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SURVEY

AI Technologies and Their Applications in Small-Scale Electric Power Systems

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ABSTRACT As the landscape of electric power systems is transforming towards decentralization, small-scale electric power systems have garnered increased attention. Meanwhile, the proliferation of artificial intelligence (AI) technologies has provided new opportunities for power system management. Thus, this review paper examines AI technology applications and their range of uses in small-scale electrical power systems. First, a brief overview of the evolution of small-scale electric power systems and the importance of AI integration is given. The background section explains the principles of small-scale electric power systems, including stand-alone systems, grid-interactive systems, microgrids, hybrid systems, and virtual power plants. A thorough analysis is conducted on the effects of AI technologies on power system aspects such as energy consumption, demand response, grid management, operation, energy generation, and storage. Based on this foundation, AI Acceleration Performance Indicators (AAPIs) for small-scale electric power systems are developed to establish a standardized framework for evaluating and comparing different studies. AAPI framework considers a binary scoring for five quantitative Key Performance Indicators (KPIs) and five qualitative KPIs examined through a three-tiered scale – established, evolved, and emerging.

INDEX TERMS Artificial intelligence, electric power systems, performance indicators.

I. INTRODUCTION

A. BRIEF OVERVIEW OF THE EVOLUTION OF SMALL-SCALE ELECTRIC POWER SYSTEMS

Significant developments in societal expectations, regulatory frameworks, and technology paradigms have shaped the evolution of small-scale electric power systems. Small-scale systems have historically served isolated locations or sectors, taking on a supporting role to centralized power grids. Due to technological breakthroughs, renewable energy sources have become more prevalent over time, and power generation equipment has become more affordable, propelling small-scale systems to become an essential component of modern-day sustainable energy solutions [1].

Decentralized energy production emerged in the early 20th century when small-scale systems used local resources like wind and water to produce electricity. These systems were distinguished by their independence from large-scale grids, and their location frequently served rural populations. There was a technological innovation boom in the late 20th century, especially in the area of renewable energy. Photovoltaic cells, wind turbines, and other clean energy technologies grew more efficient and affordable, as demonstrated by the increase in solar energy output from 30 GW to 118 GW and wind energy production from 78 GW to 167 GW within the European Union between 2010 and 2019 [2].

The need to switch to carbon-neutral energy sources has become more pressing due to growing worries about climate change and environmental pollution. As essential parts of the broader energy infrastructure, small-scale electric power systems are crucial in reducing the carbon footprint of conventional energy sources [3]. Nations all across the globe have pledged to cut greenhouse gas emissions and move toward sustainable energy practices under international

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agreements like the Paris Agreement [4]. Since small-scale electric power systems allow for localized, clean energy production with lower transmission losses, they provide a reasonable and practical solution to meet these global sustainability targets.

Although small-scale systems have evolved promisingly, there are still challenges, especially when incorporating fluctuating renewable energy sources. Advanced solutions like aggregated energy flexibility are required for efficient grid management because of the operational problems posed by the intermittent and variable nature of renewable energy sources like solar and wind [5]. In addition to benefiting the environment, small-scale electric power systems empower nearby communities by promoting energy independence, creating job opportunities, and boosting the local economy [6]. Decentralized energy resources in small-scale systems improve community sustainability overall and increase resilience to disruptions from the main grid.

B. IMPORTANCE OF INTEGRATING AI TECHNOLOGIES IN MODERN ENERGY SYSTEMS

The incorporation of artificial intelligence (AI) technology presents unique potential for enhancing the performance and reliability of small-scale electric power infrastructures. By employing machine learning, predictive maintenance algorithms can evaluate past data, identify patterns, and anticipate equipment breakdowns before they happen [7]. This lowers total maintenance costs by extending the lifespan of crucial components and minimizing downtime [8].

AI-powered load forecasting models make real-time energy demand forecasts possible, making grid management and resource allocation more effective [9]. These models improve the flexibility of small-scale systems by analyzing variables like user behavior, weather patterns, and past consumption data, guaranteeing that supply and demand are balanced [10]. Given that renewable energy sources are naturally uncertain, this capability becomes even more essential.

The introduction of AI-powered smart grid technologies is revolutionizing energy transmission, distribution, and usage. Fig. 1 demonstrates the components of small-scale power systems, which are the scope of this review paper. AI algorithms make real-time grid monitoring and control possible, allowing for automatic response to changing conditions. In addition to improving grid stability, it regulates fluctuations and keeps a steady supply of power, which facilitates the integration of various energy sources, including renewables [11].

AI plays a crucial role in coordination and control as small-scale electric power systems adopt increasingly decentralized energy resources. Decentralized energy management systems use AI to balance loads, optimize power flows, and coordinate the use of various energy sources. This raises the system's overall efficiency and strengthens the grid's resistance to disturbances [12].

Because renewable energy resources, such as wind and solar power, are unpredictable, sophisticated forecasting methods are required. To generate reliable renewable energy generation forecasts, AI algorithms analyze meteorological data, historical trends, and current conditions [13]. This makes it possible for grid operators to effectively incorporate renewable energy into small-scale power systems and manage fluctuations proactively.

For small-scale electric power systems to balance supply and demand, energy storage systems need to be optimized - AI technologies are key to this process. Optimizing energy storage devices' charging and discharging processes enhances their lifespan and efficiency, which is achieved via machine learning algorithms that analyze demand patterns, weather forecasts, and grid conditions [14].

Demand response programs powered by AI enable users to actively participate in energy-saving activities. These technologies help to increase overall energy efficiency and sustainability by allowing users to modify their energy consumption according to grid conditions through intelligent automation and real-time communication [15].

The paper is organized as follows: Section II provides background information on small-scale electric power systems. Section III is dedicated to an in-depth analysis of the existing literature related to AI applications in small-scale electric power systems. Section IV discusses the findings and proposes AI Acceleration Performance Indicators (AAIPs) that enable evaluating and comparing different studies. Section V concludes the review paper with relevant findings.

C. RELATED WORK AND MOTIVATION

The deployment of AI in power systems has become topical in the scientific literature as the number of publications related to deep learning and electric power systems in the ScienceDirect database has grown from around 20 in 2015 to 200 in 2019 [16]. Review articles related to this paper primarily focus on AI's applications in power systems [17], [18]. For example, the research status in the operation, optimization, control, dispatching, and management of Smart Grid and Energy Internet fields using AI has been reviewed in [19], where it was found that the bottlenecks for future development include the lack of training datasets, the interpretability and reliability of models, and semantic reasoning issues of language models. Machine learning algorithms, such as Support Vector Machines (SVMs) and Gradient Boosting Machines (GBMs), have been utilized to predict energy consumption patterns with high accuracy, enabling more efficient demand response and load forecasting [20], [21]. AI supports VPPs by optimizing the utilization of renewable resources based on their availability and demand predictions [22]. Deep learning models, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have demonstrated exceptional capability in identifying and diagnosing faults within microgrids, thus reducing downtime and maintenance costs [23], [24].

