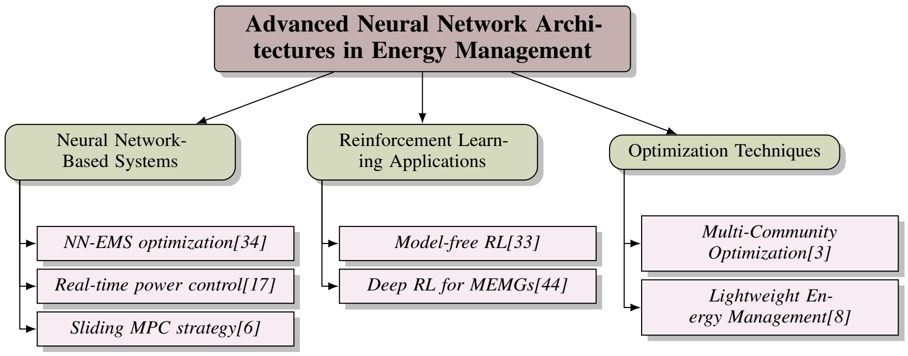
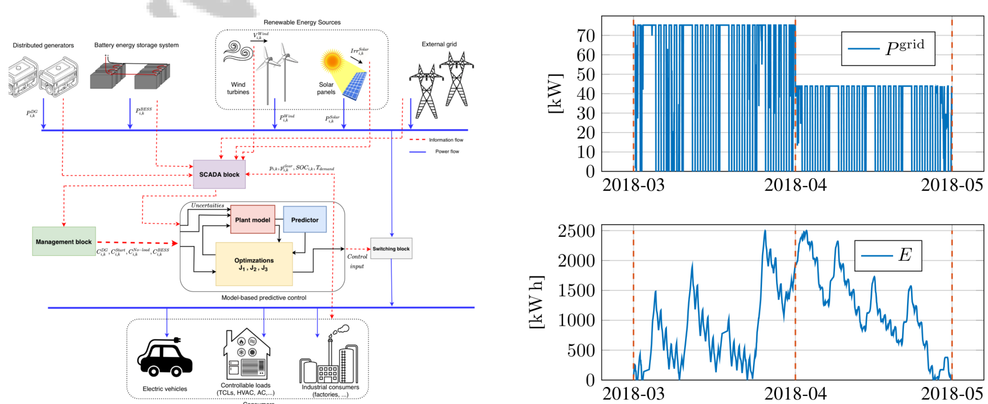


Figure 5: This figure illustrates the hierarchical categorization of advanced neural network architectures in energy management, focusing on neural network-based systems, reinforcement learning applications, and optimization techniques. Each category highlights specific methodologies and their contributions to enhancing energy management systems.

Scenario-based stochastic programming within a multi-objective optimization framework exemplifies a robust approach to managing uncertainties in energy systems. The Hybrid Grey-Wolf Optimizer-Particle Swarm Optimization (HGWO-PSO) method enhances energy management through stochastic and predictive control, providing optimal solutions that account for renewable energy variability [100]. This facilitates dynamic adjustments in energy management strategies, ensuring systems can respond effectively to changing conditions.

In microgrid operations, the two-stage optimization framework is crucial for managing uncertainties related to load demand and renewable generation. By incorporating day-ahead scheduling with real-time adjustments, this framework optimizes energy management through advanced modeling techniques, balancing supply and demand while minimizing operational costs [4]. Adapting to real-time data and forecasts enhances microgrid resilience and sustainability, promoting efficient energy utilization and grid stability.

Stochastic and predictive control frameworks are vital for optimizing energy management systems, employing methodologies like model predictive control (MPC) and stochastic dual dynamic programming (SDDP) to address modern power grid complexities. These frameworks leverage real-time data and forecasts to manage dynamic power flows, enhancing system reliability, economic efficiency, and sustainability amidst increasing renewable energy integration [57, 13, 81, 28]. By utilizing advanced optimization algorithms and real-time analytics, these frameworks bolster adaptability, efficiency, and sustainability in energy systems, addressing multifaceted challenges in contemporary energy landscapes.



(a) Renewable Energy Management System[101]

(b) Energy Consumption and Grid Power Supply Over Time[57]

Figure 6: Examples of Stochastic and Predictive Control Frameworks

As depicted in Figure 6, multiscale neural networks are pivotal in energy management, particularly within stochastic and predictive control frameworks. The Renewable Energy Management System (REMS) exemplifies this, effectively managing diverse renewable sources like wind turbines and solar panels. Equipped with a SCADA block, it efficiently collects and processes data to optimize energy distribution. The visualization of energy consumption and grid power supply over time illustrates fluctuating energy demands and supply dynamics, underscoring the importance of advanced neural network architectures in enhancing the precision and efficiency of energy management systems [101, 57].

5.3 Scenario-Based and Robust Optimization Approaches

Scenario-based and robust optimization approaches are crucial in energy management, addressing uncertainties and variabilities in renewable energy sources. These methodologies enhance resilience and efficiency by optimizing operations across potential scenarios, including extreme conditions. By integrating advanced energy storage solutions and intelligent control systems, these strategies improve reliability during emergencies and optimize energy utilization under normal circumstances. For instance, optimizing multi-energy storage configurations in integrated systems addresses economic and resilience challenges, utilizing algorithms that account for uncertainties and operational constraints [74, 20, 102, 45, 77].

The hierarchical optimization structure aligns electrolyzer operations with real-time renewable energy availability, employing distinct temporal resolutions to optimize energy management [11]. This strategy maximizes renewable resource utilization while minimizing reliance on conventional sources.

Robust optimization formulations, addressing worst-case scenarios of renewable availability, ensure energy management systems withstand fluctuations, maintaining stability and reliability even in adverse conditions [103]. By considering challenging scenarios, robust optimization enhances resilience, ensuring critical loads are prioritized.

Distributed model predictive energy management strategies align with scenario-based and robust optimization approaches, involving real-time optimization that accounts for generator efficiency and battery health, ensuring optimal operation while preserving component longevity [104]. The sliding Model Predictive Control approach incorporates battery lifecycle considerations, optimizing lifespan while prioritizing critical loads, reflecting scenario-based and robust optimization principles [6].

These approaches are integral to advancing energy management systems, offering robust solutions to modern energy landscape uncertainties and challenges. Employing advanced optimization techniques and real-time data analytics significantly improves resilience, efficiency, and sustainability. This is exemplified in battery scheduling and energy storage systems (ESSs) within smart grids, facilitating reliable energy supply amid fluctuating demands and enhancing participation in ancillary power markets. Big data analytics enable dynamic energy resource management, optimizing costs and performance while ensuring stability in forecasted data, crucial for informed decision-making in energy management systems [20, 92, 12].

