



Current breakthroughs and critical perceptions on the application of artificial intelligence in power systems: A systematic review

Yapay zekanın güç sistemlerinde uygulanmasına ilişkin güncel atılımlar ve eleştirel algılar: Sistematik bir inceleme

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Abstract

Artificial Intelligence (AI) driven solutions are rapidly transforming power systems, from power generation and distribution to consumption. This review provides a comprehensive analysis of the latest advancements, specifically focusing on how AI enhances key areas such as load forecasting, anomaly detection, predictive maintenance, energy management, renewable energy integration, and cybersecurity. Our primary aim is to systematically review and critically evaluate recent AI-based techniques, their real-world implementations, and their performance compared to traditional methods. Through a detailed examination of unique case studies, we demonstrate how these AI techniques significantly improve accuracy and enhance system reliability. While impressive progress has been made, we identify critical gaps that persist in the literature, particularly regarding the challenges of data collection and the inherent complexity of advanced AI models. This review's novelty lies in its dual focus: highlighting current breakthroughs while also providing a critical perspective on these unresolved challenges. We synthesize the limitations identified in various studies and offer concrete recommendations to guide future research toward developing more efficient and resilient power systems.

Keywords: Artificial Intelligence, Power, Grid, Energy, Detection, Cybersecurity.

Öz

Yapay Zekâ (YZ) destekli çözümler, güç üretimi ve dağıtımından tüketime kadar güç sistemlerini hızla dönüştürüyor. Bu inceleme, özellikle yük tahmini, anomali tespiti, kestirimci bakım, enerji yönetimi, yenilenebilir enerji entegrasyonu ve siber güvenlik gibi temel alanları nasıl geliştirdiğine odaklanarak, en son gelişmelerin kapsamlı bir analizini sunmaktadır. Birincil amacımız, son yapay zekâ tabanlı teknikleri, gerçek dünyadaki uygulamalarını ve geleneksel yöntemlerle karşılaştırıldığında performanslarını sistematik olarak incelemek ve eleştirel bir şekilde değerlendirmektir. Benzersiz vaka çalışmalarının ayrıntılı bir incelemesi aracılığıyla, bu YZ tekniklerinin doğruluğu nasıl önemli ölçüde artırdığını ve sistem güvenilirliğini nasıl geliştirdiğini gösteriyoruz. Etkileyici bir ilerleme kaydedilmiş olsa da, özellikle veri toplama zorlukları ve gelişmiş YZ modellerinin doğasında bulunan karmaşıklık konusunda literatürde devam eden kritik boşlukları tespit ediyoruz. Bu incelemenin yeniliği, mevcut çığır açan gelişmeleri vurgularken aynı zamanda bu çözülmemiş zorluklara eleştirel bir bakış açısı sağlamasında yatmaktadır. Çeşitli çalışmalarda tespit edilen sınırlamaları sentezliyor ve daha verimli ve dayanıklı güç sistemleri geliştirmeye yönelik gelecekteki araştırmalara rehberlik edecek somut öneriler sunuyoruz.

Anahtar kelimeler: Yapay zekâ, Güç, Şebeke, Enerji, Algılama, Siber güvenlik.

Nomenclature

Abbreviation	Description	Abbreviation	Description
ADF	Anomaly Detection Framework	KPCA	Kernel Principal Component Analysis
AE	Autoencoder	LOF	Local Outlier Factor
AI	Artificial Intelligence	LPS	Loss of Power Supply Probability
ANFIS	Adaptive Neuro-Fuzzy Inference System	LSTM	Long Short-Term Memory
ANN	Artificial Neural Network	MILP	Mixed Integer Linear Programming
BESS	Battery Energy Storage System	MOIKOA	Multi-Objective Improved Kepler Optimizer Algorithm
BOSA	Binary Orientation Search Algorithm	MLR	Multiple Linear Regression
BP	Backpropagation	MLP	Multi-Layer Perceptron
CART	Classification and Regression Tree	mOPA	Modified Orca Predation Algorithm
CNN	Convolutional Neural Network	MQR	Multivariate Quantile Regression