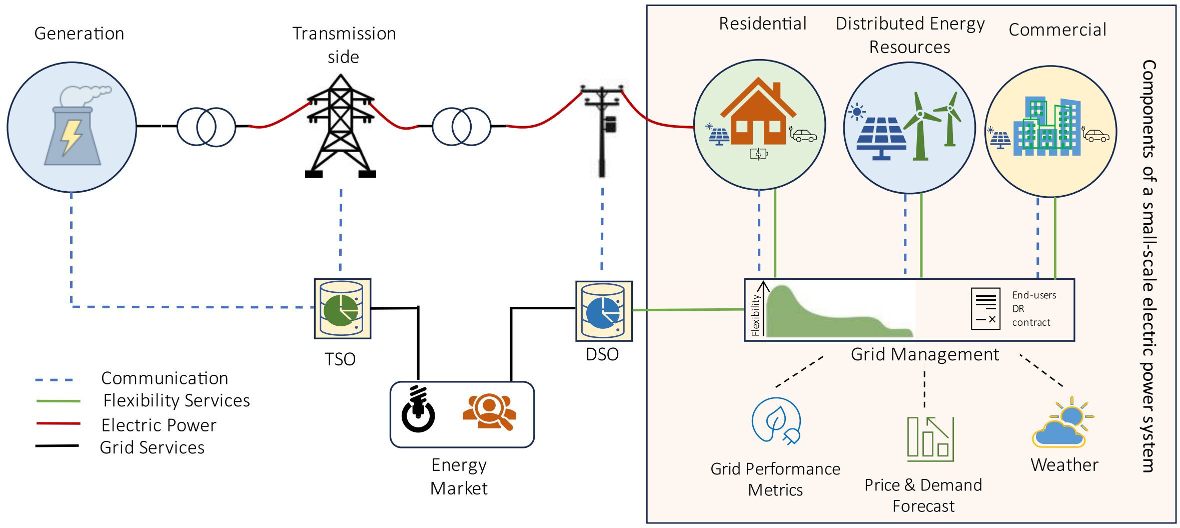

FIGURE 1. **Illustration of the structure of a power system.**

Furthermore, reinforcement learning approaches, including Deep Q-Networks (DQNs) and Proximal Policy Optimization (PPO), have been utilized to optimize microgrid operations and manage distributed energy resources more effectively, thereby enhancing overall system performance and sustainability [25], [26]. The authors of [27] reviewed Explainable Artificial Intelligence techniques for energy and power systems. The application of resilience enhancement of power systems using AI was reviewed by the authors of [28], who concluded that supervised deep learning is particularly suited for anomaly detection, classification, and damage detection. In contrast, unsupervised deep learning methods are suitable for defending against cyber-attacks. Thus, the research has primarily focused on AI applications in power systems; however, to the authors' best knowledge, there is a lack of research in evaluating and benchmarking the efficacy of AI implementations in electric power systems. Therefore, the motivation of this research paper is not only to give a comprehensive review of AI applications in small-scale electric power systems but also to provide a framework for evaluating and benchmarking the efficacy of AI implementations using the AAPI framework developed in this paper.

D. REVIEW METHODOLOGY

A thorough literature search was conducted across major academic databases such as Scopus, ScienceDirect, and IEEE Xplore. The search strategy included a combination of the following keywords and many more: "AI technologies," "small-scale electric power systems," "microgrids," "energy consumption," "demand response," "grid management," "energy generation," and "energy storage." The focus was on newer studies conducted from 2019 to 2024.

The inclusion criteria for selecting relevant studies include peer-reviewed journal articles and conference papers that specifically address the focus of this study, namely the impact of AI technologies in small-scale electric power systems. Studies that either provided insufficient information about the uses of AI technology or did not explore the relationship between AI and small-scale electric power networks were excluded from the analysis.

The key themes of the literature were identified through systematic data extraction. The data was compiled into tables based on which the objectives, methodologies, AI models, key findings, and limitations of existing research can be analyzed.

II. FUNDAMENTALS OF SMALL-SCALE ELECTRIC POWER SYSTEMS

The effective operation of small-scale electric power systems is essential in meeting the changing energy demands. The basic concepts of these systems, which include standalone, grid-interactive, microgrid, hybrid, and other configurations, including Virtual Power Plants (VPPs), are examined in this section.

A. STANDALONE SYSTEMS

Reliable electricity supply in isolated or off-grid places relies heavily on small-scale electric power systems, mainly standalone designs. These systems have become essential in addressing issues related to energy access because of their independence from the main grid [29]. Standalone systems include devices such as production units, energy storage, and loads. Energy is produced with diesel generators, combined heat and power units, or renewable energy sources like solar or wind. At the same time, the storage, which usually takes the form of batteries, guarantees a steady supply of electricity at times when production is low. Optimizing the performance of standalone systems requires understanding how these components interact [30].

Although standalone systems provide energy independence, they have maintenance, fuel supply, and reliability issues. Despite these challenges, standalone systems are viable for some applications due to their flexibility, autonomy, and lower environmental impact [31]. Examples from real life demonstrate the adaptability and efficiency of standalone systems [32]. Applications for standalone systems are diverse; they can be used to power distant communication stations or provide electricity in rural areas or areas affected by disasters. In situations when grid access is difficult or economically unreasonable, these systems showcase their importance in meeting energy demands [33].

B. GRID-INTERACTIVE SYSTEMS

Grid-interactive systems are a type of small-scale electric power systems that integrate with the main grid. By enabling bidirectional power flow, these systems allow an interchange of electricity between the main grid and the local power sources [34].

Integrating grid-interactive equipment with the main grid is a crucial component that makes a consistent and dependable power supply possible. Grid compatibility and control methods are subject to additional challenges in the context of bidirectional power flow, allowing electricity to be provided to and consumed from the grid [35].

Grid-interactive systems have several advantages, such as improved energy efficiency and higher reliability, thanks to grid assistance. However, for deployment to be effective, obstacles to maintaining grid stability and resolving regulatory concerns must be carefully considered [36].

C. MICROGRIDS

Microgrids represent a significant shift in small-scale electrical power systems, offering localized control and independence. Microgrids are characterized by having the ability to function both autonomously and alongside the main grid, i.e., in off-grid or on-grid modes. These attributes are among the major reasons for their increasing appeal. There are several use cases of microgrids, each designed to meet specific requirements, e.g., community, campus, and remote microgrids [37]. It is necessary to understand these distinctions to develop microgrids that meet the particular needs of various settings.