5.4 Hierarchical and Distributed Energy Management Systems

Hierarchical and distributed energy management systems optimize energy resources through efficient coordination and control across multiple energy infrastructure levels. These systems combine centralized and decentralized methodologies to enhance flexibility, reliability, and efficiency. By integrating advanced technologies like blockchain and federated learning, they facilitate collaboration between Distribution System Operators (DSOs), prosumers, and consumers, enabling real-time demand-side management and secure energy transactions. Proposed architectures, such as Virtual Distribution Grids (VDG), adapt to complexities introduced by distributed renewable energy sources and electric vehicles, contributing to a resilient and responsive energy grid [24, 51].

The Hierarchical Energy Management System (HEMS) operates on a multi-level architecture that facilitates global optimization of energy flows while accommodating individual participant needs, enhancing energy management by integrating diverse resources and consumer preferences [105].

Distributed energy management systems empower local decision-making and resource control, essential for adapting to real-time changes in energy demand and supply. Integrating Model Predictive

Control (MPC) within these systems significantly improves stability and efficiency, dynamically adjusting to changing load demands and generator constraints [17].

Interactive Transactive Energy (TE) mechanisms within distributed systems enhance prosumer responsiveness, allowing active participation in energy markets through a dynamic price adder mechanism that ensures grid security and facilitates balanced energy distribution [106].

Hierarchical and distributed energy management systems are essential for effective energy resource management, integrating advanced control strategies and promoting collaboration among stakeholders, including DSOs and market actors. These systems are crucial for adapting to challenges posed by high electric vehicle penetration and the deployment of distributed renewable energy sources. By leveraging innovative architectures like VDGs and intelligent microgrids, they facilitate demand-side flexibility, enabling households to engage in energy transactions and optimize resource allocation. This collaborative approach enhances grid stability and supply quality while addressing the complexities of integrating diverse energy technologies and achieving decarbonization goals [24, 10, 107]. By combining centralized and decentralized approaches, these systems enhance adaptability, efficiency, and sustainability in energy infrastructures, tackling modern power grid challenges.

5.5 Data-Driven and Machine Learning Techniques

Data-driven and machine learning techniques are pivotal in advancing energy management systems, enhancing prediction accuracy, optimizing resource allocation, and enabling real-time decision-making under dynamic conditions. These methodologies leverage sophisticated algorithms and data analytics to improve operational efficiency and reliability in modern energy systems. The integration of data-driven methodologies, such as transfer learning, highlights the importance of accurate predictions for renewable energy generation and electricity prices in optimizing energy management strategies [7].

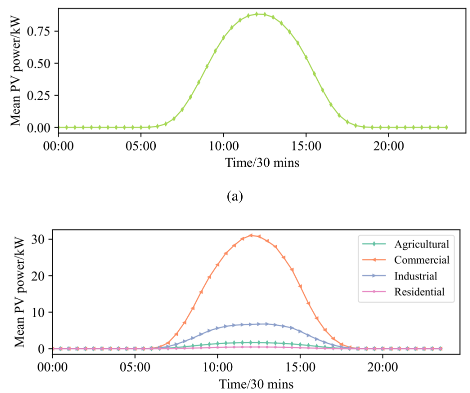
Collaborative learning frameworks, such as Federated Learning, demonstrate the potential of distributed data-driven approaches in energy management, improving forecast accuracy and optimizing energy distribution among agents while preserving data privacy [88]. Data-driven scenario generation techniques, specifically Wasserstein GANs, enhance energy management by accurately representing renewable energy output uncertainties [16].

High-precision production simulations and iterative searching algorithms optimize battery sizing while ensuring system stability, showcasing machine learning applications in energy systems [108]. Furthermore, combining evolutionary optimization techniques with probabilistic forecasting improves flexibility representation that meets operational needs, emphasizing advanced machine learning techniques' role in energy management [36].

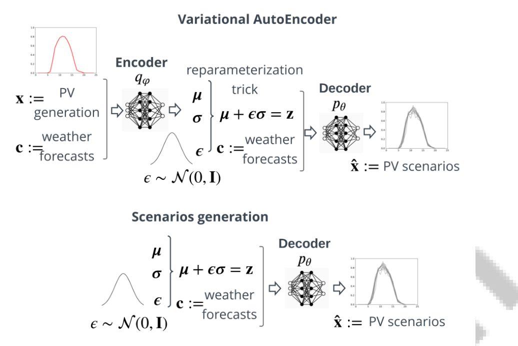
In building energy management, data-driven predictive control methods unlock energy flexibility and improve overall system performance [109]. These methods enable adaptive control of energy systems, allowing timely adjustments based on real-time data and forecasts. Approaches that combine energy cost minimization, user comfort optimization, and management of electricity selling based on pricing scenarios further illustrate data-driven techniques' application in optimizing home energy management [110].

Advanced forecasting and reinforcement learning techniques significantly enhance energy management in smart grids with renewable sources, allowing dynamic adaptation to uncertainties and improving system resilience. The implementation of virtual-queue-based online convex optimization algorithms exemplifies data-driven techniques' potential in optimizing energy management frameworks [111]. Additionally, integrating machine learning for demand prediction enhances energy management effectiveness in data centers, as highlighted in future research directions [112].

Data-driven and machine learning techniques are crucial in advancing energy management systems by providing robust, adaptive, and intelligent solutions. Utilizing predictive analytics, real-time data processing, and sophisticated optimization algorithms, these techniques improve the efficiency, reliability, and sustainability of energy systems. This approach effectively addresses modern power grid challenges, such as integrating forecasting and optimization in energy management, managing dynamic power flows, and facilitating cooperative energy management of aggregated buildings. By leveraging historical data and advanced computational methods, these techniques enhance decision-making processes, reduce operational costs, and empower consumers and micro-energy producers in the electricity market [20, 98, 28, 92].



(a) Time-of-Use (ToU) Power Distribution for Different Load Types[49]



(b) Variational AutoEncoder for Generating PV Scenarios[99]

Figure 7: Examples of Data-Driven and Machine Learning Techniques

As illustrated in Figure 7, multiscale neural networks are increasingly leveraged to optimize power distribution and enhance predictive capabilities in energy management. The integration of data-driven and machine learning techniques is pivotal, as demonstrated by two compelling examples. The first example focuses on Time-of-Use (ToU) power distribution for different load types, analyzing photovoltaic (PV) systems' mean power output over 24 hours. This analysis reveals how various load types influence overall energy consumption, highlighting optimization potential. The second example showcases a Variational AutoEncoder (VAE) for generating PV scenarios, encoding PV generation data and weather forecasts into a latent variable to reconstruct potential PV scenarios. This approach enhances energy forecast accuracy and aids in developing robust energy management strategies by simulating various potential scenarios. Together, these examples underscore the transformative impact of machine learning and data-driven methods in advancing energy management systems [49, 99].