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Nomenclature

Abbreviation	Description	Abbreviation	Description
CSO	Cockroach Swarm Optimization	MSU-ORNL	Mississippi State University and Oak Ridge National Laboratory
CSA	Cuckoo Search Algorithm	NARX-SCG	Nonlinear Autoregressive with Exogenous Inputs using Scaled Conjugate Gradient
DBN	Deep Belief Network	OBL	Opposition-based learning
DG	Distributed Generators	PHM	Prognostic Health Management
DRES	Distributed Renewable Energy Systems	PSO	Particle Swarm Optimization
DSM	Demand-Side Management	PV	Photovoltaic
EMS	Energy Management System	RBFNN	Radial Basis Function Neural Network
EV	Electric Vehicle	RBM	Restricted Boltzmann Machines
Extra-Trees	Extremely Randomized Trees	RES	Renewable Energy Sources
Faster R-CNN	Faster Region-based Convolutional Neural Network	RNN	Recurrent Neural Network
FDIA	False Data Injection Attacks	SAE	Stacked Autoencoder
FLANN	Functional Link Artificial Neural Network	SCA	Stealthy Cyber-Attacks
FPA	Flower Pollination Algorithm	SDF	Symbolic Dynamic Filtering
FRA	Frequency Response Analysis	SecFed	Secure Federated Learning
GIS	Gas-Insulated Switchgear	Seq2Seq	Sequence-to-Sequence
GRU	Gated Recurrent Unit	SSA	Sparrow Search Algorithm
GWO	Grey-Wolf Optimization	STLF	Short-Term Load Forecasting
HMG	Hybrid Microgrid	SVM	Support Vector Machine
HS	Harmony Search	SVR	Support Vector Regression
IEC	International Electrotechnical Commission	TLCC	Total Life Cycle Cost
HIS	Improved Harmony Search	TOU	Time of Use
IMFO	Improved Moth Flame Optimization	WT	Wind Turbines
IoT	Internet of Things	XGBoost	Extreme Gradient Boosting

1 Introduction

Just as highways connect cities and towns, power systems link energy generation sources to consumers, delivering the energy that powers man's daily activities. With the integration of artificial intelligence, these systems are becoming smarter, enhancing efficiency and reliability. AI can be defined as the imitation of human intellect by machines, allowing them to accomplish tasks that usually require cognitive abilities like learning, reasoning, and decision-making [1], [2]. By analyzing huge amounts of data and identifying patterns, these machines can take the right actions based on what they learn [3]-[5]. For example, machine learning, which is a popular branch of artificial intelligence, has been highly effective in AI-based systems that need accurate predictions, because of its data processing ability during perception, analysis, and decision making [6],[7]. Its role has been of utmost importance and has been increasing rapidly, especially in real-world applications such as in fields like robotics, transportation, and automation, where automated systems are frequently used to sense and react accurately to situations in their environment [8],[9]. It is worthy of note that, for AI-based systems to be deployed there are multiple stages involved in their development, from building their ability to perceive to improving their capacity to make decisions. These steps that must be executed show the amount of work and data that are required to build systems that are able to adapt to its environment and respond in real-time [10],[11]. Interestingly, as artificial intelligence continues to evolve, there will also be an expansion of its application not just in scientific experiments but in every other aspect of life [12],[13].

Globally, power systems are considered to be the foundation of modern life, because they supply the electricity that sustains industries and households [14]-[15]. Its importance cannot be overemphasized. As a result of high demand for efficient power supply, the use of technologies like artificial intelligence has become very significant for the enhancement

of power system operation in order to increase reliability [16],[17]. For example, artificial intelligence provides precise management to maintain stability, power generation, distribution, and consumption processes [18]-[21]. It was initially popular in areas like the Internet but has become very useful in power systems and other critical infrastructure because of its ability to enhance efficiency [22]. Over time, AI methods have evolved and have transformed control mechanisms and fault detection in power electronics and drive systems [23]-[24]. A huge leap for power systems. This progression demonstrates AI's ability to meet the complex demands of modern power systems, ensuring they run with greater resilience and adaptability [25].