Microgrid management is greatly aided by advanced control systems, which ensure optimal performance and coordination between various energy sources. The responsiveness and flexibility of microgrid systems are improved by integrating intelligent technologies such as optimization and machine learning algorithms [38]. Enhancing power supply reliability is one of microgrids' distinguishing features. Microgrids play an important role in attaining energy security and contribute to grid stability by offering localized solutions to energy-related problems [39].

D. HYBRID SYSTEMS

Hybrid systems are a complex solution to small-scale electric power systems since they integrate multiple energy sources. These systems combine the benefits of many technologies by integrating renewable energy sources with conventional generators [40]. The viability and versatility of this technique are demonstrated by examples of hybrid systems, such as wind-hydro or solar-diesel combinations. Intermittency-related issues are resolved by combining renewable and conventional sources to ensure a more steady power output [41]. Other benefits include better environmental sustainability, decreased dependency on fossil fuels, and enhanced efficiency. However, the challenges in designing and integrating complex systems call for both careful planning and innovative technologies [42].

E. VIRTUAL POWER PLANTS

The concept of Virtual Power Plants (VPPs) is new in the world of small-scale electric power systems. These designs provide a scalable and adaptable solution by combining distributed energy resources through the use of modern technologies. Due to their ability to coordinate operations centrally, VPPs are essential for optimizing the usage of distributed resources [43]. Beyond conventional power generation, VPPs are also applicable for energy storage and demand-side control, which improves system efficiency as a whole [44]. Improved stability of the grid, effective resource use, and a lower carbon footprint are just a few of the economic and environmental advantages that come with the deployment of VPPs [45]. It is anticipated that as technology develops, VPPs will have an even more significant impact on small-scale electric power systems.

III. AI APPLICATIONS IN SMALL-SCALE ELECTRIC POWER SYSTEMS

Integrating Artificial Intelligence into small-scale electric power systems presents a promising opportunity for managing and optimizing energy resources distinct from those encountered in large-scale systems. While AI's applications in both contexts aim to enhance efficiency, reliability, and optimization, the scale of operation significantly influences the nature and impact of these applications.

In small-scale systems, the applications of AI range from enhancing the efficiency and reliability of distributed energy resources, such as through predictive maintenance, optimal segmentation of renewable sources, and accurate forecasting, to optimizing battery energy storage and consumption by predicting remaining useful life (RUL), SoC patterns, and charging and discharging times. AI in these settings is focused on enhancing local grid stability, managing dynamic load, and integrating a higher proportion of renewable energy sources. Due to the smaller scale, AI-driven strategies are more agile, tailored to local conditions, and responsive to rapid changes in demand and supply. It plays a pivotal role in intelligent load management and demand response, providing dynamic pricing strategies and balancing supply and demand while predicting consumer behavior for optimized energy distribution. Furthermore, AI significantly boosts small-scale grid management by enabling real-time anomaly detection, predictive maintenance, and dynamic reconfiguration in microgrids to enhance grid stability and resilience and maintain continuous and efficient power delivery.

On the other hand, AI applications in large-scale power systems typically deal with the complexity of interconnected networks and centralized generation facilities, focusing more on high-level grid management, large-scale energy trading, and maintaining the reliability and security of supply across vast geographical areas.

The scope of AI in small systems extends to sophisticated applications such as coordinating VPP and community energy systems, aggregating, and intelligently managing diverse energy resources. Following the overview, the subsequent sections will thoroughly discuss the specifics of each area, exploring the enhancement of energy generation, storage, consumption, grid management, and advanced applications within small-scale electric power systems through AI technologies.

A. ENERGY CONSUMPTION AND DEMAND RESPONSE

In the domain of small-scale electric power systems, the application of artificial intelligence in energy consumption and demand response offers model-free solutions as compared to traditional mathematical models to analyze consumption patterns, predict demand peaks, exploit consumer energy flexibility, and implement dynamic load adjustments, perform real-time pricing and offering innovative solutions for intelligent energy management at both household and building scales either with residential or community settings.

A DRL algorithm to schedule ESS and HVAC loads in a smart home without building thermal dynamics is proposed in [46]. The results indicate 8.10%–15.21% cost minimization compared to rule-based control approaches. In [47], the Temporal Convolutional Networks (TCNs) are utilized for community energy management using PV and ESS. Energy consumption optimization includes data-driven models for occupant behavior, user comfort, and RES management using Random Forest [48], NARX ANN [49], DNN [50], and Q-Learning [51]. Similarly, energy demand prediction for economic and energy savings is also a key aspect of DR strategies. In the literature, authors employed different machine-learning techniques for short-term [52], [53], [54] and day-ahead load forecasting [55], [56], [57] to enhance consumer engagement in energy trading, renewable energy integration, and dynamic tariff schemes. Table 1 comprehensively examines AI-driven strategies for enhancing energy consumption patterns and refining demand response mechanisms for small-scale electric power systems.

B. GRID MANAGEMENT AND OPERATIONS

Energy fluctuations from intermittent renewable energy generations introduce vulnerability in grid operations [69]. ML plays a crucial role in transforming grid management, particularly in enhancing the capabilities for on-grid system optimizations, dynamic reconfiguration in microgrids, and anomaly detection in power systems. For example, the LSTM-based reinforcement learning model improved renewable energy integration and load balancing optimization in a smart grid with 92% accuracy as compared to other ML algorithms [70]. On-grid system optimization involves interactions between various microgrid components such as consumers, renewable energy producers, electricity suppliers, and storage systems. This interaction is characterized by dynamic reconfiguration, adapting microgrid operations to varying factors like renewable energy production, consumption patterns, and storage capacities [71]. A techno-environmental-economic strategy using multi-agent DRL for microgrid planning and optimization is presented in [72]. Effective grid management requires improved prediction stability of microgrids. This includes load-shifting, demand offsetting, decision-making in virtual power plants, and providing ancillary services, thereby focusing on urban scales and their inherent complexities [73]. To ensure grid reliability and security, federated learning techniques allow for on-device model training and parameter updating, significantly enhancing privacy and reducing data transmission requirements. These approaches, secured with SSL/TLS protocols, effectively mitigate challenges related to bandwidth, latency, and security, aligning with stringent privacy regulations [74]. To provide security to client data in microgrids from being compromised, a CNN-BiLSTM categorization criterion for cyber-attacks has shown a success rate of 99% compared with traditional approaches [75]. Table 2 summarizes the research on AI applications in grid management and operations of small-scale electric power systems.