6 Ensuring Grid Stability

6.1 Ensuring Grid Stability with Advanced Control Systems

Advanced control systems are integral to maintaining grid stability amidst increasing renewable energy integration and complex power systems. Utilizing real-time data analytics and optimization, these systems ensure reliable energy distribution by addressing the variability and intermittency of renewables. Energy Management Systems (EMS) play a pivotal role, coordinating output from photovoltaic (PV) and fuel cell (FC) generators to meet grid demands, enhancing resilience during voltage sags [2]. Incorporating saturation in droop control and innovative dispatch strategies further enhances grid stability by enabling precise power flow control and dynamic adjustments to mitigate low generation reserves and power quality fluctuations [30, 10, 63]. Effective wind energy variability management and optimized energy storage participation are crucial for balancing supply and demand, minimizing operating costs, and mitigating energy scarcity risks, thereby contributing to a sustainable energy management framework [1, 85, 45, 12]. In microgrid management, advanced control systems like sliding Model Predictive Control (MPC) optimize resource management and prioritize critical loads during disruptions, enhancing sustainability and reliability [77, 113, 6]. These systems are indispensable for achieving stability, efficiency, and resilience in modern energy systems, fostering better coordination among diverse generation units and promoting user participation in energy management [31, 92, 10].

6.2 Advanced Control Systems and Real-time Monitoring

Advanced control systems and real-time monitoring are essential for grid stability as renewable energy integration increases. These systems employ real-time data analytics and algorithms to manage energy flows effectively, ensuring reliable power distribution. Real-time monitoring within Energy Management Systems (EMS) enables continuous assessment, allowing rapid detection and correction of anomalies to maintain stability [2]. Advanced systems like Model Predictive Control (MPC) predict future load demands, adjusting power generation to maintain balance during fluctuating periods [17]. Integrating real-time monitoring with advanced strategies enhances Distributed Energy Resource (DER) management, optimizing coordination and addressing challenges posed by DERs like rooftop photovoltaics. Innovative strategies like grid-supporting energy management (GSEM) and MPC facilitate virtual power plant management and flexible power trading, improving grid reliability and resilience [114, 115, 116]. These systems, leveraging real-time data and predictive analytics, effectively address power grid challenges, ensuring reliable and sustainable energy distribution [77, 10, 109, 11].

6.3 Optimization Techniques for Grid Stability

Optimization techniques are pivotal for maintaining grid stability amid rising renewable energy integration and dynamic demand. These methodologies enhance reliable and efficient energy distribution, addressing modern power grid challenges. High-performance energy management systems (EMS) minimize computational time and enhance responsiveness to real-time changes [23]. The Energy Circuit Model (ECM) captures dynamic energy flow behavior, facilitating real-time management of large-scale Integrated Energy Systems (IESs) [117]. Optimally coordinated energy management methodologies improve load profile management and reduce load deviation indices (LDI), indicating enhanced operational performance [118]. The Software-Defined Energy Network (SDEN) method dynamically allocates resources for stable operations, while emission-aware energy storage scheduling (EASS) reduces emissions, highlighting optimization techniques' environmental benefits [73, 9]. These techniques enhance reliability and sustainability, optimizing renewable integration and enabling dynamic management, empowering consumers and producers in the electricity market [92, 15, 31, 10, 13].

6.4 Demand Response and Energy Management Systems

Demand response and energy management systems are crucial for grid stability as power systems integrate more renewables and face dynamic demands. These systems facilitate flexible energy consumption adjustments, optimizing transactions and promoting adaptability. Bi-directional power flows from distributed storage devices and renewables enhance stability and management flexibility [119]. Strategic deployment of Battery Energy Storage Systems (BESS) reduces costs through peak shaving and market arbitrage, contributing to grid stability [26]. Centralized Model Predictive Control (MPC) strategies optimize energy flow in residential settings, ensuring efficient management [120]. Integrating optimal Electric Vehicle (EV) charging with railway energy management minimizes peak loads and operational costs [121]. Advanced energy management systems like Stochastic Capacity and Hydrogen Storage Systems (SCHSS) reduce costs and emissions, enhancing renewable integration [72]. The Multi-Objective Reinforcement Learning (MORL) framework improves decision-making in energy management, supporting renewable integration [33]. These systems, incorporating advanced strategies and real-time data, enhance reliability and efficiency, supporting seamless renewable integration and ensuring a sustainable energy distribution framework [28, 31, 109, 24, 13].

7 Renewable Integration and Challenges

7.1 Challenges of Variability and Intermittency

The integration of renewable energy sources into power systems presents significant challenges due to their inherent variability and intermittency, complicating energy management and scheduling. The unpredictable nature of renewable generation can lead to supply-demand imbalances, which traditional deterministic models often fail to address, necessitating stochastic approaches to better accommodate these uncertainties [14]. Accurate predictions of renewable energy generation and user load are critical, yet hindered by stochastic weather patterns and consumer behavior, especially in local energy trading environments where prosumers face variable generation and consumption patterns [1].

Innovative Optimal Power Flow (OPF) strategies are essential for addressing renewable variability, enabling power systems to dynamically respond to fluctuating generation levels. The VDG architecture coordinates distribution grids, tackling key challenges associated with renewable integration and electric vehicle adoption [24]. Existing benchmarks often struggle with modeling temporal and spatial relationships effectively due to a lack of extensive historical data. Additionally, current methods fail to quantify and manage uncertainties in power exchange between residential battery systems and the grid, with seasonal variations posing further obstacles [78].

Innovative solutions are necessary to optimize network capacity, minimize costs, and dynamically manage line failures. Advanced technologies such as energy storage systems and corrective grid management strategies enhance grid stability and efficiency, potentially yielding long-term cost savings while ensuring resilience against renewable variability [30, 10, 31, 63, 64]. Furthermore, cyberattack challenges that distort electricity pricing information complicate energy management, leading to variability and suboptimal outcomes.

Addressing the variability and intermittency of renewable energy sources requires advanced methodologies and technologies for stable and efficient power system operations. Implementing innovative strategies and utilizing advanced analytics enable energy systems to manage the complexities of integrating wind, solar, and hydropower into modern grids, enhancing reliability and efficiency while supporting decarbonization goals [30, 92, 18, 10, 31].

7.2 Advanced Energy Management Strategies

Advanced energy management strategies are crucial for integrating renewable energy sources into power grids, addressing challenges of variability and intermittency. These strategies employ sophisticated methodologies to optimize energy consumption and enhance grid stability. The integration of solar generation into energy management, particularly within XFCS, underscores the importance of precise sizing and management of battery energy storage systems to accommodate fluctuating solar output [122].

The CLSF framework optimizes residential energy use, contributing to grid stability and facilitating efficient renewable integration [35]. Improved demand predictions and optimal price signals generated by the Flexibility Function (FF) enhance renewable integration, mitigating variability challenges [58].

Vehicle-to-Grid (V2G) technology exemplifies significant advancement in energy management, enhancing system flexibility and supporting renewable incorporation [123]. This approach not only contributes to sustainability but also optimizes the viability of renewable sources by utilizing electric vehicles' storage capacity.

