Operation and Optimization of Shared and Centralized Energy Storage Systems: A Survey

www.surveyx.cn

Abstract

This survey paper delves into the strategic management and optimization of shared and centralized energy storage systems (ESS) in the context of modern energy management and renewable integration. The increasing penetration of renewable energy sources (RES) poses significant challenges to grid stability and reliability, necessitating advanced operational strategies and optimization techniques for ESS. Shared ESS facilitate efficient energy distribution and cost-effective management in interconnected microgrids, while centralized systems enhance stability in high RES penetration scenarios through advanced control and optimization frameworks. The integration of machine learning and novel algorithmic approaches, such as deep reinforcement learning and hierarchical reinforcement learning, further optimizes ESS operations by enhancing predictive capabilities and adaptive control. Privacy-preserving technologies and robust cybersecurity measures are crucial for safeguarding data and ensuring secure communication in energy systems. The survey also highlights the role of demand response strategies and flexibility measures in optimizing energy management, particularly in dynamic environments. Real-world applications demonstrate the effectiveness of ESS in enhancing energy efficiency and grid stability, with case studies illustrating successful integration with renewable energy and grid management. Future research directions emphasize emerging technologies, modeling and simulation enhancements, and economic considerations, underscoring the potential for innovative solutions to advance ESS capabilities. By addressing these multifaceted challenges, energy infrastructures can achieve a more sustainable and resilient energy landscape, effectively integrating renewable energy sources and managing distributed energy resources.

1 Introduction

1.1 Importance of Energy Storage Systems

Energy storage systems (ESS) are essential to modern energy infrastructure, enhancing efficiency and sustainability. As the electrical power network shifts towards decentralized generation with increased renewable energy sources (RES), it encounters challenges such as frequency stability issues due to reduced system inertia [1]. ESS mitigate these challenges by stabilizing power fluctuations and ensuring reliable operation in carbon-neutral power systems [2]. The rising penetration of RES demands high-speed voltage control to maintain system reliability [3].

During peak demand periods, such as the Winter Olympic Games, ESS are critical for managing energy supply and reducing reliance on carbon-intensive sources [4]. In the building sector, which contributes significantly to global energy consumption and emissions, ESS enhance energy efficiency, lower operational costs, and reduce emissions [5]. Integrating ESS with renewable technologies, such as photovoltaic (PV) arrays, maximizes power extraction under varying conditions, improving system efficiency [6]. In electric vehicle (EV) charging stations, ESS manage uncertainties in charging patterns, ensuring efficient energy distribution [7].

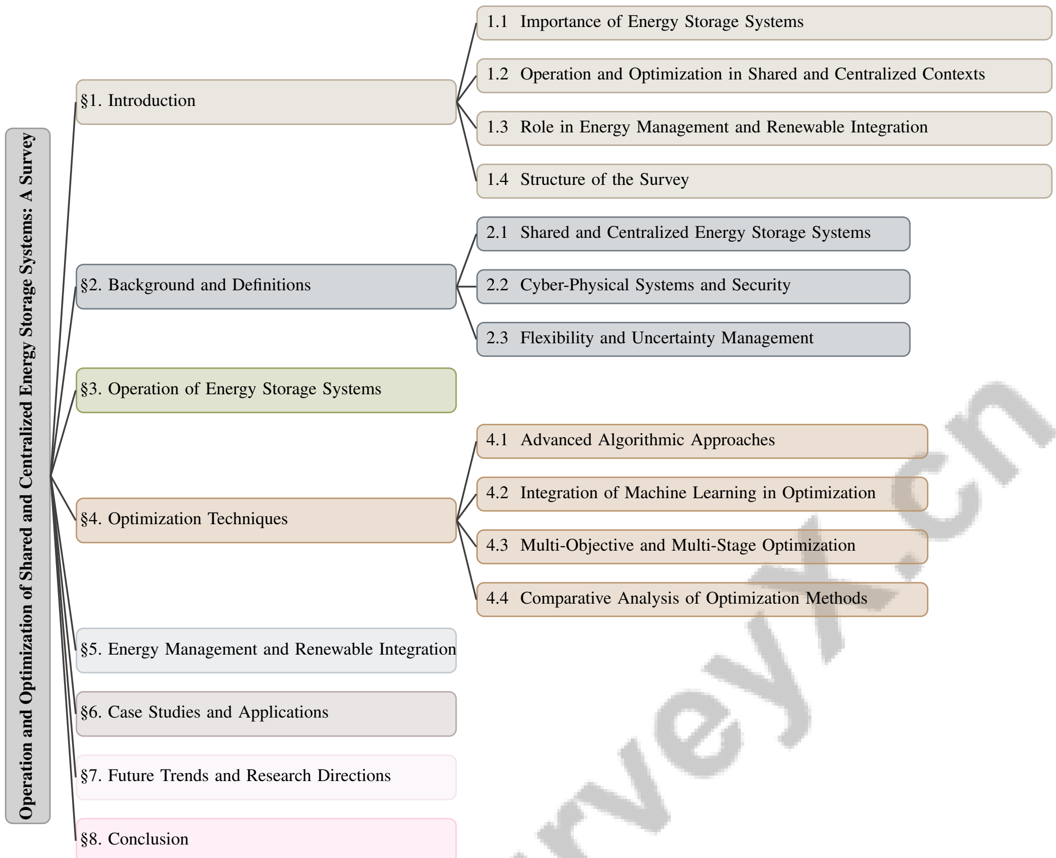

Figure 1: chapter structure

ESS also bolster energy system resilience during emergencies, such as extreme weather events that can disrupt the grid [8]. The rapid growth of solar and wind energy has led to challenges like energy curtailment due to limited transmission capacity, where ESS play a crucial role in mitigation [9]. Furthermore, power quality issues have emerged due to significant changes in low voltage distribution networks, exacerbated by the COVID-19 pandemic and the increasing energy crisis [10].

In summary, ESS are vital for addressing the complex challenges of contemporary energy infrastructure, including the integration of variable renewable resources, enhancing economic viability, and promoting environmental sustainability. They ensure reliable and efficient energy supply by accommodating short-term load surges, managing network congestion, and supporting carbon neutrality initiatives, as evidenced in high-demand scenarios like the Winter Olympic Games. Innovative market frameworks and operational strategies, including financial storage rights and virtual transmission services, are being developed to optimize energy storage deployment and performance, fostering a more resilient and sustainable energy landscape [9, 4, 11, 12].

1.2 Operation and Optimization in Shared and Centralized Contexts

Optimizing operations in shared and centralized energy storage systems is crucial for enhancing performance, ensuring efficient energy distribution, and supporting the integration of renewable energy sources. As reliance on intermittent RES increases, flexibility in energy storage systems becomes essential for maintaining operational reliability [13]. In shared contexts, inefficiencies in energy storage usage by end users, driven by high costs and limited options, highlight the need for optimized operations to improve accessibility and efficiency [14].

Decentralized market mechanisms in energy communities are vital for optimizing operations, adapting to the dynamic nature of energy generation and consumption, especially with renewable resources [15]. The Conditional Cooperation Model Predictive Control (CC-MPC) enhances interactions between interconnected microgrids, improving performance in shared energy contexts [16].

Centralized energy storage systems benefit from advanced optimization techniques. For example, a learning-based model predictive control (LB-MPC) strategy adapts to varying conditions, enhancing operations in hybrid electric vehicles (HEVs) [17]. Distributionally robust optimization (DRO) frameworks, incorporating multiple conditional ambiguity sets, provide a robust method for managing uncertainties in demand and renewable generation, thus optimizing centralized energy storage operations [18].