C. ENERGY GENERATION

Smart grid technology has enabled the potential benefits of RES for consumers in small-scale electric power systems. In this context, the application of AI becomes instrumental in enhancing energy generation capabilities by optimally positioning and controlling RES to maximize the efficiency of these installations, specifically for the task of maximum power point tracking (MPPT) and adaptive power management [76]. By analyzing historical data from various sensors, AI algorithms predict potential failures, remaining useful life (RUL), and schedule timely maintenance of equipment, thus minimizing downtime and extending the lifespan of the generation equipment. Furthermore, accurate solar irradiance and wind speed forecasts enable proper load scheduling and grid power allocation, ensuring a steady and reliable energy supply [77]. A SHAP cat-boost algorithm improves MPPT control in PV systems by minimizing steady-state error during low irradiance and partial shading conditions [78].

TABLE 1. Summary of AI studies for energy consumption and demand response.

Ref.	Objective	AI Technology	Data Source	Methodology	Scale	Key Findings	Limitations	Further Research
[58]	Efficient residential demand control	Deep Learning	German building dataset for PV and WWO API for weather data	rTPNN-FES algorithm for concurrent RES forecasting and appliance scheduling optimization	Household	Single algorithm provides near-optimal appliance scheduling 37.5 times faster than traditional methods	Lacks integration of thermal models with HVAC control systems	Application to microgrid dispatch and intelligent energy distribution
[59]	Manage energy demand by exploiting consumer flexibility for participation in energy trading	Deep Learning	MATLAB simulation data	LSTM for demand predictions and matrix-based control system to maximize RES consumption	Community	21% demand reduction during DR events, 15% reduced interaction with the electricity network	Only considers residential load	Integration with other renewable sources and wider geographical application
[60]	Analyze energy consumption patterns to enhance consumer engagement in energy markets	Unsupervised Learning, Data Mining	Five house data UK-Dale dataset	K-means clustering for appliance-time association and FP Growth for appliance-to-appliance association.	Household	Identification of Appliances of Interest for efficient demand management and end-user participation	Focuses on the frequency of appliance usage rather than their actual energy consumption or duration of use.	Predicting appliance usage on a short-term and long-term basis to analyze consumer preferences
[61]	Characterize the flexibility of residential electricity consumption for demand response	Interactive Learning (IL)	IRISE Energy dataset	NILM for disaggregation, Random Forest to estimate appliance ON-OFF events, and k-means for flexibility curves	Residential	High accuracy in characterizing flexible appliances using IL-based disaggregation	Limited to low-resolution smart-meter data	Integration of more diverse datasets, including EVs, solar PV, and batteries
[62]	Balance energy consumption and production in buildings to work as a local power plant	Machine Learning	DesignBuilder Simulation	By managing energy supply and demand using PV systems, XGBoost is used to predict future energy balance.	Urban Building Complex	Surplus energy generation from April to December for peak demand management	Accurate system modeling challenges, need for extensive data	Optimizing PV plant siting and operation to maximize profits
[63]	Improve Short-term Load Forecasting accuracy and privacy for residential users	Federated Learning	Australian SGSC customer dataset	K-means based privacy-preserving user clustering with a hierarchal federated ANN forecasting model to enhance fault tolerance	Residential	Compared with benchmark methods, 37.25% improvement in prediction accuracy	Vulnerable to eavesdropping attacks, does not account for social relationships in clustering	Expansion to diverse residential environments, Integration of encryption technologies for enhanced security
[64]	Optimize energy management through occupancy forecasting	Semi-supervised, Deep Reinforcement Learning	Real-world datasets from Belgium and Germany	LSTM integrated LTPWE for occupancy estimation integrated with SAC for energy scheduling	Residential and Commercial	Reduced energy cost by 18.79%–55.79% without sacrificing thermal comfort	Dependency on ambient data quality and labeling frequency	Optimization with varying environmental conditions
[65]	Optimize energy consumption and maximize user comfort	Transfer Learning	UK-DALE, REFIT datasets	Deep Q-learning is employed to transfer knowledge from the expert's	Household	Significant reduction in energy consumption with minimum user discomfort	Preprocessing and fine-tuning requirements in knowledge transfer	Use of graph neural networks for enhanced TL efficiency

TABLE 1. *(Continued.)* **Summary of AI studies for energy consumption and demand response.**

	in smart homes			home to the learner's home.				
[66]	Optimize energy consumption in the home energy management system	Deep Reinforcement Learning (DRL)	UK Power Networks and Nordpool database.	DRL is utilized in an MDP framework with a state set of appliances, EV, and ESS attributes, and a reward function	Household	Minimized electricity cost and reduced transformer load. Power peak cut of 24% in some instances	Black-box nature of DRL, high-dimensional state-action space	Interpretability and scalability of the DRL model
[67]	Designing DR programs for prosumers	Clustering Algorithms	Smart meter data from Italian utility	Utilized k-means, k-medoids, and agglomerative clustering to identify and optimize DR program for prosumers	Community	Effective DR segmentation minimized reverse power flow, a PPS of 0.689 for k-means	Low volume of data, limited to a specific community	Deployment as an application for aggregators, incorporating forecasts and dynamic DR strategies
[68]	Mitigate high rate of change of frequency in PV-operated grid systems	Deep Learning	Grid emulator data with PV systems, Malaysia	Development and testing of ANN-based DR controller for frequency regulation in high PV intermittency areas	University Campus	Reduced frequency deviation by 23%, improved ROCOF by 19.7%	Specific to conditions near the equatorial line, requires high-quality data	Expansion to different geographic and grid conditions

A Q-learning-based control strategy has identified optimal equilibrium policies for various power system operating conditions and improved control performance by around 10% compared to other ML algorithms [79]. Similarly, for predicting the RUL of rotating machines, a DNN-based model is utilized that considers time–frequency-wavelet joint features to effectively represent the degradation of bearings [80]. A deep learning-based RNN model is designed to forecast short-term intra-hour solar irradiance by using infrared sky images, resulting in reduced algorithm computational cost and grid operational cost with high participation of solar energy [81]. Table 3 provides a detailed overview of AI applications for optimizing energy generation in small-scale electric power systems.

D. ENERGY STORAGE

Efficient energy storage management is essential for the effectiveness and reliability of small-scale electric power systems that rely on intermittent renewable energy sources, such as solar and wind [101]. The development of energy storage system (ESS) technologies such as compressed air, flywheel, pumped hydro storage, and batteries can increase the ESS capacity to store energy from power grids. This stored energy can then be used when needed. The advancement of ESS technologies with microgrid utilization has created a large market for ESS to offer bulk energy storage, transmission and distribution support, ancillary services, and energy management solutions [102]. AI technologies significantly enhance the capabilities and functionalities of ESS by providing battery-based control and monitoring solutions, predicting battery health, optimizing charging cycles based on real-time energy demands, and identifying degradation patterns [103]. A predictive control mechanism has demonstrated an 84% overall efficiency in microgrid peak shaving by managing the flow rate of energy storage systems for stable power generation [104]. To improve the real-time charging/discharging decision-making of ESS, RL-based actor-critic agents are used to optimize the power flow while minimizing the energy cost [105]. Battery state of health is determined with a mean absolute error of 1.39% by using a simple ANN with a small amount of data. This helps optimize the operation and management of energy storage systems [106]. A degradation model of lithium batteries is developed to predict the remaining useful life using ensemble learning methods for fault diagnosis during the equipment operation service period to ensure an effective energy supply [107].