Advanced systems like SEMS improve prediction and management capabilities, addressing variability challenges of renewable sources [124]. The application of Generative Adversarial Networks (GANs) in scenario planning enhances power distribution modeling under variable conditions, strengthening integration strategies [50].

Integrating real-time data on base load and PV power production optimizes electric vehicle charging and discharging, illustrating advanced strategies in microgrid operations [125]. Future research should focus on incorporating these control schemes into secondary and tertiary control systems, examining interactions with different inverter types to enhance resilience and efficiency [126].

Advanced energy management strategies are pivotal in optimizing renewable energy integration, ensuring reliable and efficient energy distribution while addressing modern grid challenges. By leveraging advanced technologies and methodologies, these strategies significantly improve adaptability, efficiency, and sustainability, facilitating the integration of wind and solar power into the grid and addressing issues of intermittency and reliability. This comprehensive approach supports the transition to a sustainable energy future by enhancing system performance, promoting energy storage solutions, and enabling effective coordination among energy generation units and smart grid infrastructures [13, 10, 18, 31].

7.3 Demand Response and Grid Flexibility

Demand response is essential for enhancing grid flexibility, especially amid increasing renewable integration. By dynamically adjusting energy consumption patterns in response to real-time grid conditions, demand response strategies improve energy efficiency and facilitate renewable incorporation. These strategies leverage consumer flexibility in appliance usage, optimizing scheduling of HVAC systems, electric vehicles (EVs), and energy storage systems (ESS) to reduce peak demand and costs while maintaining user comfort, supporting a resilient and sustainable energy infrastructure [60, 59, 127, 65].

Integrating demand response within energy management systems enhances distributed energy resource (DER) utilization, allowing adaptive control over energy flows. This adaptability is vital in systems with high renewable penetration, where variability necessitates advanced response mechanisms to fluctuations in generation and demand. The integration of renewable sources significantly alters grid dynamics, reducing system inertia and introducing challenges like low fault ride-through capability and diminished power quality. Employing cutting-edge technologies—including sophisticated control strategies, optimization techniques, and energy storage solutions—is crucial for maintaining stability and reliability amidst these fluctuations [30, 128]. By incentivizing consumers to adjust energy usage, demand response programs balance supply and demand, reduce peak loads, and minimize the need for additional generation capacity.

Demand response strategies enhance grid flexibility by facilitating EV and other DER integration, enabling effective energy management through real-time pricing adjustments. This optimization of appliance scheduling improves overall energy efficiency. Additionally, EVs can function as both energy consumers and storage units via V2G technology, aiding in supply-demand balance and maximizing intermittent renewable use in smart grid systems [31, 18, 65]. By optimizing charging schedules and coordinating energy flows, demand response programs bolster power systems' capacity to accommodate variable renewable generation while minimizing operational disruptions. This flexibility is further enhanced by advanced control algorithms and real-time data analytics, allowing precise and responsive energy management.

Demand response is a vital component of modern energy systems, providing necessary flexibility and adaptability for effective renewable integration. By employing innovative strategies and technologies, demand response enhances grid stability and facilitates the transition to a sustainable energy future, addressing complex challenges faced by contemporary power grids. This includes optimizing decentralized resource integration, utilizing advanced data analytics for improved decision-making, and enabling consumer participation through scheduling frameworks that balance energy consumption with personal comfort. Consequently, demand response plays a crucial role in maximizing energy management efficiency and reducing costs associated with renewable integration [25, 63, 12, 24, 59].

7.4 Technological Solutions and Innovations

Technological innovations are pivotal in facilitating renewable integration into modern power systems, addressing variability and intermittency challenges while enhancing stability and efficiency. The advancement of energy storage technologies, such as lithium-ion batteries and hydrogen storage systems, exemplifies how technological solutions optimize energy management and support seamless renewable incorporation [72]. These storage technologies provide essential flexibility and resilience, enabling power systems to dynamically balance supply and demand and maintain reliable operations under fluctuating conditions.

Smart grid technologies further enhance energy systems' adaptability and responsiveness, allowing real-time monitoring and control of energy flows across the grid. By leveraging advanced communication networks and data analytics, smart grids optimize energy distribution, ensuring efficient utilization and integration of renewable energy into existing infrastructure [21]. This approach not only improves grid stability but also supports the transition to a sustainable energy future by reducing reliance on conventional generation resources.

Innovative demand response strategies, supported by advanced control algorithms and real-time data analytics, significantly contribute to grid flexibility and renewable integration. By incentivizing consumers to adjust energy usage in response to real-time grid conditions, demand response programs help balance supply and demand, reduce peak loads, and enhance overall energy system efficiency [62]. This adaptability is crucial in systems with high renewable energy levels, where responding to fluctuations in generation and demand is vital for maintaining grid stability.

The deployment of V2G technology represents another significant innovation, enhancing energy systems' flexibility by utilizing electric vehicles' storage capacity to support grid operations. V2G technology enables bidirectional energy flows between EVs and the grid, providing additional capacity for balancing supply and demand and facilitating renewable integration [123].

Technological solutions and innovations are essential for overcoming challenges associated with renewable integration, enhancing the efficiency, reliability, and sustainability of modern power systems. By employing advanced technologies and methodologies, energy systems can effectively address the intricate challenges of integrating renewable sources such as wind, solar, and hydroelectric power. This integration is crucial for achieving decarbonization goals while maintaining system reliability. Strategies such as energy storage systems, demand response technologies, and smart grid architectures enhance power system stability and efficiency, paving the way for a more resilient and sustainable energy future. Furthermore, developing a comprehensive solution matrix can prioritize cost-effective technologies, facilitating a smoother transition to high-level renewable energy penetration and mitigating risks associated with intermittent energy generation [30, 10, 31, 18].

8 Conclusion

8.1 Challenges and Future Directions

Energy optimization in contemporary power systems faces considerable challenges, yet it also presents substantial opportunities for future exploration. A significant hurdle is the scalability and real-time application of advanced control strategies, such as Model Predictive Control (MPC), within intricate systems like multi-zone shipboard power systems (SPSs). Enhancements to MPC frameworks, particularly through integrating health-monitoring processes for generators and energy storage systems, could significantly boost real-time adaptability and operational efficiency. Moreover, refining control algorithms to improve adaptability in large-scale power-to-hydrogen systems remains a promising research direction.

The computational demands of deep learning methods, especially in practical scenarios, remain largely unexplored. Future research should focus on incorporating these methods into scalable frameworks applicable across diverse energy systems to ensure adaptability to real-time conditions. This endeavor involves refining fine-tuning methodologies and expanding datasets to address ongoing challenges in energy optimization.