In battery energy storage systems (BESS), optimizing operations is critical for ensuring reliable energy supply while accommodating renewable sources. BESS can serve as a virtual transmission solution for congestion mitigation in power systems, providing an effective benchmark for evaluating performance [9]. This is particularly relevant in scenarios with high EV penetration, where optimizing charging station operations minimizes carbon emissions and operational costs [7]. Additionally, traditional energy management systems face adaptability challenges, underscoring the need for advanced solutions to optimize operations [5].

Understanding discharge processes and electrolyte composition changes in lithium metal batteries (LMBs) is essential for optimizing operations and enhancing performance [19]. The optimization of operations in both shared and centralized contexts is integral to enhancing system resilience, reducing costs, and facilitating the seamless integration of renewable energy, contributing to a more sustainable and efficient energy landscape while addressing challenges like frequency stability and grid disruptions.

1.3 Role in Energy Management and Renewable Integration

Energy storage systems (ESS) are pivotal in facilitating energy management and the seamless integration of renewable energy sources (RES) into the grid. The integration of flexible deterministic energy systems with stochastic RES enhances energy management by providing ancillary services to local distribution system operators, ensuring grid stability and efficiency [20]. The microgrid concept supports this integration by enabling coordinated power exchange among interconnected systems, optimizing energy management while preserving individual microgrids' autonomy [16].

Incorporating ESS into energy management strategies is particularly beneficial for off-grid photovoltaic (PV) systems, where the long-term health of Li-ion battery systems is critical. Analyzing extensive energy data, including daily operation patterns, C-rate, temperature, and accumulated energy distributions, is essential for assessing battery health and optimizing energy management [21]. Moreover, the environmental impact and reliability concerns of activities like cryptocurrency mining necessitate effective energy management to mitigate adverse effects and enhance system reliability [22].

Innovative business models, such as virtual energy storage sharing, improve energy management by allowing storage aggregators to invest in central physical storage units, which are then virtualized into separable capacities. These virtual capacities are sold to users, enabling cost reduction and efficient energy utilization [14]. Additionally, coordinating multiple master distributed generators (DGs) within islanded microgrids enhances resilience and efficiency during restoration processes, further supporting effective energy management [8].

ESS are crucial for optimizing energy management and enabling the seamless integration of RES. By addressing challenges such as load surges, frequency stability, and operational efficiency, ESS significantly contribute to developing a sustainable and resilient energy infrastructure. For instance, during major events like the Winter Olympic Games, battery energy storage systems (BESS) can provide reliable power and support carbon neutrality efforts. The integration of intelligent energy management systems in buildings further enhances operational efficiency and reduces greenhouse gas emissions, underscoring the importance of ESS in modern energy systems [23, 9, 5, 4, 24].

1.4 Structure of the Survey

This survey is structured to provide a comprehensive examination of the operation and optimization of shared and centralized energy storage systems within the context of modern energy management and renewable integration. Organized into eight primary sections, each focuses on distinct yet interconnected aspects of energy storage systems.

The introductory section elucidates the importance of ESS in enhancing the efficiency and sustainability of energy infrastructures, emphasizing their critical role in integrating RES. It discusses the optimization of operations in shared and centralized contexts and highlights the role of energy storage in energy management and renewable integration.

The second section provides background and definitions, offering an overview of key concepts such as shared and centralized energy storage systems, cyber-physical systems, security, flexibility, and uncertainty management, establishing a foundational understanding relevant to the survey's theme.

The third section examines operational strategies for energy storage systems, focusing on management techniques to ensure efficient energy distribution and reliability. It explores inverter management, coordination and scheduling techniques, and methods to enhance resilience.

The fourth section discusses various optimization techniques, including advanced algorithmic approaches, machine learning integration, multi-objective and multi-stage optimization, and a comparative analysis of different optimization methods applied to energy storage systems.

The fifth section analyzes the role of energy management in integrating RES, addressing challenges, communication and security in energy management, demand response strategies, and optimizing energy management across diverse environments.

Section six presents real-world case studies and applications demonstrating effective implementation of shared and centralized energy storage systems. It emphasizes successful integration strategies with RES and grid management, highlighting innovative approaches like virtual energy storage sharing models that significantly reduce costs. Additionally, it explores operational challenges and benefits of integrating solar PV systems into existing power grids and the economic implications of using BESS for virtual transmission services, illustrating how energy storage solutions enhance grid stability and facilitate a sustainable energy landscape [23, 9, 12, 14, 11].

The penultimate section explores future trends and research directions, identifying emerging technologies, advancements in modeling and simulation, and economic and market considerations shaping the future of energy storage systems.

The conclusion synthesizes key findings from the survey, emphasizing the critical roles of operation and optimization in both shared and centralized energy storage systems. It highlights how these systems improve energy management and facilitate RES integration, ultimately enhancing efficiency and reducing costs for users and operators alike. The findings underscore the significance of innovative business models, such as virtual energy storage sharing and financial storage rights, in optimizing energy storage operations and ensuring market stability amidst increasing reliance on variable renewable energy [14, 11, 12, 25]. This structured approach ensures a thorough exploration of the topic, providing valuable insights into the strategic management and enhancement of energy systems.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Shared and Centralized Energy Storage Systems

Shared and centralized energy storage systems (ESS) are crucial to modern energy infrastructures, each offering distinct operational features. Shared ESS, often functioning as interconnected microgrids, enable power exchange and offer cost advantages over isolated systems [16]. These systems are particularly effective in distributed energy resource (DER) settings, such as residential photovoltaic installations, where they help mitigate overvoltage and enhance grid stability through optimal inverter dispatch [14]. Addressing high costs and unpredictable energy demand at the user level can be achieved through innovations like virtual energy storage sharing [14].

Multi-mode inverters in shared systems provide greater flexibility and adaptability than traditional fixed-mode systems, thus improving grid stability [26]. The incorporation of decentralized power sources differentiates shared systems from conventional large power plants, emphasizing localized energy solutions [27]. The complexity of managing power networks, with numerous potential actions and states, highlights the operational intricacies of shared ESS [28].

Conversely, centralized ESS are characterized by large-scale, centralized control over energy resources, playing a pivotal role in markets with high penetration of variable renewable energy (VRE), where they stabilize wholesale electricity markets [11]. These systems often employ advanced optimization techniques similar to those in wireless powered sensor networks (WPSN) for energy management [29]. A centralized microgrid control system (CMCS) exemplifies this strategy by managing power flow and battery State-of-Charge (SoC) in grid-connected microgrids using real-time data from Phasor Measurement Units (PMUs) and a centralized controller [30].

Operational strategies further distinguish shared and centralized ESS. Shared systems facilitate the interconnection of multiple DERs, promoting distributed control and flexibility [20]. Centralized systems focus on maximizing efficiency and stability on a broader scale, often using sophisticated forecasting models to navigate risks and uncertainties in energy markets [31]. Ensuring that generation, power flows, and voltages remain within specified limits, despite renewable generation uncertainties, underscores the need for robust control in centralized systems [32].

Both shared and centralized ESS are essential for integrating renewable energy, each offering unique solutions to challenges posed by the volatility of sources like solar and wind [23]. By leveraging the distinct characteristics of these systems, energy infrastructures can be optimized for sustainable and resilient management.

2.2 Cyber-Physical Systems and Security

The integration of cyber-physical systems (CPS) in energy storage frameworks is vital for enhancing coordination and security in modern power systems. CPS deployment enables advanced load coordination, ensuring robust cybersecurity and risk management crucial for reliable operations [33]. As energy infrastructures incorporate distributed energy resources (DERs), the complexity of cyber-physical coordination increases, introducing vulnerabilities that could compromise system reliability [34].