Because AI has the capacity to process huge data from sensors and perform the required computations with remarkable speed, it has reduced the time power systems spend on data computations, lowered cost, and strengthened dependability [26], [27]. These advantages are particularly important for tasks like maintaining system frequency, optimizing voltage profiles, minimizing transmission losses, reducing fault rates in distributed networks, improving market operations, and protecting smart grids from cyberattacks [28]- [30]. As the use of AI in power systems continues to increase, further revolution is expected, especially in design and maintenance to improve performance [31],[32]. This paper systematically and extensively reviews various artificial intelligence (AI) methodologies applied to power systems to enhance efficiency. Even though so many research works have explored the application of artificial intelligence in power systems, a lot of them still have significant deficiencies. First of all, most prior reviews have focused on providing summaries of AI techniques without properly evaluating the strengths, weaknesses, and real-world applications of these techniques. Secondly, available research works largely analyzed the use of AI in each power system task in isolation, thereby only providing limited cross-domain comparison, which does not provide sufficient insights into how different AI techniques

would perform under different computational and operational conditions. Thirdly, many prior works do not provide challenges experienced during practical implementation of the various techniques they used in their research. To address the aforementioned challenges, this review has the primary aim of providing a holistic evaluation of AI's transformative role in power systems, showing its application, benefits, practical implementation, and challenges across different domains.

This review will be providing four major contributions. First, the development of a structured taxonomy that organizes the literature across seven domains, which includes load forecasting, anomaly detection, power optimization, predictive maintenance, energy management, renewable energy integration, and cybersecurity, thereby giving us an understanding of how AI supports the operations and reliability of modern power systems. Second, for each domain, the review provides an analysis that compares the performance of different models, showing common causes of failures, limitations, and their readiness for real-world deployment. Third, this review also provides a cross-domain synthesis by integrating insights from different AI domains, highlighting the trade-offs between machine learning, deep learning, and hybrid or metaheuristic techniques with respect to accuracy, interpretability, and applicability. Finally, based on the findings and limitations of the different techniques, this review provides clear and actionable future research directions and recommendations that directly address existing gaps and practical grid deployment. These contributions will offer researchers and practitioners a clearer understanding of the current state of AI applications in power systems and also provide a road-map for advancing the field.

The remainder of this work is structured as follows: Section 2 discusses the role of AI in improving the reliability of load forecasting. Sections 3 and 4 cover anomaly detection and system optimization, respectively, as a result of incorporating AI. We then discuss predictive maintenance and robust energy management in Sections 5 and 6. The integration of renewable energy and cybersecurity in AI-driven power systems are discussed in Sections 7 and 8. Additionally, the use of AI in battery energy storage and power quality monitoring was discussed in section 9. Finally, the cross-domain synthesis, concluding remarks and future research recommendations are provided in Section 10, 11, and 12 respectively.

2 Load forecasting

Load forecasting is an important feature of modern power systems [33], where artificial intelligence plays an important role in ensuring future prediction [34]. Forecasting is highly needed for adequate resource management and proper infrastructure planning in order to provide reliable power supply [35]. Different robust AI-based models that effectively forecasted load consumption for both residential and industrial settings were introduced. [36]-[40]. These studies made use of different Neural networks, deep learning, and fuzzy logic approach, and were tested for its efficiency and reliability. The strength of these models addresses the dynamic nature of electricity demand. They offer utilities more accurate and reliable forecasts, which are essential for optimizing power system operations and resource planning. A summary of the key findings from these studies, including their respective techniques and outcomes, is presented in Table 1.

Table 1. Key findings on the applications of AI in load forecasting [36]-[40].