Table 4 analyzes AI-based techniques to improve the operation of energy storage systems in small-scale electric power systems.

IV. DISCUSSION

A. AI ACCELERATION PERFORMANCE INDICATORS (AAPIS) FOR SMALL-SCALE ELECTRIC POWER SYSTEMS

In the rapidly evolving field of small-scale electric power systems, the integration of AI has shown promising potential. However, a critical gap exists in the standardization of evaluating and comparing the diverse AI methodologies being employed for similar tasks. This requires a set of baseline assessment parameters to establish a standardized

TABLE 2. Summary of AI studies for grid management and operations.

Ref.	Objective	AI Model	Data Source	Methodology	Scale	Key Findings	Limitations	Further Research
[82]	Implementing efficient energy management in microgrids	Deep Reinforcement Learning	Data from Institut Polytechnique de Paris microgrid	Deep LSTM for time series prediction, ILP for optimal action calculation, and reinforcement learning for decision-making	Microgrid	DRL system achieves up to 95% accuracy compared to optimal actions, outperforming the Q-learning method	Complexity in model representation with ILP, long execution time of Q-learning	Further exploration of DRL in various use cases, including deployment on micro-controllers
[70]	Optimize renewable energy production in smart grids	Deep Learning, Reinforcement Learning	Smart Meter Power Consumption Data in London Households	LSTM-RL for demand patterns; RL-SA for load balancing; CNN-PSO for energy production forecasting	Smart Grid	LSTM-RL accuracy: 0.92; RL-SA load balancing accuracy: 0.91; CNN-PSO's RMSE: 18.57.	Reliance on precise input data, computational complexity in large-scale systems	Dynamic pricing and DR strategies, alternative optimization methods
[83]	Enhance Smart Grid security via theft detection	Federated Learning	US Open Energy Data Initiative (OEDI) portal	FL-ConvGRU decentralized model for theft detection by capturing spatial patterns and temporal dependencies	Smart Grid	High efficacy in detecting theft with data privacy at 0.980 accuracy, 0.970 Recall, 0.980 F1-Score	Complexity of the model and data synchronization	Hyperparameter optimization, alternative deep-learning architectures for improved theft detection
[84]	Simulate critical scenarios to optimize smart grid operation and flexibility	Deep Learning, Reinforcement Learning	European ebalance-plus project data	LSTM for prediction, DQN for optimizing multi-agent systems to achieve operational flexibility	DC Microgrid	Optimal actions were achieved with 90% accuracy in consumption patterns and NMAE of 0.72	System's non-scalability due to environmental requirements	Expand scalability with a more dynamic environment definition
[85]	Energy management in vehicular ad hoc networks (VANETs) using IoT and microgrids	Reinforcement Learning	VANET system data	Variational Encoder NN algorithm within an IoT-based edge cloud computing framework and integration with smart microgrid architecture	Microgrid	The model achieved 96% energy efficiency while reducing communication overhead by 55%	Security, privacy, interoperability in VANET-Cloud	Addressing VANET-Cloud challenges
[86]	Improve smart grid prediction stability to enhance system efficiency	Supervised Learning	UCI ML database	Cascade ML system with feature selection and FCMFW-Bagged Tree algorithm-based classification.	Smart Grid	Achieved 99.9% accuracy in predicting SG stability	Specific to the dataset used, may require adaptation for other SG systems	IoT-based E-stability determination systems
[87]	Identify and classify transient conditions in microgrid	Supervised Learning	MATLAB simulation of WBREDA and WBSEDCL distribution system	Signal processing through Discrete Wavelet Transform.	Microgrid	100% accuracy in detecting and discriminating transient events	Generalizability to different microgrid configurations or noise sensitivity.	Exploration of transient events and grid-connected hybrid network

TABLE 2. *(Continued.)* **Summary of AI studies for grid management and operations.**

				Training Decision Tree classifier using extracted features.				with nonlinear load
[88]	Optimize control strategies for multiple VPPs integrating EVs	Federated Deep Reinforcement Learning (FDRL)	VPP operation data, EV charging/discharging data	FDRL with a stochastically controlled stochastic gradient with Markov decision process formulation	Virtual Power Plant	Achieved the highest reward values at 3.85×10^5, indicating better VPP control strategies	Complexity in managing disturbances, data privacy concerns	Expansion of FDRL application to larger grid systems
[89]	Optimize VPP decision-making in urban areas	Reinforcement Learning	BRCET database	Utilized DDPG for optimal VPP control, addressing spatial/temporal uncertainties via scenario analysis	Urban VPP	Improved economic benefits via load-shifting, demand offset, and market participation	Simulation interval limits, electricity market bidding process not considered	Integrating RL with game theory for electricity market bidding, extending VPP modeling with RL
[90]	Optimize EV charging/discharging for V2G integration	Reinforcement Learning	KEPCO's EV charging data	Model-free sequential decision-making using MDP and DDPG algorithm	Smart Grid	Reduced user costs by 59%-62% and extended battery lifespan	Uncertainties in driving behavior and battery degradation	Inclusion of detailed user requirements, improving the DDPG algorithm,
[91]	Anomaly detection in smart grids	Federated Learning	Ausgrid, KDD 99, NSL-KDD, CIDDS datasets	Locally train global models (RNN, 1D-CNN, LSTM) while securely updating the central model via SSL/TLS	Smart Grid	FL-1D-CNN Classifier showed the highest 0.981 accuracy with 0.871 precision.	Limited by data and device heterogeneity	Optimizing FL for lower resource consumption on edge devices

framework that enables evaluating and comparing different studies. Considering the variations in methodologies and outcomes in energy sector research, the AI-Acceleration Performance Indicators (AAPIs) are proposed as an initial proposition to provide a consistent benchmark for AI-accelerated approaches. It involves identifying key performance indicators (KPIs) crucial for evaluating AI in small-scale electric power systems. The process is guided by the dual objectives of ensuring technological viability and enhancing user-centric outcomes. AAPI framework serves as a starting point for standardization in the field, with the main purpose of establishing a foundation upon which further research and validation can be built.