Intentional misinformation by adverse agents in peer-to-peer (P2P) markets exacerbates these vulnerabilities, potentially causing financial losses and physical constraint violations [35]. Innovative control methodologies, such as Implicit Invariant-Set-Driven Model Predictive Control (IIS-MPC), mitigate these risks by integrating an implicit representation of a controlled invariant set into a model predictive control framework, ensuring safe operation [36].

With increasing reliance on inverter-based resources, managing reduced inertia from synchronous generators is critical, highlighting the need for advanced CPS integration [37]. Limitations of existing phase-locked loop (PLL) algorithms under low short-circuit-ratio (SCR) and inertia conditions necessitate improved methods for grid angle and frequency estimation for grid-connected voltage source converters (VSCs) [38]. A DRL-based voltage control method enhances resilience and efficiency in energy storage systems by focusing on high-speed state estimation without requiring real-time full system data [3].

Furthermore, the integration of simultaneous wireless information and power transfer (SWIPT) technology in reconfigurable intelligent surfaces (RISs) underscores the importance of cybersecurity and risk management related to energy transfer and control signaling [33]. The decentralized privacy-preserving EV charging control algorithm (DPP-EVCC) employs state obfuscation to protect EV owners' privacy while optimizing charging schedules, emphasizing the critical role of privacy preservation in CPS [39].

2.3 Flexibility and Uncertainty Management

Flexibility and uncertainty management are critical in operating energy storage systems (ESS), particularly with the integration of renewable energy sources and electric vehicles (EVs) into the power grid. The inherent variability and intermittent nature of renewable energy, such as wind and solar, present significant challenges for grid stability and reliability. The flexibility index quantifies a system's ability to maintain feasible operations despite uncertainties, formulated as a flexibility test problem identifying recourse variables to counteract these uncertainties [40].

The integration of EVs complicates uncertainty management due to unpredictable charging patterns. A two-stage online algorithm has been proposed to characterize the aggregate power flexibility of EVs, facilitating effective management of these uncertainties and enhancing energy distribution reliability [7]. This approach is essential for preventing voltage violations and grid congestion, which can arise from inadequate monitoring of uncertainties associated with renewable energy and EV integration [41].

Additionally, cryptocurrency mining operations introduce further complexity, as their electricity consumption data reflect operational flexibility and location-based characteristics [22]. Modeling and analyzing these consumption patterns is crucial for optimizing ESS utilization and ensuring efficient energy management across diverse environments.

In recent years, the advancement of energy storage systems has become increasingly critical in supporting sustainable energy solutions. A comprehensive understanding of these systems necessitates an exploration of their operational strategies, which are essential for optimizing performance and reliability. Figure 2 illustrates the hierarchical structure of these operational strategies, highlighting key categories such as inverter management, coordination, scheduling, and resilience enhancement. Each of these categories is further subdivided into specific methods and techniques, providing a detailed overview of the various approaches employed to enhance system functionality. This structured representation not only clarifies the interrelationships among different strategies but also underscores the complexity involved in managing energy storage systems effectively.

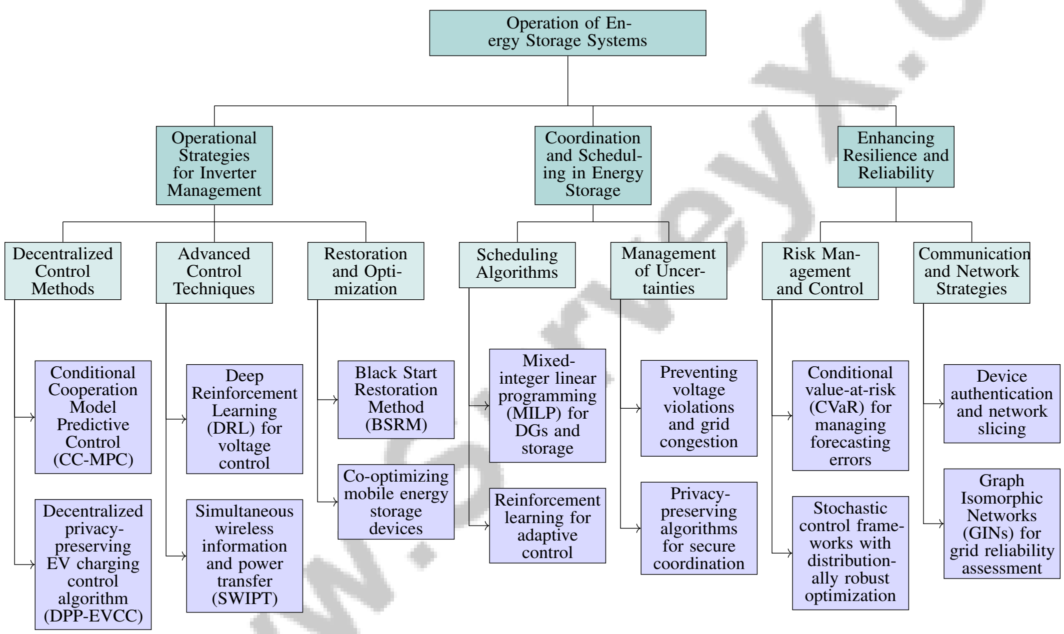

Figure 2: This figure illustrates the hierarchical structure of operational strategies in energy storage systems, highlighting key categories such as inverter management, coordination, scheduling, and resilience enhancement. Each category is further divided into subcategories, detailing specific methods and techniques employed to optimize system performance and reliability.

3 Operation of Energy Storage Systems

3.1 Operational Strategies for Inverter Management

Optimizing inverter management is critical for enhancing energy storage systems, particularly in the context of renewable energy integration. The Conditional Cooperation Model Predictive Control (CC-MPC) method facilitates decentralized power exchange among microgrids, improving operational efficiency and reliability [16]. In photovoltaic (PV) systems, the two-stage Maximum Power Point Tracking (MPPT) method addresses partial shading by continuously adjusting the duty cycle to track the global maximum power point (GMPP), thereby enhancing energy conversion efficiency [6].

Advanced control frameworks, such as Deep Reinforcement Learning (DRL)-based algorithms, frame voltage control as a Markov decision process (MDP) to optimize inverter performance in real-time [3]. The integration of simultaneous wireless information and power transfer (SWIPT) in reconfigurable intelligent surfaces (RISs) enables concurrent reception of control signals and energy, further enhancing system performance [33].

The Black Start Restoration Method (BSRM) employs mixed-integer linear programming (MILP) to coordinate distributed generators (DGs) for restoring islanded microgrids, ensuring reliable inverter operation during restoration [8]. Privacy-preserving strategies, such as the decentralized privacy-preserving EV charging control algorithm (DPP-EVCC), allow electric vehicles (EVs) to obscure charging profiles while optimizing control [39].

These strategies underscore the importance of optimizing inverter management in energy storage systems. As illustrated in Figure 3, the hierarchical categorization of operational strategies for inverter management emphasizes decentralized control, advanced control frameworks, and energy and signal integration methods. Key techniques such as CC-MPC, DRL-based voltage control, and SWIPT are highlighted, showcasing their roles in enhancing energy storage systems and facilitating renewable energy integration. By leveraging decentralized control, sophisticated MPPT techniques, DRL algorithms, and privacy-preserving methods, systems can enhance performance and reliability, which are crucial for renewable energy integration and grid stability. For instance, decentralized algorithms optimize EV charging while safeguarding data, and advanced hydrogen storage solutions in microgrids enhance resilience and reduce costs. Additionally, co-optimizing mobile energy storage devices minimizes energy losses across power and transportation networks, contributing to a more efficient energy ecosystem [39, 42, 43].