In the realm of home energy management systems, robust wireless connectivity and cybersecurity are crucial for maintaining energy distribution integrity and reliability. Future investigations should delve into advanced battery degradation models to refine energy management strategies and tackle ongoing optimization challenges. Additionally, the instability in training Differentiable Decision Tree (DDT) agents highlights the need for further refinement of energy optimization strategies.

The integration of distributed energy resources (DERs) and the development of sophisticated power flow models are vital for optimizing energy management and enhancing coordination among diverse sources. Future research should prioritize expanding multi-agent deep reinforcement learning (DRL) frameworks in interconnected multi-energy microgrids (MEMGs) to augment privacy and economic benefits. Furthermore, exploring personalized preferences and stochastic optimization models can enhance the efficiency of energy community discovery methods.

Developing large-scale Stochastic Capacity and Hydrogen Storage Systems (SCHSS) projects and optimizing hydrogen production and storage technologies are also critical for creating more efficient, reliable, and sustainable energy systems. The challenges in achieving optimal results compared to complex algorithms like MPC underscore the need for further research into lightweight energy management methods.

Addressing these challenges through innovative research and development can significantly propel the field of energy optimization. By concentrating on flexible resource integration, refining existing models, and exploring new methodologies, future research will contribute to advancing more efficient, reliable, and sustainable energy systems.

8.2 Future Research Directions

Future research in energy optimization strategies should focus on several key areas to enhance the efficiency, reliability, and sustainability of energy systems. A promising direction involves optimizing battery sizes and configurations based on historical data to improve the performance and economic viability of energy storage systems. Additionally, enhancing model adaptability for larger electric vehicle (EV) fleets and optimizing vehicle-to-grid (V2G) services can significantly advance energy optimization by bolstering grid stability and flexibility.

In residential energy management, exploring consensus-based distributed control methods is crucial for enhancing the effectiveness of energy management systems in larger setups. This approach can improve coordination among distributed energy resources and facilitate efficient energy distribution. Furthermore, optimizing virtual inertia and addressing the long-term impacts of energy storage device lifetimes on system performance are critical areas for exploration to ensure the resilience and reliability of power systems with high renewable penetration.

Integrating adaptive algorithms that automatically adjust to real-time changes affecting user comfort presents another promising research avenue, particularly in home energy management systems. This integration could enhance user satisfaction while optimizing energy consumption patterns. Additionally, refining algorithms to improve constraint satisfaction and applying them in complex scenarios with varying energy demands and generation profiles could further advance energy optimization strategies.

In the context of data centers, future research should focus on developing hybrid architectures, improving workload modeling, and implementing advanced control strategies that combine energy storage with workload modulation. These efforts could lead to more efficient energy use and reduced operational costs in data-intensive environments.

These research directions aim to address the multifaceted challenges of modern power grids by leveraging innovative technologies and methodologies. By concentrating on these areas, future research will contribute to developing more efficient, reliable, and sustainable energy systems, supporting the transition towards a more sustainable energy future.

References

[1] VVSN Murty and Ashwani Kumar. Retracted article: Multi-objective energy management in microgrids with hybrid energy sources and battery energy storage systems. *Protection and Control of Modern Power Systems*, 5(1):2, 2020.

[2] Adeel Sabir. Energy management of a hybrid photovoltaic-fuel cell grid-connected power plant with low voltage ride-through control, 2018.

[3] Ahmed S. Alahmed, Lang Tong, and Qing Zhao. Co-optimizing distributed energy resources in linear complexity under net energy metering, 2024.

[4] Wuhua Hu, Ping Wang, and Hoay Beng Gooi. Towards optimal energy management of microgrids with a realistic model, 2016.

[5] Xiaoling Chen, Cory Miller, Mithun Goutham, Prasad Dev Hanumalagutti, Rachel Blaser, and Stephanie Stockar. Development and evaluation of an online home energy management strategy for load coordination in smart homes with renewable energy sources, 2023.

[6] Mohammad Hossein Nejati Amiri, Fawaz Annaz, Mario De Oliveira, and Florimond Gueniat. Strategies for resilience and battery life extension in the face of communication losses for isolated microgrids, 2024.

[7] Gargya Gokhale, Jonas Van Gompel, Bert Claessens, and Chris Develder. Transfer learning in transformer-based demand forecasting for home energy management system, 2023.

[8] Mohsen Banaei, Razgar Ebrahimy, and Henrik Madsen. A lightweight energy management method for hybrid pv/battery/load systems, 2025.

[9] Rishikesh Jha, Stephen Lee, Srinivasan Iyengar, Mohammad H. Hajiesmaili, David Irwin, and Prashant Shenoy. Emission-aware energy storage scheduling for a greener grid, 2020.

[10] fnm Erdiwansyah, fnm Mahidin, H Husin, fnm Nasaruddin, M Zaki, and fnm Muhibbuddin. A critical review of the integration of renewable energy sources with various technologies. *Protection and control of modern power systems*, 6:1–18, 2021.

[11] Vincent Henkel, Lukas Peter Wagner, Felix Gehlhoff, and Alexander Fay. Combination of site-wide and real-time optimization for the control of systems of electrolyzers, 2024.

[12] Hao Chen, Zhenhua Liu, Ayse K. Coskun, and Adam Wierman. Optimizing energy storage participation in emerging power markets, 2016.

[13] Semih Atakan, Harsha Gangammanavar, and Suvrajeet Sen. Towards a sustainable power grid: Stochastic hierarchical planning for high renewable integration, 2021.

[14] David P. Chassin, Sahand Behboodi, and Ned Djilali. Optimal subhourly electricity resource dispatch under multiple price signals with high renewable generation availability, 2017.

[15] Ognjen Kundacina, Gorana Gojic, Mile Mitrovic, Dragisa Miskovic, and Dejan Vukobratovic. Supporting future electrical utilities: Using deep learning methods in ems and dms algorithms, 2023.

[16] Yang Li, Bin Wang, Zhen Yang, Jiazheng Li, and Chen Chen. Hierarchical stochastic scheduling of multi-community integrated energy systems in uncertain environments via stackelberg game, 2021.

[17] Mehrzad Mohammadi Bijaieh, Satish Vedula, and Olugbenga Moses Anubi. Model and load predictive control for design and energy management of shipboard power systems, 2021.

[18] Integration of renewable energy.

[19] having with battery energy stora.

[20] Evgenii Genov, Julian Ruddick, Christoph Bergmeir, Majid Vafaeipour, Thierry Coosemans, Salvador Garcia, and Maarten Messagie. Predict. optimize. revise. on forecast and policy stability in energy management systems, 2025.

[21] Atefeh Alirezazadeh and Vahid Disfani. A peer-to-peer energy management solution for maximum social welfare, 2024.

[22] Sakshi Mishra and Praveen Palanisamy. Efficient power flow management and peak shaving in a microgrid-pv system, 2018.

[23] Guangyi Liu, Chen Yuan, Xi Chen, Jingjin Wu, Renchang Dai, and Zhiwei Wang. A high-performance energy management system based on evolving graph, 2019.