The accelerated KPIs are designed to speed up the commercialization of AI technologies in energy systems by ensuring user comfort, scalability, and practical applicability while enhancing user engagement. The framework categorizes KPIs into quantitative and qualitative measures, as outlined in Table 5.

Key performance areas critical to AI applications in energy systems are identified, such as cost-effectiveness, demand management, and prediction accuracy, along with qualitative aspects like innovation level and practical applicability. AAPIs framework employs a binary scoring system for quantitative KPIs to highlight which aspects are clearly covered in the studies. In contrast, the qualitative aspects are examined through a three-tiered scale – established, evolved, and emerging, where established indicator shows real-world, data-driven, and validated AI solutions with reliable results in different operating scenarios, evolving parameter shows the ongoing development and incremental improvements in the research with simulated analysis to enhance practical viability. In contrast, emerging shows new machine learning concepts and early-stage AI solutions that are yet to be extensively tested but point to new directions that could drive future advancements. This assessment approach guides the field towards practical, user-oriented, and commercially sustainable AI solutions.

These indicators are applicable across various types of AI applications, be they computational, experimental, or integrative. Researchers can track the evolution and performance enhancements of these systems by consistently

TABLE 3. Summary of AI studies for optimizing energy generation for small-scale electric power systems.

Ref.	Objective	AI Technology	Data Source	Methodology	Scale	Key Findings	Limitations	Further Research
[78]	Improve MPPT in PV systems	Supervised Learning	MATLAB Simulated PI controller data	SHAP-CatBoost is used to minimize steady-state error during low irradiance and partial shading.	Household	Adjustable MLGB controller outperforms traditional PI with response	Lack of real-world experimental validation	Experimental HIL validation; scalability analysis for microgrid integration
[92]	Accurate RES prediction to reduce consumer energy cost	Deep Learning	NREL, NSRDB dataset	MH-CNN based forecasting model for efficient energy management	Community	Decrease energy bills by 58.32% without ESS and 63.02% with ESS	Limited to residential area	Implementation in a real-world scenario
[93]	Improve short-term wind and solar power prediction	Deep Learning	Chinese State Grid data	CNN-LSTM enhanced with the Coati Optimization Algorithm for hyperparameter tuning	Community	RMSE decreased by 0.5% and 5.8% for 1hr and day-ahead predictions	Potential limitations in the applicability across different environments	Scaling to various geographic and climatic conditions
[94]	Predictive maintenance in wind turbine gearboxes	Ensemble Learning	Vibration and acoustic sensor data	Sensor data were processed using DWT, and by using entropy features faults were classified	Microgrid	92% fault classification accuracy	Stationary load and speed operating conditions	Consideration of dataset imbalance and different condition monitoring schemes
[95]	Estimate global solar radiation and quantify simulation uncertainty	Supervised Learning, Deep Learning	AERONET, BSRN, LIESMARS database	Radiative transfer model coupled with XGBoost, RF, MARS, MLP, DNNs, LightGBM	Small-scale solar PV systems	RTM-RF is most efficient with MAE of 15.57 W/m^2 and R^2 of 0.98	Limited data, less accuracy in cloudy and rainy conditions	Improving accuracy in diverse environmental conditions
[96]	Optimize hybrid solar PV and wind energy generation	Deep Learning	MATLAB environment operating cases	ZOA-ANFIS for MPPT in PV and wind systems; integration of novel HEPMSG design	Microgrid	ZOA-ANFIS computes 26.17% faster for PV and 35.5% for Wind than GTO	Study conducted on a small scale; cost not considered	Including cost optimization in analysis while maintaining performance
[97]	Improve PV panel segmentation for capacity estimation	Deep Learning	Remote sensing images from Germany	GenPV model employing multi-scale feature learning with inductive learning and Focal loss function	Community	Outperformed U-Net and FPN with 0.916 precision and 0.651 IoU.	Difficulty in segmenting small PV panels and similar object	Integration of LiDAR, hyperspectral imagery, and application of explainable AI
[98]	Optimize RES generation by considering cost and life cycle	Supervised Learning	Home Pro simulation, 100 buildings data	Decision tree to forecast life cycle, weighted sum model for optimal decision-making	Community	84% and 54.59% reduction in cost and environmental impact	Algorithm scalability, linear decision-making model	Expansion to different geographic locations and larger scales
[99]	Predictive maintenance of generation equipment	Supervised Learning	Simulated turbine data	Developing a binary classification system for maintenance prediction using DT and ANN	Microgrid	98% accuracy in maintenance identification	Specific to hydroelectric, dependent on the quality of sensor data	Application in other industrial contexts, testing new approaches like SGTM
[100]	Fault detection for PV system operational planning	Supervised Learning	GPVS-Faults data	Three ML models (LR, RF, NB) were benchmarked using classification metrics on a noisy dataset.	Microgrid	0.96 F-score by RF and 1.76 seconds training time	Noisy measurements, scalability issues with LR	Exploration of more efficient algorithms

TABLE 4. Summary of AI studies for energy storage in small scale power systems.