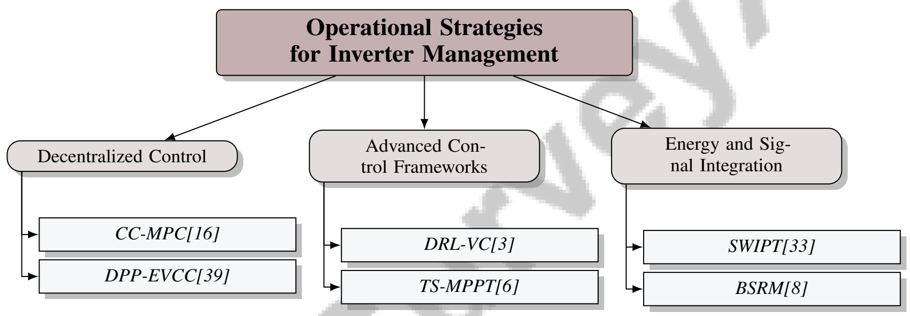

Figure 3: This figure illustrates the hierarchical categorization of operational strategies for inverter management, focusing on decentralized control, advanced control frameworks, and energy and signal integration methods. It highlights key methods such as Conditional Cooperation Model Predictive Control (CC-MPC), Deep Reinforcement Learning-Based Voltage Control (DRL-VC), and Simultaneous Wireless Information and Power Transfer (SWIPT), emphasizing their roles in enhancing energy storage systems and renewable energy integration.

3.2 Coordination and Scheduling in Energy Storage

Effective coordination and scheduling are essential for optimizing energy storage operations, particularly with renewable energy integration and distributed energy resources (DERs). Advanced scheduling algorithms enhance efficiency and reliability by managing the temporal distribution of energy resources, crucial in environments with high renewable penetration where variability requires robust strategies for grid stability [5, 20].

In microgrids, coordinating multiple DGs and storage units is vital for optimizing energy distribution and ensuring reliable operation. Mixed-integer linear programming (MILP) models facilitate optimal scheduling of DGs and storage resources, enhancing microgrid resilience and efficiency [8]. Decentralized market mechanisms dynamically adapt to changing energy demands and generation patterns, optimizing resource coordination [15].

Machine learning techniques, particularly reinforcement learning, enhance scheduling through adaptive and predictive control, enabling real-time optimization of energy resource allocation [5]. Privacy-preserving algorithms ensure secure coordination, protecting sensitive data while optimizing distribution [39].

Managing uncertainties from renewable energy sources and EVs is crucial. Advanced algorithms that account for these uncertainties prevent voltage violations and grid congestion, ensuring reliable and efficient energy supply [7]. Employing these techniques allows energy storage systems to achieve optimized performance, contributing to a resilient and sustainable energy landscape.

3.3 Enhancing Resilience and Reliability

Enhancing the resilience and reliability of energy storage systems (ESS) is crucial for stable power supply, especially with increased renewable energy integration. Risk measures like conditional value-at-risk (CVaR) manage forecasting errors and prevent overvoltage conditions, significantly improving system resilience [44].

Advanced control strategies balance optimal performance with robustness against potential attacks or failures. Stochastic control frameworks incorporating distributionally robust optimization maintain system reliability under various conditions, as demonstrated through simulations [45].

In communication networks supporting smart grid operations, device authentication and slice-based network slicing schemes enhance resilience against communication failures, utilizing dynamic resource allocation to isolate unauthorized access and improve overall ESS reliability [46]. Integrating IT perspectives into smart grid simulations emphasizes robust communication strategies for grid stability, supported by experiments quantifying communication failure impacts [47].

Experimental testbeds enable controlled experimentation and rapid iteration of control schemes, facilitating strategy evaluation and optimization in real-world contexts, thereby enhancing energy storage systems' stability and performance [48].

Maintaining critical coupling strength between generators is essential for stable synchronization and frequency stability, particularly in systems with high renewable penetration. Proper damping values optimize stability metrics, contributing to overall grid resilience [37]. Additionally, Graph Isomorphic Networks (GINs) provide a faster, reliable method for assessing grid reliability, significantly reducing prediction times compared to traditional mathematical optimization approaches [49].

4 Optimization Techniques

4.1 Advanced Algorithmic Approaches

Method Name	Optimization Techniques	Integration Strategies	Energy Management
FCS[50]	Advanced Algorithms	Demand Response	Optimizing Energy Distribution
SWIPT[33]	Optimization Problems	Swipt Methods	Autonomous Updates
BSRM[8]	Graphical Analysis	Demand Response	Load Management
HRL-PNC[28]	Advanced Algorithms	-	Reduce Costs
CHIL[1]	Advanced Algorithms	Hardware-in-the-loop	Energy Distribution
DTA[10]	Advanced Algorithms	Demand Response	Optimizing Energy Distribution

Table 1: This table presents a comparative analysis of various advanced algorithmic methods employed in optimizing energy storage systems. Each method is evaluated based on its optimization techniques, integration strategies, and energy management capabilities, highlighting their roles in enhancing grid reliability and operational efficiency.

Table 1 provides a comprehensive overview of the advanced algorithmic approaches utilized in optimizing energy storage systems, detailing the specific optimization techniques, integration strategies, and energy management methods employed by each approach. Optimizing energy storage systems (ESS) hinges on advanced algorithmic approaches that enhance efficiency and performance. The flexible contract scheme exemplifies innovation by incentivizing demand information disclosure, optimizing demand-side management, and bolstering grid reliability [50]. Simultaneous wireless information and power transfer (SWIPT) methods within reconfigurable intelligent surfaces (RIS) further illustrate algorithmic advancements, optimizing reflective element updates for superior energy management [33].

In microgrid restoration, integrating incentive-based demand response with graphical analysis optimizes restoration sequences, enhancing resilience [8]. Hierarchical reinforcement learning (HRL) reduces action space complexity, improving learning efficiency and optimizing energy distribution [28]. The Controller Hardware-in-the-Loop (CHIL) method combines simulations, modeling, and hardware testing for grid-connected PV inverter evaluation, ensuring stability [1]. Additionally, the demand time-shifting algorithm optimizes electricity consumption periods, mitigating power quality disturbances in low voltage networks [10].

These algorithmic strategies are pivotal in enhancing operational efficiency and energy management. Models like virtual energy storage sharing, optimal configurations for storage during high-demand events, and co-optimization of mobile energy storage devices for electricity and transportation networks exemplify this potential, evidenced by significant reductions in storage investment and user costs [14, 43, 4]. By leveraging sophisticated algorithms, energy infrastructures achieve enhanced resilience and adaptability, fostering a sustainable energy landscape.

4.2 Integration of Machine Learning in Optimization

Incorporating machine learning into energy storage system (ESS) optimization enhances decision-making and operational efficiency. Deep learning architectures, such as Long Short-Term Memory (LSTM) networks, model complex systems and predict consumption patterns, improving forecasting accuracy critical for ESS operations [51]. In cyber-physical systems, deep learning models, like the cyber-attack detection model (CADM) using bidirectional LSTM (BLSTM), enhance security and resilience by detecting cyber threats in real-time [52].