Related Works	Applications in Power Systems	AI Techniques Used	Case Studies	Advantages over common traditional methods	Limitations of the AI technique used	Proposed Recommendations
[36]	Power load forecasting	RNN	European Intelligent Technology Network competition data	This model effectively captures long-term dependencies in data, simplifies the computational process, reduces training time, and leverages information from both previous and upcoming data points to improve forecasting accuracy.	The complexity of the model, requiring substantial computational resources and time for data reprocessing and training is a notable limitation.	Simplification of the model's architecture without compromising accuracy, making it more accessible for practical applications in diverse power system contexts.
		LSTM				
		GRU				
[37]	Electrical load forecasting, for power system planning and operation.	CNN	Bangladesh power system, using time series load with the first five years for training and 2019 for testing.	The model can handle time series data and precise future load prediction.	The model's complexity and high computational demands are significant weaknesses.	Future research could explore integrating Gated Recurrent Units (GRU) with CNN to further enhance forecasting precision and reduce model complexity.
		LSTM				
[38]	Load forecasting for Hellenic and Cretan power systems	STLF	Hourly forecasts for one week ahead for the Hellenic and Cretan power systems	Improved accuracy and reduced overfitting as a result of its capability to handle complex and nonlinear data	The model has high computational requirements and may not perform well with complex data structures.	Explore the incorporation of weather conditions as inputs and refining the choice of input frames to mitigate the impact of weather variability.
		ANN				
		RBFNNs				

Table 1. Continued.

Related Works	Applications in Power Systems	AI Techniques Used	Case Studies	Advantages over common traditional methods	Limitations of the AI technique used	Proposed Recommendations
[39]	Forecasting residential load profiles	Seq2Seq	Residential load profiles with a dataset of 31,680 minute-wise observations over 22 days.	Capable of managing non-linear and stochastic behavior in load profiles and improving prediction accuracy.	It has scalability issues with complex data and requires significant computational resources.	Optimization of the model for larger and more complex datasets and integrating additional factors, such as weather conditions, to enhance accuracy.
		LSTM				
		SAEs				
[40]	Probabilistic industrial load forecasting	MQR	The proposed method was validated using actual load data from an Italian factory.	The MQR model improves the accuracy of load forecasts by effectively combining individual forecasts of active and reactive power.	Weaknesses include the method's complexity and the computational demands of linear programming optimization.	There should be further exploration of different predictors and industry-specific features to enhance the model's accuracy and robustness

Despite the strong performance of advanced models such as LSTM, CNN-LSTM hybrids, Seq2Seq, and GRU, several fundamental weaknesses remain consistent across the reviewed studies. A challenge that was recurrent is the heavy dependence on large historical datasets, which strongly limited the use of these models in regions where there is scarce or poor data quality. Also, while LSTM-based techniques generally outperform classical ML techniques due to their ability to model long-term temporal dependencies, their cost of computation is significantly higher, thereby making it difficult to train or update in real-world operational settings. In the reviewed studies, CNN-based techniques demonstrated excellent capacity in capturing short-term fluctuations but struggled with long-range dependencies. This was largely observed during periods of extreme weather changes. AI techniques with hybrid models that combined CNN and RNN layers showed improved performance but required significant specialized computational resources, which may be difficult to find, especially in developing regions. Additionally, the lack of robustness in situations where non-stationary load patterns as a result of seasonal changes or socioeconomic activities can become a critical limitation. Real-world challenges during deployment were also not addressed sufficiently, as most of them assumed ideal conditions such as noise-free measurements and stable communication channels, whereas in reality power systems frequently deal with issues like meter failure and bandwidth limitations. Regardless of the data drift and computational challenges experienced by these models discussed, they have significantly advanced the accuracy of load forecasting. The incorporation of physics-informed architectures and real-time adaptive learning into future research would significantly sustain performance in dynamic grid environments.

3 Anomaly detection

Recent advancements in anomaly detection for power systems have integrated AI techniques, significantly enhancing the accuracy of identifying irregular patterns in electricity consumption [41]-[42]. This process is crucial for addressing issues like energy theft, metering defects, cyberattacks, and technical losses [43]-[45]. Different AI techniques for real-time anomaly detection in power consumption data, management of complex data patterns, and extraction of critical information

from load profiles, enhancing the efficiency of anomaly detection were presented by [46]-[50]. Specifically, an innovative method for identifying cable fault and its localization using a deep-belief network (DBN) model, as shown in Figure 1 was proposed by [50].