Ref.	Objective	AI Technology	Data Source	Methodology	Scale	Key Findings	Limitations	Further Research
[108]	SOC estimation for lithium-ion batteries	Deep Learning	Localized testing platform dataset	Combined CNN for spatial feature extraction and LSTM for time series analysis	PV energy storage system	0.31% RMSE, 0.18% MAE, with minimal deviation during voltage jumps	Focuses on a specific type of battery and system configuration	Exploration of model applicability to different battery types and larger systems
[109]	Improve SoC estimation for different batteries	Transfer Learning	Lab batteries under different loading conditions	Deep Domain Adaptation Network with domain adversarial mechanism and maximum mean discrepancy	Battery energy storage system	Average error of 1.8% - 2.4% for the target battery	Limited to similar battery chemistries; not considering battery aging.	Exploring model mechanism for transfer learning in SoC estimation
[110]	Monitor and predict Flywheel energy storage remaining useful life	Supervised Learning	Accelerated life test platform PRONOSTIA	PCA for health indicator construction, EMD-Kriging for RUL prediction	hybrid energy storage system	Accurate prediction with RMSE of 0.0425	Verified only under constant operating conditions	Adaptive RUL prediction for variable conditions
[111]	Optimize BESS scheduling with the PV system	Reinforcement Learning	Chungbuk PV distribution data	RL-based optimal scheduling model using various algorithms: A2C, PPO, TD3, SAC	Building PV energy storage system	The PPO model was most effective in maximizing self-sufficiency and economic profits	Data limitations, focus on a specific residential setting	Scale-up to include various battery sizes and regional energy-sharing communities
[112]	Optimal energy storage planning under renewable energy uncertainty	Deep Reinforcement Learning	California ISO curtailment data, Edison TOU plans	A policy-based DRL approach for real-time decisions while considering the stochastic nature of RES.	Microgrid	Outperformed scenario-based stochastic optimization; achieved 90% profit accuracy	Need for extensive training data, potential for overfitting	Enhancing model accuracy and application in larger grid systems
[113]	Predict the remaining useful life (RUL) of lithium-ion batteries	Deep Learning	NASA and CALCE battery datasets	Use of ISSA-LSTM for accurate RUL prediction based on battery capacity analysis	Portable energy storage system	ISSA-LSTM outperformed with 0.0112 MAE and 0.0147 RMSE for CS33	Specific to datasets used	Potential for real-time RUL prediction in electric vehicle batteries
[114]	Predict RUL of lithium-ion batteries	Deep Learning	Severson 124 batteries dataset	Evaluation of 7 ANN models with Feature extraction and hyperparameter optimization	Battery energy storage system	ResNet attains 10.7% MAPE using 30% of data as the training	Complexity in capturing patterns from extensive time dependencies	Exploration of additional architectural configurations and cycle windows
[115]	SOC estimation for Li-ion batteries	Deep Learning	INR 18650-20R and Panasonic NCR18650PF batteries datasets	Multi-variable data was sent to CNN-TCN and RNN layers for temporal and spatial feature extraction to estimate SOC	Battery management system	Over 45% improvement in estimation accuracy with KF integration	Computational Complexity, Limited to specific battery models and dynamic conditions	Optimization of deep learning models and KF for broader battery types
[116]	Optimize energy storage in hybrid grids	Supervised Learning	Solar, wind, and battery simulation data	GA is used for discharge-charge cycle calculation and battery health, and TD-Lambda is used for grid dynamic optimization.	Standalone hybrid grid	Enhanced optimization of load demand, efficient battery health management, and energy pricing	Scalability limitations, Generalization of the Model	Potential for real-time adaptation, refining optimization techniques

TABLE 4. ***(Continued.)*** **Summary of AI studies for energy storage in small scale power systems.**

[117]	Optimize energy storage system operation and maintenance	Reinforcement Learning	Microgrid simulated data	DRL-based framework with imitation learning pre-training to reproduce a user-defined heuristic	Microgrid	15% increase in profit, reduced ESS replacements	Real-world data application, Large computational effort	More accurate ESS degradation modeling, extension to islanded microgrids,

TABLE 5. **Overview of assessment criterion for AI applications.**

AI Acceleration Performance Indicators	
Quantitative KPIs	**Qualitative KPIs**
a. Cost Effectiveness: Evaluate the cost benefits of AI-based solutions.	a. Innovation Level: Evaluate the novelty or significant improvement of the AI methodology.
b. Demand Management: Assess the effectiveness of AI in reducing energy demand.	b. Practical Applicability: Assess real-world implementation or effective simulation.
c. Prediction Accuracy: Measure the improvement in algorithm forecasting accuracy.	c. Scalability Potential: Examine the adaptability of AI findings to various operational scales
d. Computational Simplicity: Evaluate the computational requirements of AI solutions.	d. Operational Efficiency: Evaluate the effectiveness of AI in managing grid operations.
e. User Comfort: Assess whether AI outcomes maintain user comfort levels or not	e. Reliability in Residential Settings: Assess AI effectiveness in home environments.

applying AAPIs in the development and assessment of new AI-based energy platforms. This standardized approach enables comparing varied AI algorithms, from traditional algorithm-based systems to more advanced, innovative applications such as deep neural network models. To provide context and demonstrate the potential application of the AAPIs, the paper applies the framework to various AI-driven studies in the realm of small-scale electric power systems. As a demonstration, these KPIs are applied to various studies to evaluate their accelerated performance for different applications of electric power systems, as shown in Table 6.

The quantitative assessment of the reviewed literature highlights distinct trajectories in the application of AI across various domains of small-scale electric power systems. Regarding energy generation and energy storage, AI plays a significant role in grid management and operations, energy consumption, and demand response with respect to optimizing renewable energy production in smart grids and managing energy flexibility for demand response and other processes. The advancement in AI technologies, especially deep learning, makes the prediction accuracy more accurate but at the cost of higher computational demand and complex ML algorithms. The assessment of demand management indicates enhanced AI capability in managing energy demand by improving load forecasting and performing complex operational decisions by executing real-time analytics to modulate energy supply in correspondence with consumption patterns. However, energy generation and energy storage register a less pronounced engagement with AI for demand management, implying that current research has not fully exploited the potential of AI in this regard. Fig. 2 demonstrates the comparative performance of key indicators by scoring AI-based reviewed articles in various application areas – such as energy storage, grid management and operations, energy generation, and energy consumption and demand response against the quantitative KPIs of cost-effectiveness, demand management, prediction accuracy, computational simplicity, and user comfort to highlight emerging research trends.

The qualitative assessment of the reviewed articles provides information about the advancement and maturity of AI-accelerated solutions within diverse domains of small-scale electric power systems. In the case of energy storage, AI applications are mainly in the evolving phase as methods are being developed for more accurate battery RUL and SOC predictions. In the same way, AI applications seem more established for grid management and operations due to the proven effectiveness of reinforcement learning in optimizing the decision-making process of integrating and maximizing the use of renewables in microgrids and virtual power plants. Similarly, the higher innovation level in the case of energy consumption and demand response indicates real-world implementation of most of the AI applications in forecasting demand, optimizing energy consumption, and scheduling controllable appliances with more research focused on improving the already developed solutions for better grid operational efficiency. The scalability potential for energy generation shows the dynamic phase of AI solutions, such as federated and transfer learning, in improving renewable energy generation and predicting the maintenance of generation equipment while delving into expanding the impact of AI in larger systems. Fig. 3 highlights the qualitative spectrum of small-scale electric power systems across multiple operational domains ranging from established practices to emerging innovations within energy storage, grid management and operations, energy consumption, and energy generation.

Similarly, the research trends are more oriented towards microgrids with household-level energy management to address various objectives related to renewable energy

TABLE 6. Demonstration of the use of KPIs in evaluating the performance of AI-driven research in electric power systems.