Machine learning also optimizes control strategies within energy systems. The Multi-Agent Reinforcement Learning Embedded in Game theory (MARLEG) methodology merges machine learning with game theory to enhance HVAC control strategies, optimizing energy consumption and efficiency [53]. Unsupervised adversarial autoencoders (AAE) integrated with LSTM networks improve anomaly detection and reliability by capturing temporal dependencies in time-series data [54]. The SNN-RII method employs unsupervised learning for real-time adaptation to dynamic power grid conditions, enhancing energy efficiency [34].

The CHIL method simulates real-world conditions to test PV inverters' compliance with grid codes, particularly focusing on low voltage ride-through (LVRT) capabilities, demonstrating machine learning's impact on operational robustness [1]. These advancements underscore machine learning's transformative role in optimizing energy storage systems, enabling greater efficiency, resilience, and adaptability, contributing to a sustainable energy landscape.

4.3 Multi-Objective and Multi-Stage Optimization

Method Name	Optimization Techniques	Application Domains	Performance Improvements
PAMSO[55]	Derivative-free Optimization	Electrified Chemical Plants	Improved Solution Quality
CMCS[30]	Cascaded Control System	Microgrid Systems	Improved Stability
Microgrid-UC[56]	Two-stage Algorithm	Islanded Microgrid	Improved Energy Management
SOF[57]	Sequential Optimization	Hybrid Electric Vehicles	Energy Savings

Table 2: Summary of optimization methods, their corresponding techniques, application domains, and the specific performance improvements they achieve. The table highlights the diverse applications of multi-objective and multi-stage optimization in energy management systems, including electrified chemical plants, microgrid systems, islanded microgrids, and hybrid electric vehicles.

Multi-objective and multi-stage optimization techniques are crucial for effective energy management, particularly in integrating renewable energy sources and managing distributed energy resources (DERs). These techniques facilitate advanced algorithms, such as constraint-aware reinforcement learning and mixed-integer nonlinear programming models, optimizing complex operational schedules while adhering to critical constraints and managing uncertainties [58, 25, 26, 18, 24]. Table 2 provides a comprehensive overview of various optimization methods applied in energy management, detailing their optimization techniques, application domains, and the performance improvements achieved.

The Parametric Auto-tuning Multi-time Scale Optimization (PAMSO) framework exemplifies advanced multi-objective optimization by transferring optimal parameters across similar problems, enhancing scalability and solution quality [55]. In microgrid systems, adaptive control of power references based on demand fluctuations optimizes energy management and ensures reliable operation [30].

Multi-stage optimization enhances energy management by enabling strategic decision-making at different temporal scales. A novel feeder-level microgrid unit operates in two stages, optimizing operational efficiency and load management by proactively adjusting to anticipated demand and generation fluctuations [56]. In electric vehicles (EVs), sequential optimization techniques utilizing traffic data minimize energy consumption and enhance vehicle efficiency [57].

These techniques improve energy storage systems' performance and efficiency by enabling effective resource management, reducing user costs, and enhancing power systems' reliability amid renewable energy intermittency challenges. They facilitate innovative business models for virtual energy storage sharing and optimize unit commitment under dynamic uncertainties, leading to significant reductions in investment and operational costs while maintaining system stability [59, 26, 14, 11, 43].

4.4 Comparative Analysis of Optimization Methods

Benchmark	Size	Domain	Task Format	Metric
NIE-BM[60]	1,000,000	Hydropower Management	Forecasting	Bias, Mean Absolute Error
QC-OPF[61]	33	Power Systems	Optimal Power Flow	QC Gap
CryptoImpact[22]	1,000,000	Electricity Market Analysis	Impact Assessment	Carbon Footprint, Reliability Index
VT[9]	24	Power System Operations	Day-ahead Energy Scheduling	Operation cost reduction, Average No. of congested lines per hour

Table 3: This table presents a comprehensive overview of representative benchmarks utilized in the analysis of optimization methods within energy systems. It details the size, domain, task format, and performance metrics associated with each benchmark, providing a foundation for evaluating diverse strategies in energy storage and distribution optimization.

The comparative analysis of optimization methods in energy storage systems (ESS) reveals diverse strategies addressing renewable energy integration and grid stability complexities. Distributionally robust optimization frameworks, such as the ECCG method, outperform traditional methods in solution quality and computational efficiency, managing uncertainties in demand and renewable generation [18]. Reliability-constrained power expansion planning incorporates risk measures into power system planning, providing a comprehensive optimization framework for ESS [58].

Advanced grid synchronization methods, like gSRF-PLL and gATAN-PLL, enhance voltage source converters (VSCs) reliability under challenging conditions, optimizing renewable energy integration [38]. Assessing forecast bias in hydropower management through structured benchmarks emphasizes accurate forecasting's importance in optimizing energy storage and distribution [60]. Analyzing graphlet patterns reveals significant correlations with optimization outcomes, providing insights into structural factors influencing optimization [61].

Performance metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE) are crucial for evaluating optimization methods, as demonstrated in the ST-MAN method's analysis, providing a quantitative basis for assessing ESS optimization approaches [62]. Table 3 provides a detailed overview of the representative benchmarks used in the study to assess the efficacy of various optimization methods in energy storage systems.

This analysis underscores diverse strategies to enhance energy storage systems' performance and efficiency. Implementing advanced optimization frameworks, like distributionally robust optimization for transmission expansion planning, and sophisticated synchronization techniques enhances decentralized generators' spatial uniformity, improving resilience and adaptability. Accurate forecasting methodologies account for renewable energy sources' dynamic uncertainties, allowing for more effective unit commitment and operational scheduling, contributing to a sustainable and reliable energy landscape [63, 59, 27, 26, 18].

5 Energy Management and Renewable Integration

The integration of renewable energy sources (RES) into energy management introduces significant challenges and opportunities. This section examines the complexities of renewable generation variability, emphasizing the need for strategies that bolster energy system reliability as reliance on RES grows.

5.1 Challenges in Renewable Integration

Integrating RES with energy storage systems (ESS) is challenging due to the inherent variability of renewable generation, which can destabilize systems, especially in islanded grids [1]. Traditional Optimal Power Flow methods struggle with uncertainties from renewables like wind and solar, necessitating advanced optimization techniques [32]. The complexity of managing large-scale renewable integration is heightened by the high-dimensional state and action spaces in power networks, where conventional algorithms often falter [28]. Furthermore, integrating electric vehicles (EVs) raises privacy concerns due to the sensitive information exchanged with system operators [39].

Reconfigurable intelligent surfaces (RISs) introduce additional complexity with control signaling and energy transfer, particularly when channel estimation errors degrade performance [33]. Demand-side management is also challenged by uncertain demand from large customers, which impacts capacity costs [50]. The practical implementation of Virtual Transmission (VT) adds further complexity to renewable integration with ESS [9]. High-speed voltage control, while reducing real-time data dependency, poses challenges for robust control under varying conditions [3]. Addressing these challenges requires advanced optimization techniques, robust control mechanisms, and accurate forecasting models, essential for efficient and reliable RES integration with ESS, ultimately fostering a sustainable energy landscape [10].

5.2 Communication and Security in Energy Management

Secure communication and robust cybersecurity are critical in modern energy systems, especially with increasing distributed energy resources (DERs) and RES. The rise of DERs introduces vulnerabilities, particularly in peer-to-peer energy trading via IoT devices, necessitating advanced cybersecurity frameworks like deep learning-based detection models to safeguard operations [41, 35, 52, 26]. Privacy concerns in EV charging control are addressed by strategies like the decentralized privacy-preserving EV charging control algorithm (DPP-EVCC), which uses state obfuscation to secure communication between EVs and charging stations [39].