[24] José Horta, Daniel Kofman, and David Menga. Novel paradigms for advanced distribution grid energy management, 2017.

[25] Ferhat Ucar. A comprehensive analysis of smart grid stability prediction along with explainable artificial intelligence. *Symmetry*, 15(2):289, 2023.

[26] T. Ortmeyer and T. Vu. Energy storage peak shaving feasibility: Case studies in upstate new york, 2021.

[27] C. Zugschwert, S. Göschl, F. Martin Ibanez, and K. Pettinger. Development of a multi-timescale method for classifying hybrid energy storage systems in grid applications, 2022.

[28] Nicholas Moehle, Enzo Busseti, Stephen Boyd, and Matt Wytock. Dynamic energy management, 2019.

[29] Yusuf Gupta and Mohammad Amin. A neural network-based energy management system for pv-battery based microgrids, 2022.

[30] Md Shafiul Alam, Fahad Saleh Al-Ismail, M. A. Abido, and Aboubakr Salem. High-level penetration of renewable energy with grid: Challenges and opportunities, 2020.

[31] Imane Worighi, Abdelilah Maach, Abdelhakim Hafid, Omar Hegazy, and Joeri Van Mierlo. Integrating renewable energy in smart grid system: Architecture, virtualization and analysis. *Sustainable Energy, Grids and Networks*, 18:100226, 2019.

[32] Zigang Chen. Optimal power flow in renewable-integrated power systems: A comprehensive review, 2024.

[33] M. Vivienne Liu, Patrick M. Reed, David Gold, Garret Quist, and C. Lindsay Anderson. A multiobjective reinforcement learning framework for microgrid energy management, 2023.

[34] Satish Vedula, Ayobami Olajube, Koto Omiloli, and Olugbenga Moses Anubi. Battery degradation heuristics for predictive energy management in shipboard power systems, 2024.

[35] Babak Jeddi, Yateendra Mishra, and Gerard Ledwich. Distributed load scheduling in residential neighborhoods for coordinated operation of multiple home energy management systems, 2021.

[36] Rui Pinto, Ricardo Bessa, and Manuel Matos. Multi-period flexibility forecast for low voltage prosumers, 2017.

[37] Tsung-Hui Chang, Mahnoosh Alizadeh, and Anna Scaglione. Coordinated home energy management for real-time power balancing, 2012.

[38] Hafiz Majid Hussain, Arun Narayanan, Subham Sahoo, Yongheng Yang, Pedro H. J. Nardelli, and Frede Blaabjerg. Home energy management systems: Operation and resilience of heuristics against cyberattacks, 2021.

[39] Claudia Rahmann, Benjamin Mac-Clure, Vijay Vittal, and Felipe Valencia. Break-even points of battery energy storage systems for peak shaving applications. *Energies*, 10(7):833, 2017.

[40] Qingchun Hou, Yanghao Yu, Ershun Du, Hongjie He, Ning Zhang, Chongqing Kang, Guojing Liu, and Huan Zhu. Embedding lithium-ion battery scrapping criterion and degradation model in optimal operation of peak-shaving energy storage, 2020.

[41] Qiuyu Lu, Xiaoman Zhang, Yinguo Yang, Qianwen Hu, Guobing Wu, Yuxiong Huang, Yang Liu, and Gengfeng Li. Multi-time-scale energy storage optimization configuration for power balance in distribution systems. *Electronics*, 13(7):1379, 2024.

[42] Vivek Deulkar, Jayakrishnan Nair, and Ankur A. Kulkarni. Sizing storage for reliable renewable integration: A large deviations approach, 2019.

[43] Han-I Su and Abbas El Gamal. Limits on the benefits of energy storage for renewable integration, 2012.

[44] Yang Cui, Yang Xu, Yang Li, Yijian Wang, and Xinpeng Zou. Deep reinforcement learning based optimal energy management of multi-energy microgrids with uncertainties, 2023.

[45] Alexis Lagrange, Miguel de Simón-Martín, Alberto González-Martínez, Stefano Bracco, and Enrique Rosales-Asensio. Sustainable microgrids with energy storage as a means to increase power resilience in critical facilities: An application to a hospital. *International Journal of Electrical Power & Energy Systems*, 119:105865, 2020.

[46] Alwyn Mathew, Abhijit Roy, and Jimson Mathew. Intelligent residential energy management system using deep reinforcement learning, 2020.

[47] Fulong Yao, Wanqing Zhao, Matthew Forshaw, and Yang Song. A holistic power optimization approach for microgrid control based on deep reinforcement learning, 2024.

[48] Amin Shojaeighadikolaei, Arman Ghasemi, Kailani Jones, Yousif Dafalla, Alexandru G. Bardas, Reza Ahmadi, and Morteza Haashemi. Distributed energy management and demand response in smart grids: A multi-agent deep reinforcement learning framework, 2022.

[49] Hui Song, Zheng Miao, Ali Babalhavaeji, Saman Mehrnia, Mahdi Jalili, and Xinghuo Yu. Clustering-based multitasking deep neural network for solar photovoltaics power generation prediction, 2024.

[50] Jens Schreiber, Maik Jessulat, and Bernhard Sick. Generative adversarial networks for operational scenario planning of renewable energy farms: A study on wind and photovoltaic, 2019.

[51] Muhammad Shoaib Farooq and Azeen Ahmed Hayat. A federated learning model for electric energy management using blockchain technology, 2023.

[52] Gargya Gokhale, Bert Claessens, and Chris Develder. Explainable reinforcement learning-based home energy management systems using differentiable decision trees, 2024.

[53] Jonas Engels, Bert Claessens, and Geert Deconinck. Optimal combination of frequency control and peak shaving with battery storage systems, 2020.

[54] Gautham Ram Chandra Mouli, Mahdi Kefayati, Ross Baldick, and Pavol Bauer. Integrated pv charging of ev fleet based on dynamic energy prices and offer of reserves, 2017.

[55] Yuanyuan Shi, Bolun Xu, Di Wang, and Baosen Zhang. Using battery storage for peak shaving and frequency regulation: Joint optimization for superlinear gains, 2017.

[56] T. Sayfutdinov and P. Vorobev. Optimal utilization strategy of the lifepo$_4$ battery storage, 2022.

[57] Benjamin Flamm, Guillermo Ramos, Annika Eichler, and John Lygeros. Multiperiod stochastic peak shaving using storage, 2020.

[58] Seyed Shahabaldin Tohidi, Henrik Madsen, Davide Calì, and Tobias K. S. Ritschel. Optimal price signal generation for demand-side energy management, 2024.

[59] Farzam Fanitabasi and Evangelos Pournaras. Appliance-level flexible scheduling for socio-technical smart grid optimisation, 2020.