Application Area	Article	Quantitative KPIs					Qualitative KPIs				
		a	b	c	d	e	a	b	c	d	e
Energy Generation	[92]	★	★	★			Evolving	Emerging	Emerging	Evolving	Evolving
	[118]			★		★	Established	Established	Established	Emerging	Established
Energy Consumption and Demand Response	[58]			★	★	★	Established	Evolving	Established	Emerging	Established
	[119]		★	★		★	Evolving	Emerging	Evolving	Emerging	Evolving
Grid Management and Operations	[70]		★				Evolving	Evolving	Established	Established	Evolving
	[120]	★	★		★	★	Evolving	Established	Evolving	Established	Established
Energy Storage	[112]	★	★		★	★	Established	Emerging	Emerging	Established	Evolving
	[121]			★	★		Emerging	Evolving	Emerging	Emerging	Evolving

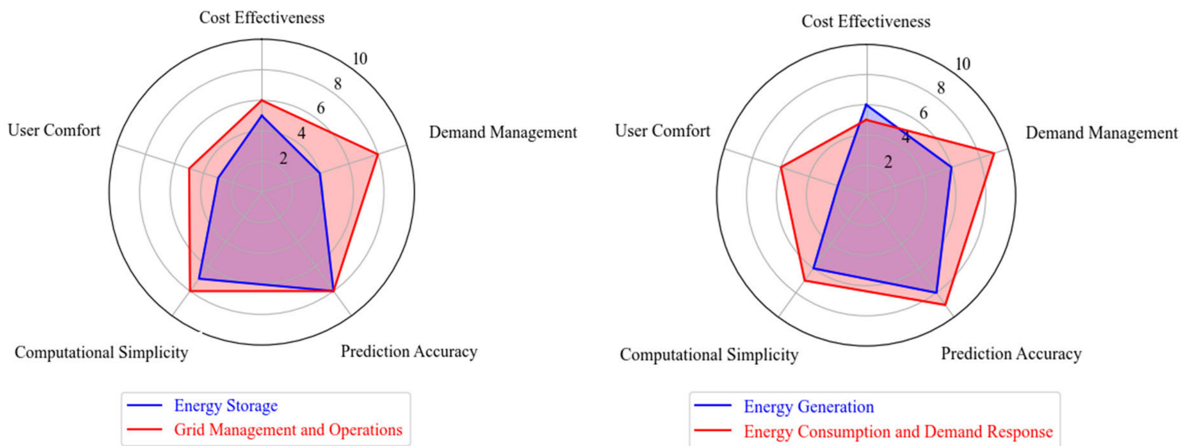

FIGURE 2. Comparative radar charts illustrating the performance of reviewed articles across key quantitative indicators for small-scale electric power systems.

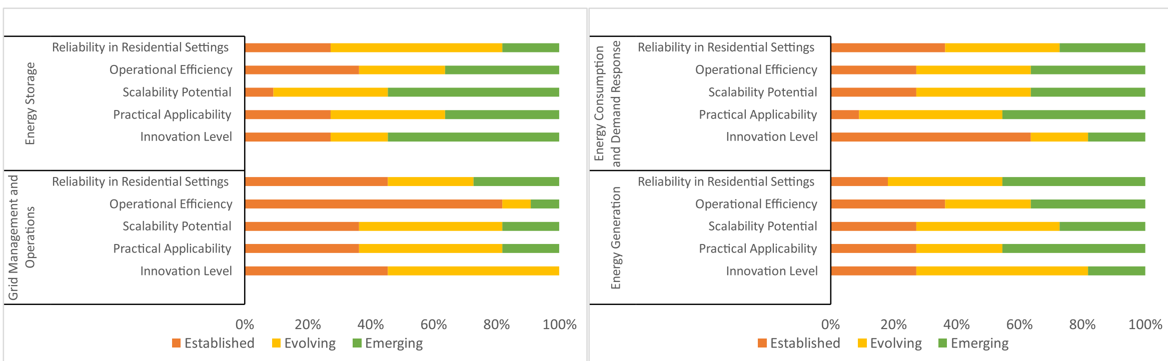

FIGURE 3. Qualitative analysis of AI application across different domains in small-scale electric power systems.

optimization, energy efficiency, and load forecasting. Microgrids-related studies represent 29.4% of the literature, while smart grids and VPPs account for 14.7% and 8.8%, respectively, thus pointing towards a trend of decentralized, consumer-focused energy solutions. Compared to building-level studies, which comprise 13.3% of the studies, household-level studies make up 26.5% of the research, indicating the significant emphasis on AI in the residential sector.

AI applications show promising results in several small-scale power system domains. However, based on AAPI analysis, certain application limitations and areas require further research to fully exploit AI's potential in this sector. Many AI applications are data-dependent and are confined to specific scenarios. For instance, studies using federated learning or interactive learning require large, diversified datasets for training and validation that impact the performance and generalizability of AI models to different environments, operational conditions, and grid configurations. Most of the studies focus on the specific area of energy management systems, such as only consideration of shiftable appliances while lacking integration of thermal models with HVAC control systems, which hinders practical applicability. Computational complexity, data synchronization, and resource demands of advanced AI systems pose significant challenges to scalability and real-time application. AI applications in power systems also pose security and privacy concerns, such as vulnerability to eavesdropping attacks and IoT integration in microgrids that affect reliability in the residential sector. In the case of energy storage, AI-based battery energy storage system shows limited focus on different battery chemistries and aging factors. By incorporating a broader range of datasets, enhancing the processing capability of AI models in dynamic environments, implementing robust security protocols, and exploring unified AI models that can adapt to various power system scenarios related to energy storage and grid management will significantly contribute to the user-centric and feasible AI solution in small-scale electric power systems.

V. CONCLUSION

Small-scale electric power systems have been instrumental in enhancing energy resilience and sustainability. These systems allow for a more flexible and efficient energy management approach, facilitating the local generation, storage, and distribution of energy, thereby mitigating the challenges associated with the integration of renewables. This review paper presents an extensive analysis of AI applications within these systems, highlighting the transformative role AI plays across various aspects of energy generation, storage, and consumption, offering a unique perspective on the future trajectory of AI in enhancing the efficiency and reliability of small-scale electric power systems.

Firstly, a brief overview of small-scale electric power systems' evolution is presented. Subsequently, the review explores their key role in enhancing the resilience and efficiency of modern energy distribution. A detailed analysis of AI across various domains of power systems is presented, from optimizing energy consumption and demand response through smart load management and dynamic pricing to enhancing grid operations with real-time anomaly detection and predictive maintenance. The discussion converges on the AAPIs framework, representing an initial step towards establishing a standardized evaluative framework for AI applications in small-scale electric power systems. This framework incorporates both quantitative and qualitative KPIs, such as cost-effectiveness, prediction accuracy, and innovation level, providing a comprehensive metric for assessing AI technologies. The AAPIs framework reveals significant research trends, with 70% of studies focusing on computational simplicity and only 10% considering user comfort in energy storage methodologies. Conversely, research related to grid management and operations has shown a robust interest in prediction accuracy and demand management, with 80% of articles emphasizing these aspects. Qualitatively, innovation in energy generation has emerged as a critical area with approximately 60% of research marked as 'Emerging', indicating a promising frontier for future research. The AAPIs framework serves not only as a benchmarking tool for current research performance but also guides future AI applications toward achieving user-centric and economically viable solutions.

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