Simultaneous wireless information and power transfer (SWIPT) technology underscores the need for secure communication in energy management by allowing concurrent reception of control signals and energy in RISs, optimizing performance while safeguarding against security breaches [33]. Advanced cybersecurity measures, including deep learning-based cyber-attack detection models, enhance threat detection and response capabilities, ensuring the secure operation of energy storage systems [52].

5.3 Demand Response and Flexibility Measures

Demand response strategies and flexibility measures are vital for optimizing energy management, particularly in integrating RES and managing DERs. These strategies enable systems to adapt to demand and supply fluctuations, ensuring efficient and reliable grid operations [41]. Advanced demand response mechanisms dynamically adjust energy consumption patterns, optimizing supply-demand balance. The unpredictability of RES and stochastic EV consumption patterns pose significant challenges for distribution grids, necessitating robust flexibility measures like advanced grid monitoring and modeling techniques to maintain stability and efficiency under fluctuating conditions [18, 63].

Incentive-based demand response programs enhance system flexibility by motivating consumers to adjust energy consumption in response to price signals or incentives, coordinating between electricity suppliers and large users to manage demand variability, reduce capacity costs, and mitigate future demand uncertainties [50, 11, 15, 13]. This approach optimizes energy consumption and alleviates grid strain during peak demand, contributing to a sustainable energy landscape.

5.4 Optimizing Energy Management in Diverse Environments

Optimizing energy management across diverse environments is crucial for enhancing efficiency and sustainability, particularly in RES integration and DER management. Learning-based model predictive control (LB-MPC) strategies significantly advance energy management, demonstrating substantial fuel savings and effective management in environments like hybrid electric vehicles (HEVs) [17]. In off-grid photovoltaic (PV) systems, energy management optimization must address the long-term performance of Li-ion batteries, particularly in extreme environments [21].

The Tango project's exploration of transparent heterogeneous hardware platforms offers another optimization avenue by refining architecture through real-world applications and developing energy-aware programming models, enhancing system adaptability and efficiency [64]. Additionally, exploring Spiking Neural Networks (SNN) in grid conditions highlights potential for establishing system resiliency without communication layers, with future research focusing on SNNs' online learning capabilities in unseen grid conditions [34].

6 Case Studies and Applications

6.1 Real-World Applications of Shared Energy Storage

Shared energy storage systems (ESS) are pivotal in real-world applications, enhancing energy management and distribution efficiency. The Conditional Cooperation Model Predictive Control (CC-MPC) strategy exemplifies this in interconnected microgrids, as demonstrated in a study involving four microgrids, optimizing power exchange and operational efficiency [16]. Additionally, shared ESS have been applied in energy communities, with a hypothetical community of 20 residential customers illustrating decentralized market mechanisms that enhance energy distribution and community management [15].

The critical role of shared ESS in remote areas is highlighted by an analysis of Li-ion battery systems at Paiyun Lodge over 1376 days, showcasing their ability to manage energy supply and optimize battery performance under varying conditions [21]. Their versatility is further demonstrated through virtual energy storage sharing during events like the Winter Olympic Games, improving transmission operations and reducing energy losses in transportation networks via mobile energy storage devices [14, 9, 43, 4]. These applications underscore the essential role of shared ESS in fostering sustainable and resilient energy infrastructures.

6.2 Integration with Renewable Energy and Grid Management

The integration of ESS with renewable energy sources and grid management is critical for enhancing energy efficiency and grid stability, as evidenced by various case studies. The SNN-RII method, for instance, significantly improves energy efficiency and adaptability, particularly in reactive power sharing and voltage regulation, optimizing renewable energy integration into the grid [34].

Experiments using a distribution network model to manage Thermostatically Controlled Loads (TCLs) further highlight the practical applications of advanced methods in energy system management, facilitating the seamless incorporation of renewable sources into existing grid infrastructures [36]. The IEEE 118-Bus power system serves as a case study for stability-constrained optimization frameworks, enhancing energy management and grid stability, illustrating the efficacy of ESS integration in complex power systems [2].

These case studies underscore the critical role of ESS in supporting renewable energy integration and improving grid management. Advanced optimization techniques and innovative control strategies significantly enhance the efficiency, reliability, and sustainability of modern energy infrastructures. Techniques like stability-constrained optimization frameworks ensure optimal equilibrium in power grids, improving steady-state efficiency and dynamic performance while maintaining stability under disturbances. Intelligent energy management systems such as MetaEMS use reinforcement learning to optimize building operations, reduce costs, and lower greenhouse gas emissions. Constraint-aware deep reinforcement learning algorithms like MIP-DQN facilitate effective scheduling of renewable energy resources by enforcing operational constraints, ensuring real-time feasibility. Collectively, these advancements contribute to a more resilient and efficient energy landscape [2, 26, 5].

7 Future Trends and Research Directions

7.1 Emerging Technologies and Applications

Emerging technologies are pivotal in enhancing the efficiency and adaptability of energy storage systems (ESS), particularly for renewable energy integration. Key advancements include the refinement of simultaneous wireless information and power transfer (SWIPT) methods, which are projected to be evaluated in more complex network environments to improve control and energy transfer

[33]. Additionally, advanced droop control variants and strategies to address the stochastic nature of non-dispatchable distributed energy resources (DERs) in microgrid restoration are promising research areas, aiming to enhance ESS robustness and efficiency [8].

Optimization research is also focusing on integrating N-1 security constraints and improving convergence in chance-constrained AC optimal power flow models, reflecting the need for reliable energy management amid uncertainties [32]. The application of hierarchical reinforcement learning (HRL) frameworks to larger grids, alongside graph neural networks for enhanced representation, is a significant trend in energy management, offering improved capabilities for modeling and optimizing complex systems [28]. Privacy-preserving technologies are evolving, with research aimed at refining obfuscation techniques to protect user privacy during electric vehicle (EV) charging without compromising computational efficiency [39]. Collectively, these advancements are steering the future of ESS towards greater efficiency and adaptability, facilitating the transition to a sustainable energy landscape that effectively manages distributed energy resources and addresses the challenges posed by high shares of variable renewables, ensuring stability in electricity markets while minimizing carbon footprints [22, 11, 13].

7.2 Modeling and Simulation Enhancements

Advancements in modeling and simulation techniques are crucial for optimizing energy storage systems (ESS), particularly in integrating renewable energy sources and managing distributed energy resources (DERs). The development of advanced modeling frameworks, such as stability-constrained optimization for Lure systems, illustrates the potential for enhancing grid stability and energy management through sophisticated simulations [2]. Integrating machine learning into simulation models, like deep reinforcement learning (DRL), enhances predictive capabilities, optimizing real-time voltage control actions in active distribution networks [3].

Graph neural networks (GNNs) represent a significant advancement, providing powerful tools for analyzing complex grid structures and developing accurate, scalable simulation models [28]. Experimental testbeds further validate and refine models under real-world conditions, providing platforms for testing new control strategies and optimization algorithms [48]. These advancements improve the precision and efficiency of simulation models, aiding in forecasting energy demand, optimizing system scheduling, and effectively managing DERs. This approach contributes to a more sustainable and resilient energy landscape, as demonstrated by studies on cryptocurrency mining, residential load coordination, and real-time wind farm optimization [22, 48, 26, 51, 65].

7.3 Economic and Market Considerations

Economic and market dynamics are critical in shaping the development and deployment of energy storage systems (ESS), influencing their strategic direction and operational efficiency. A key consideration is the computational resources required for solving complex optimization problems in larger distribution networks, particularly for optimizing residential photovoltaic (PV) systems where efficient dispatch strategies are crucial for minimizing costs and maximizing energy utilization [44]. As the penetration of variable renewable energy sources (VRES) increases, the profitability of energy arbitrage declines, highlighting the need for innovative market mechanisms and pricing strategies to sustain the economic viability of ESS in high VRES scenarios [11].