[60] Zheming Liang, Desong Bian, Xiaohu Zhang, Di Shi, Ruisheng Diao, and Zhiwei Wang. Optimal energy management for commercial buildings considering comprehensive comfort levels in a retail electricity market, 2018.

[61] Yuanyuan Shi, Bolun Xu, Di Wang, and Baosen Zhang. Using battery storage for peak shaving and frequency regulation: Joint optimization for superlinear gains. *IEEE transactions on power systems*, 33(3):2882–2894, 2017.

[62] Thijs Peirelinck, Chris Hermans, Fred Spiessens, and Geert Deconinck. Combined peak reduction and self-consumption using proximal policy optimization, 2022.

[63] Amin Shokri Gazafroudi, Elisabeth Zeyen, Martha Frysztacki, Fabian Neumann, and Tom Brown. Long-term benefits of network boosters for renewables integration and corrective grid security, 2022.

[64] Andrew A. Chien, Fan Yang, and Chaojie Zhang. Characterizing curtailed and uneconomic renewable power in the mid-continent independent system operator, 2016.

[65] Mohammad Rasoul Narimani. Demand side management for homes in smart grids, 2019.

[66] Jiarong Li. A multi-stack power-to-hydrogen load control framework for the power factor-constrained integration in volatile peak shaving conditions, 2023.

[67] Cheng Lyu, Youwei Jia, and Zhao Xu. Real-time operation optimization of microgrids with battery energy storage system: A tube-based model predictive control approach, 2021.

[68] Yichen Zhang, Alexander Melin, Mohammed Olama, Seddik Djouadi, Jin Dong, and Kevin Tomsovic. Battery energy storage scheduling for optimal load variance minimization, 2018.

[69] Abdulelah H Habib, Vahid R. Disfani, Jan Kleissl, and Raymond de Callafon. Market-driven energy storage planning for microgrids with renewable energy systems using stochastic programming, 2017.

[70] Benoît Richard, Xavier Le Pivert, and Yves-Marie Bourien. Bess optimal sizing methodology -degree of impact of several influencing factors, 2020.

[71] Jie Zhu, Yiwei Qiu, Yangjun Zeng, Yi Zhou, Shi Chen, Tianlei Zang, Buxiang Zhou, Zhipeng Yu, and Jin Lin. Exploring the optimal size of grid-forming energy storage in an off-grid renewable p2h system under multi-timescale energy management, 2024.

[72] Xueqian He, Tianguang Lu, Jing Li, Wanxing Sheng, and Rui Li. Power system capacity planning considering seasonal hydrogen storage by salt caverns, 2023.

[73] Pedro H. J. Nardelli, Hafiz Majid Hussein, Arun Narayanan, and Yongheng Yang. Virtual microgrid management via software-defined energy network for electricity sharing, 2021.

[74] Zhe Chen, Zihan Sun, Da Lin, Zhihao Li, and Jian Chen. Optimal configuration of multi-energy storage in an electric–thermal–hydrogen integrated energy system considering extreme disaster scenarios. *Sustainability*, 16(6):2276, 2024.

[75] Katayoun Rahbar, Mohammad R. Vedady Moghadam, Sanjib Kumar Panda, and Thomas Reindl. Energy management for demand responsive users with shared energy storage system, 2016.

[76] I. Khan, A. Mahmood, N. Javaid, S. Razzaq, R. D. Khan, and M. Ilahi. Home energy management systems in future smart grids, 2013.

[77] Ninad Gaikwad, Naren Srivaths Raman, and Prabir Barooah. Smart home energy management system for power system resiliency, 2020.

[78] Akın Taşcikaraoğlu and Ozan Erdinç. A profit optimization approach based on the use of pumped-hydro energy storage unit and dynamic pricing, 2018.

[79] Alexey Györi, Mathis Niederau, Violett Zeller, and Volker Stich. Evaluation of deep learning-based prediction models in microgrids, 2019.

[80] Adrien Le Franc, Pierre Carpentier, Jean-Philippe Chancelier, and Michel de Lara. Emsx: a numerical benchmark for energy management systems, 2021.

[81] François Pacaud, Pierre Carpentier, Jean-Philippe Chancelier, and Michel De Lara. Stochastic optimal control of a domestic microgrid equipped with solar panel and battery, 2018.

[82] Rosemarie Velik and Pascal Nicolay. Energy management in storage-augmented, grid-connected prosumer buildings and neighbourhoods using a modified simulated annealing optimization, 2015.

[83] Mina Razghandi, Hao Zhou, Melike Erol-Kantarci, and Damla Turgut. Smart home energy management: Sequence-to-sequence load forecasting and q-learning, 2021.

[84] Eli Brock, Lauren Bruckstein, Patrick Connor, Sabrina Nguyen, Robert Kerestes, and Mai Abdelhakim. An application of reinforcement learning to residential energy storage under real-time pricing, 2021.

[85] Per Aaslid, Magnus Korpås, Michael M Belsnes, and Olav B Fosso. Stochastic operation of energy constrained microgrids considering battery degradation, 2021.

[86] Hussein Sharadga, Ahmad Dawahdeh, Golbon Zakeri, Abdullah Hayajneh, and Geoff Pritchard. Real-time building energy storage scheduling under electrical load uncertainty: A dynamic markov decision process approach with comprehensive analysis of different pricing policies, 2024.

[87] Tiago Fonseca, Luis Ferreira, Bernardo Cabral, Ricardo Severino, and Isabel Praca. Energaize: Multi agent deep deterministic policy gradient for vehicle to grid energy management, 2024.

[88] Yuhan Du, Nuno Mendes, Simin Rasouli, Javad Mohammadi, and Pedro Moura. Federated learning assisted distributed energy optimization, 2023.

[89] Daniele Ioli, Alessandro Falsone, Alessandro Vittorio Papadopoulos, and Maria Prandini. A compositional modeling framework for the optimal energy management of a district network, 2017.

[90] Spyridon Chapaloglou, Erick Alves, Vincenzo Trovato, and Elisabetta Tedeschi. Optimal energy management in autonomous power systems with probabilistic security constraints and adaptive frequency control, 2022.

[91] David Pérez-Piñeiro, Sigurd Skogestad, and Stephen Boyd. Home energy management with dynamic tariffs and tiered peak power charges, 2023.

[92] Panagiotis D. Diamantoulakis, Vasileios M. Kapinas, and George K. Karagiannidis. Big data analytics for dynamic energy management in smart grids, 2015.

[93] Oriol Gomis-Bellmunt, Saman Dadjo Tavakoli, Vinicius A. Lacerda, and Eduardo Prieto-Araujo. Grid-forming loads: Can the loads be in charge of forming the grid in modern power systems?, 2022.

[94] Josimar Edinson Chire Saire, José Armando Gastelo Roque, and Franco Canziani. Study of a hybrid photovoltaic-wind smart microgrid using data science approach, 2021.

[95] Valliappan Muthukaruppan, Rongxing Hu, Ashwin Shirsat, Mesut Baran, Ning Lu, Wenyuan Tang, and David Lubkeman. Multi-feeder restoration using multi-microgrid formation and management, 2023.

[96] Clementine Straub, Sorin Olaru, Jean Maeght, and Patrick Panciatici. Zonal congestion management mixing large battery storage systems and generation curtailment, 2018.

[97] Jesus Silva-Rodriguez, Elias Raffoul, and Xingpeng Li. Lstm-based net load forecasting for wind and solar power-equipped microgrids, 2024.

[98] Georgios Darivianakis, Angelos Georghiou, Roy S. Smith, and John Lygeros. The power of diversity: Data-driven robust predictive control for energy efficient buildings and districts, 2016.

[99] Jonathan Dumas, Antoine Wehenkel Damien Lanaspeze, Bertrand Cornélusse, and Antonio Sutera. A deep generative model for probabilistic energy forecasting in power systems: normalizing flows, 2021.

[100] Mohammad Rasoul Narimani, Ali Azizivahed, and Ehsan Naderi. An efficient scenario-based stochastic energy management of distribution networks with distributed generation, pv module, and energy storage, 2019.

[101] Anahita Moradmand, Mehrdad Dorostian, and Bahram Shafai. Energy scheduling for residential distributed energy resources with uncertainties using model-based predictive control, 2020.

[102] Analytical uncertainty propagation for multi-period stochastic optimal power flow.

[103] Yu Zhang, Nikolaos Gatsis, and Georgios B. Giannakis. Robust energy management for microgrids with high-penetration renewables, 2013.

[104] Satish Vedula, Seyyed Shaho Alaviani, and Olugbenga Moses Anubi. Distributed model-predictive energy management strategy for shipboard power systems considering battery degradation, 2024.

[105] Antonino Capillo, Enrico De Santis, Fabio Massimo Frattale Mascioli, and Antonello Rizzi. An online hierarchical energy management system for energy communities, complying with the current technical legislation framework, 2024.

[106] Peng Hou, Guangya Yang, Junjie Hu, Philip J. Douglass, and Yusheng Xue. An interactive transactive energy mechanism integrating grid operators, aggregators and prosumers, 2019.

[107] Hajir Pourbabak, Tao Chen, Bowen Zhang, and Wencong Su. Control and energy management system in microgrids, 2017.

[108] Jie Zhu. A full-time scale energy management and battery size optimization for off-grid renewable power to hydrogen systems: A battery energy storage-based grid-forming case in inner mongolian, 2024.

[109] Anjukan Kathirgamanathan, Mattia De Rosa, Eleni Mangina, and Donal P. Finn. Data-driven predictive control for unlocking building energy flexibility: A review, 2020.

[110] Huy Truong Dinh and Daehee Kim. An optimal energy-saving home energy management supporting user comfort and electricity selling with different prices, 2021.

[111] Ning Qi, Kaidi Huang, Zhiyuan Fan, and Bolun Xu. Long-term energy management for microgrid with hybrid hydrogen-battery energy storage: A prediction-free coordinated optimization framework, 2024.

[112] Mehiar Dabbagh, Bechir Hamdaoui, and Ammar Rayes. Peak power shaving for reduced electricity costs in cloud data centers: Opportunities and challenges, 2020.

[113] Le Anh Dao, Alireza Dehghani-Pilehvarani, Achilleas Markou, and Luca Ferrarini. A hierarchical distributed predictive control approach for microgrids energy management, 2020.

[114] Katayoun Rahbar, Mohammad R. Vedady Moghadam, and Sanjib Kumar Panda. Real-time shared energy storage management for renewable energy integration in smart grid, 2017.

[115] Cunzhi Zhao and Xingpeng Li. A novel real-time energy management strategy for grid-supporting microgrid: Enabling flexible trading power, 2021.

[116] Mahraz Amini, Adil Khurram, Andrew Klem, Mads Almassalkhi, and Paul D. H. Hines. A model-predictive control method for coordinating virtual power plants and packetized resources, with hardware-in-the-loop validation, 2019.

[117] Binbin Chen, Qinglai Guo, Guanxiong Yin, Bin Wang, Zhaoguang Pan, Yuwei Chen, Wenchuan Wu, and Hongbin Sun. Energy circuit-based integrated energy management system: Theory, implementation, and application, 2022.

AI-generated, for reference only.

[118] Rayees Ahmad Thokar, Nikhil Gupta, K. R. Niazi, Anil Swarnkar, Nand K. Meena, and Jin Yang. Optimally coordinated energy management framework for profit maximization considering dispatchable and non-dispatchable energy resources, 2023.

[119] Adetokunbo Ajao, Jingwei Luo, Zheming Liang, Qais H. Alsafasfeh, and Wencong Su. Intelligent home energy management system for distributed renewable generators, dispatchable residential loads and distributed energy storage devices, 2017.

[120] Sayani Seal, Benoit Boulet, and Vahid Raissi Dehkordi. Centralized model predictive control strategy for thermal comfort and residential energy management, 2019.

[121] Georgia Pierrou and Gabriela Hug. Integrating optimal ev charging in the energy management of electric railway stations, 2023.

[122] Waqas ur Rehman, Rui Bo, Hossein Mehdipourpicha, and Jonathan Kimball. Sizing battery energy storage and pv system in an extreme fast charging station considering uncertainties and battery degradation, 2022.

[123] Freddy Tuxworth and Adnan Aijaz. Vehicle-to-grid technology meets packetized energy management: A co-simulation study, 2024.

[124] Kultan Jaroslav and Kultan Matej. Computer networks new generation in the use of res, 2014.

[125] Hojun Jin, Sarvar Hussain Nengroo, Sangkeum Lee, and Dongsoo Har. Power management of microgrid integrated with electric vehicles in residential parking station, 2021.

[126] Sabine Auer, Casper Roos, Jobst Heitzig, Frank Hellmann, and Jürgen Kurths. The contribution of different electric vehicle control strategies to dynamical grid stability, 2017.

[127] Duong Tung Nguyen. Optimal energy management for smartgrids considering thermal load and dynamic pricing, 2016.

[128] Benjamin Kroposki, Brian Johnson, Yingchen Zhang, Vahan Gevorgian, Paul Denholm, Bri-Mathias Hodge, and Bryan Hannegan. Achieving a 100% renewable grid: Operating electric power systems with extremely high levels of variable renewable energy. *IEEE Power and energy magazine*, 15(2):61–73, 2017.

Disclaimer:

SurveyX is an AI-powered system designed to automate the generation of surveys. While it aims to produce high-quality, coherent, and comprehensive surveys with accurate citations, the final output is derived from the AI's synthesis of pre-processed materials, which may contain limitations or inaccuracies. As such, the generated content should not be used for academic publication or formal submissions and must be independently reviewed and verified. The developers of SurveyX do not assume responsibility for any errors or consequences arising from the use of the generated surveys.