Future research should prioritize developing fast computation techniques for large-scale applications in cyber-physical systems (CPS), including power grid management, which are essential for enhancing ESS scalability and efficiency [45]. Exploring nonlinear energy harvesting models and robust designs can offer economic benefits by improving ESS efficiency and reliability [66]. Integrating sophisticated forecasting models that accurately capture trends and biases in natural intermittent energy (NIE) data is another vital research area, enhancing predictive accuracy and operational efficiency for informed economic decision-making [60].

Moreover, developing joint optimization strategies for pre-contingency and during-contingency operations is essential for enhancing microgrid resilience, offering economic advantages by reducing downtime and improving system reliability [42]. Extending algorithms to manage microgrids with multiple grid-forming resources further enhances applicability and robustness, providing economic incentives for broader adoption [56]. Future research should focus on extending the ECCG methodology to explore different ambiguity set configurations, developing metrics for optimal scenario selection, and investigating strategies for managing and updating the scenario set over time [18]. Additionally, refining optimization methods for larger networks and exploring integration with other transit planning aspects are critical for advancing the economic feasibility of ESS [67].

8 Conclusion

The survey underscores the critical importance of optimizing shared and centralized energy storage systems (ESS) to enhance energy management and facilitate the integration of renewable energy sources. The deployment of solar photovoltaic (PV) systems, despite their relatively low penetration, poses challenges to operational stability, necessitating continuous research and adaptive strategies to maintain infrastructure stability. The case study of the off-grid photovoltaic system at Paiyun Lodge highlights the effectiveness of strategic energy management, demonstrated by the Li-ion battery system's impressive capacity retention, which bolsters the durability and stability of the power system.

A comprehensive approach to operations management is advocated, integrating diverse operational elements to achieve strategic goals within the energy sector. The strategic management of ESS, both shared and centralized, is pivotal for optimizing performance, ensuring efficient energy distribution, and supporting the seamless integration of renewable energy. By leveraging advanced optimization techniques, innovative control strategies, and robust cybersecurity measures, energy infrastructures can enhance resilience, adaptability, and sustainability. These efforts collectively contribute to a more reliable and efficient energy landscape, adept at addressing the dynamic challenges associated with the growing integration of renewable energy and the evolving demands of modern energy systems.

References

[1] Christina N. Papadimitriou, Chrysanthos Charalambous, Andreas Armenakis, Zoran Miletic, Werner Tremmel, Anja Banjac, Thomas I. Strasser, Venizelos Efthymiou, and George E. Georghiou. Stability studies for photovoltaic integration using power hardware-in-the-loop experiments, 2023.

[2] Qifeng Li, Qiushi Wang, and Konstantin Turitsyn. A stability-constrained optimization framework for lur'e systems with applications in power grids, 2017.

[3] Mohammad Golgol and Anamitra Pal. High-speed voltage control in active distribution systems with smart inverter coordination and deep reinforcement learning, 2024.

[4] He Meng, Hongjie Jia, Tao Xu, Wei Wei, Yuhan Wu, Lemeng Liang, Shuqi Cai, Zuozheng Liu, and Rujing Wang. Optimal configuration of cooperative stationary and mobile energy storage considering ambient temperature: A case for winter olympic game, 2022.

[5] Huiliang Zhang, Di Wu, and Benoit Boulet. Metaems: A meta reinforcement learning-based control framework for building energy management system, 2022.

[6] Mohammad Amin Ghasemi, Hossein Mohammadian Foroushani, and Mostafa Parniani. Partial shading detection and smooth maximum power point tracking of pv arrays under psc, 2018.

[7] Dongxiang Yan, Shihan Huang, Sen Li, Xiaoyi Fan, and Yue Chen. A two-stage online algorithm for ev charging station energy management and carbon trading, 2024.

[8] Ogbonnaya Bassey and Karen L. Butler-Purry. Islanded microgrid restoration studies with graph-based analysis, 2022.

[9] Qiushi Wang and Xingpeng Li. Evaluation of battery energy storage system to provide virtual transmission service, 2025.

[10] Tomislav Antic and Tomislav Capuder. A geographic information system-based modelling, analysing and visualising of low voltage networks: The potential of demand time-shifting in the power quality improvement, 2023.

[11] Aviad Navon, Juri Belikov, Ariel Orda, and Yoash Levron. On the stability of strategic energy storage operation in wholesale electricity markets (extended version), 2024.

[12] Daniel Munoz-Alvarez and Eilyan Bitar. Financial storage rights in electric power networks, 2017.

[13] Elena Raycheva, Jared B. Garrison, Christian Schaffner, and Gabriela Hug. The value of flexibility in a carbon neutral power system, 2022.

[14] Dongwei Zhao, Hao Wang, Jianwei Huang, and Xiaojun Lin. Virtual energy storage sharing and capacity allocation, 2021.

[15] Ahmed S. Alahmed, Guido Cavraro, Andrey Bernstein, and Lang Tong. A decentralized market mechanism for energy communities under operating envelopes, 2024.

[16] A. K. Sampathirao, S. Hofmann, J. Raisch, and C. A. Hans. Distributed conditional cooperation model predictive control of interconnected microgrids, 2023.

[17] David Theodor Machacek, Stijn van Dooren, Thomas Huber, and Christopher Onder. Learning-based model predictive control for the energy management of hybrid electric vehicles including driving mode decisions, 2023.

[18] Alexandre Velloso, David Pozo, and Alexandre Street. Distributionally robust transmission expansion planning: a multi-scale uncertainty approach, 2020.

[19] Omar E. Godinez-Brizuela, Carolina Duczek, Norbert Weber, and Kristian E. Einarsrud. A continuous multiphase model for liquid metal batteries, 2023.

[20] Paul Stadler, Araz Ashouri, and Francois Marechal. Distributed model predictive control for energy systems in microgrids, 2015.

[21] Hsien-Ching Chung. Long-term usage of the off-grid photovoltaic system with lithium-ion battery-based energy storage system on high mountains: A case study in payiun lodge on mt. jade in taiwan, 2024.

[22] Ali Menati, Xiangtian Zheng, Kiyeob Lee, Ranyu Shi, Pengwei Du, Chanan Singh, and Le Xie. High resolution modeling and analysis of cryptocurrency mining's impact on power grids: Carbon footprint, reliability, and electricity price, 2023.

[23] Taulant Kerci, Manuel Hurtado, Simon Tweed, Marta Val Escudero, Eoin Kennedy, and Federico Milano. Emerging challenges of integrating solar pv in the ireland and northern ireland power systems, 2024.

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

[25] M. Hadi Amini and Orkun Karabasoglu. Optimal operation of interdependent power systems and electrified transportation networks, 2017.

[26] Hou Shengren, Pedro P. Vergara, Edgar Mauricio Salazar Duque, and Peter Palensky. Optimal energy system scheduling using a constraint-aware reinforcement learning algorithm, 2023.

[27] Mi Jin Lee and Beom Jun Kim. Spatial uniformity in power-grid system, 2017.

[28] Blazej Manczak, Jan Viebahn, and Herke van Hoof. Hierarchical reinforcement learning for power network topology control, 2023.

[29] Yifan Gu, He Chen, Yonghui Li, and Branka Vucetic. Exploiting energy accumulation against co-channel interference in wireless energy harvesting mimo relaying, 2016.

[30] Amir Valibeygi, Raymond de Callafon, Mark Stanovich, Michael Sloderbeck, Karl Schoder, James Langston, Isaac Leonard, Sourindu Chatterjee, and Rick Meeker. Microgrid control using remote controller hardware-in-the-loop over the internet, 2018.

[31] Katarzyna Maciejowska, Tomasz Serafin, and Bartosz Uniejewski. Probabilistic forecasting with a hybrid factor-qra approach: Application to electricity trading, 2024.

[32] Line Roald and Göran Andersson. Chance-constrained ac optimal power flow: Reformulations and efficient algorithms, 2019.

[33] Steven Kisseleff, Konstantinos Ntontin, Wallace A. Martins, Symeon Chatzinotas, and Björn Ottersten. Simultaneous control information and power transmission for reconfigurable intelligent surfaces, 2021.

[34] Xiaoguang Diao, Yubo Song, and Subham Sahoo. Inferring ingrained remote information in ac power flows using neuromorphic modality regime, 2024.

[35] Hamed Haggi and Wei Sun. Cyber-physical vulnerability assessment of p2p energy exchanges in active distribution networks, 2022.

[36] Sunho Jang, Necmiye Ozay, and Johanna L. Mathieu. An invariant set construction method, applied to safe coordination of thermostatic loads, 2022.

[37] Mark Walth, Amir Sajadi, Marc Carbone, and Bri-Mathias Hodge. Lunar power grid: Network structure and spontaneous synchronization, 2024.

[38] Daniele Zonetti, Oriol Gomis-Bellmunt, Eduardo Prieto-Araujo, and Marc Cheah-Mane. Passivity-based design and analysis of phase-locked loops, 2022.

[39] Xiang Huo and Mingxi Liu. On privacy preservation of electric vehicle charging control via state obfuscation, 2023.

[40] Joshua L. Pulsipher and Victor M. Zavala. A mixed-integer conic programming formulation for computing the flexibility index under multivariate gaussian uncertainty, 2021.

[41] Manijeh Alipour and Omid Alizadeh-Mousavi. Estimating required flexibility for secure distribution grid operation considering the uncertainties of ev and pv, 2023.

[42] Shreshtha Dhankar, Cong Chen, and Lang Tong. Enhancing microgrid resilience with green hydrogen storage, 2023.

[43] Young-Jin Kim. Optimal v2g and route scheduling of mobile energy storage devices using a linear transit model to reduce electricity and transportation energy losses, 2019.

[44] Emiliano Dall'Anese, Sairaj V. Dhople, Brian B. Johnson, and Georgios B. Giannakis. Optimal dispatch of residential photovoltaic inverters under forecasting uncertainties, 2014.

[45] Nishanth Venkatesh, Aditya Dave, Ioannis Faros, and Andreas A. Malikopoulos. Stochastic control with distributionally robust constraints for cyber-physical systems vulnerable to attacks, 2023.

[46] Jian Zhong, Chen Chen, Yuqi Qian, Yiheng Bian, Yuxiong Huang, and Zhaohong Bie. Secure and scalable network slicing with plug-and-play support for power distribution system communication networks, 2024.

[47] Martin Lévesque, Christophe Béchet, Eric Suignard, Martin Maier, Anne Picault, and Géza Joós. From co- toward multi-simulation of smart grids based on hla and fmi standards, 2014.

[48] Drew A. Geller and Johanna L. Mathieu. Tunable experimental testbed for evaluating load coordination methods, 2023.

[49] Charlotte Cambier van Nooten, Tom van de Poll, Sonja Füllhase, Jacco Heres, Tom Heskes, and Yuliya Shapovalova. Graph isomorphic networks for assessing reliability of the medium-voltage grid, 2023.

[50] Pan Lai, Lingjie Duan, and Xiaojun Lin. Learning large electrical loads via flexible contracts with commitment, 2020.

[51] Nameer Al Khafaf, Mahdi Jalili, and Peter Sokolowski. Application of deep learning long short-term memory in energy demand forecasting, 2019.

[52] Mojtaba Mohammadi, Abdollah KavousiFard, Mortza Dabbaghjamanesh, Mostafa Shaaban, Hatem. H. Zeineldin, and Ehab Fahmy El-Saadany. A cyber-physical architecture for microgrids based on deep learning and lora technology, 2023.

[53] Jun Hao. Multi-agent reinforcement learning embedded game for the optimization of building energy control and power system planning, 2019.

[54] Mehdi Jabbari Zideh, Mohammad Reza Khalghani, and Sarika Khushalani Solanki. An unsupervised adversarial autoencoder for cyber attack detection in power distribution grids, 2024.

[55] Asha Ramanujam and Can Li. Pamso: Parametric autotuning multi-time scale optimization algorithm, 2024.

[56] Rongxing Hu, Ashwin Shirsat, Valliappan Muthukaruppan, Si Zhang, Yiyan Li, Lidong Song, Bei Xu, Victor Paduani, Ning Lu, Mesut Baran, and Wenyuan Tang. A novel feeder-level microgrid unit commitment algorithm considering cold-load pickup, phase balancing, and reconfiguration, 2023.

[57] Mohammad Reza Amini, Xun Gong, Yiheng Feng, Hao Wang, Ilya Kolmanovsky, and Jing Sun. Sequential optimization of speed, thermal load, and power split in connected hevs, 2019.

[58] Luiz Carlos da Costa Jr. au2, Fernanda Souza Thomé, Joaquim Dias Garcia, and Mario V. F. Pereira. Reliability-constrained power system expansion planning: A stochastic risk-averse optimization approach, 2019.

[59] Alvaro Lorca and Xu Andy Sun. Multistage robust unit commitment with dynamic uncertainty sets and energy storage, 2016.

[60] Arthur Brigatto, Alexandre Street, Cristiano Fernandes, Davi Valladao, Guilherme Bodin, and Joaquim Dias Garcia. Assessing the optimistic bias in the natural inflow forecasts: A call for model monitoring in brazil, 2024.

[61] Nafis Sadik and Mohammad Rasoul Narimani. Assessing the impact of higher order network structure on tightness of opf relaxation, 2023.

[62] Sungho Suh, Dhruv Aditya Mittal, Hymalai Bello, Bo Zhou, Mayank Shekhar Jha, and Paul Lukowicz. Remaining useful life prediction of lithium-ion batteries using spatio-temporal multimodal attention networks, 2024.

[63] Amritanshu Pandey, Marko Jereminov, Martin R. Wagner, David M. Bromberg, Gabriela Hug, and Larry Pileggi. Robust power flow and three-phase power flow analyses, 2018.

[64] Karim Djemame, Django Armstrong, Richard Kavanagh, Jean-Christophe Deprez, Ana Juan Ferrer, David Garcia Perez, Rosa Badia, Raul Sirvent, Jorge Ejarque, and Yiannis Georgiou. Tango: Transparent heterogeneous hardware architecture deployment for energy gain in operation, 2016.

[65] Trevor Werho, Junshan Zhang, Vijay Vittal, Yonghong Chen, Anupam Thatte, and Long Zhao. Scenario generation of wind farm power for real-time system operation, 2021.

[66] Zheng Chu, Pei Xiao, De Mi, Wanming Hao, Mohsen Khalily, and Lie-Liang Yang. A novel transmission policy for intelligent reflecting surface assisted wireless powered sensor networks, 2021.

[67] Rémi Lacombe, Nikolce Murgovski, Sébastien Gros, and Balázs Kulcsár. Integrated charging scheduling and operational control for an electric bus network, 2023.

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.