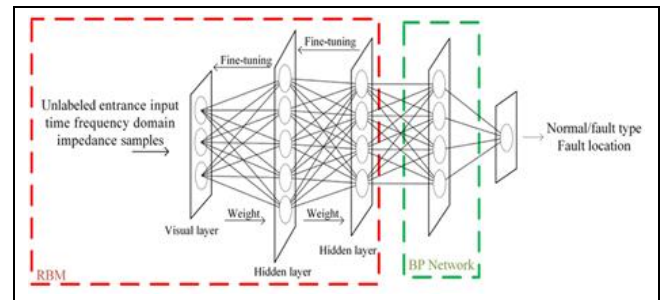


Figure 1. The fundamental framework of the DBN model in [50].

It accurately identified fault types and their locations, suggesting its potential for practical applications in smart grids. While the methods reviewed demonstrate notable strengths, Table 2 outlines their comparative advantages and limitations, stressing the importance for further studies to address present problems and boost overall performance. While anomaly and fault detection models such as LSTM autoencoders, DBNs, and Transformer-KMeans hybrids achieve strong detection accuracy in controlled experiments, a consistent limitation across the literature is the lack of real-time labeled datasets. The majority of the studies reviewed in this section relied on historic or simulated anomalies or disturbances that were artificially injected into the system, and this does not fully represent the noisy or irregular signatures of faults in real-time grid environments. Consequently, techniques in the laboratory setting that appear to be highly accurate may generate excessive false alarms or even miss subtle anomalies when deployed. Unsupervised models like autoencoders and k-means clustering reduce dependence on labeled data but tend to suffer from high false-positive rates, especially when load patterns shift due to seasonal or behavioral changes. Very few works address concept drift, even though real-world anomaly detection systems require continuous adaptation to evolving customer behavior, DER penetration, and operational policies.

Table 2. Key findings in the application of AI in anomaly detection [46]-[50].

Related Works	Applications in Power Systems	AI Techniques Used	Case Studies	Advantages over common traditional methods	Limitations of the AI technique used	Proposed Recommendations
[46]	Real-time anomaly detection method for power consumption	LSTM Negative Selection technologies.	A building's power consumption data recorded over 20 weeks	Elimination of the need for direct error calculation between predicted and observed values.	The intricacy of LSTM networks and the need for substantial computational resources are significant weaknesses. There is also need for the integration of alternative energy systems to enhance the method's applicability and efficiency.	Integration of alternative energy sources could improve the method's ability to handle extreme power consumption variations and enhance overall energy management strategies.
[47]	Power forecasting prediction and anomaly detection.	Transformer with K-means clustering	This technique was tested on real hourly electric energy consumption data	computationally efficient and capable of handling larger datasets accurately.	The model's complexity and the requirement for extensive computational resources are potential limitations.	Developing approaches to lessen the computational difficulty and data requirements of the model will make it more accessible for practical applications in diverse power system environments.
[48]	Systematic review of energy theft practices and autonomous detection through AI methods	LSTM	Italian distribution company on adopting third-party software on AI algorithms	LSTM's ability to handle long-term dependencies and the autoencoder's reconstruction error-based anomaly detection offer a robust solution compared to simpler methods.	There is a need for extensive training of data and computational resources.	Future research should focus on developing methods for automatic data labeling and reducing the computational complexity of the models.
[49]	Anomaly Detection Framework to identify abnormal energy consumption in buildings.	CART MLP	The framework was validated using real electricity consumption data from around 1,000 buildings managed by a national telecommunications service provider in Italy.	The combination of CART and MLP models in this framework offers a robust solution by leveraging the strengths of both approaches—interpretability from CART and high accuracy from MLP.	The complexity and computational demands of this method are significant weaknesses.	Future studies should focus on improving the framework for lower computational costs and exploring automated techniques for reducing false alarms
[50]	cable anomaly and fault identification and localization	DBN	Simulated data from a 10kV single-core XLPE-cable mode	DBN excels in maintaining the original data characteristics during dimensionality reduction. This allows for more precise anomaly and fault identification and localization, reducing the likelihood of misclassification and improving overall diagnostic reliability.	There is longer training times and potential scalability challenges	Optimization of the DBN model for faster training and exploring its scalability in larger networks.

A major weakness of these techniques was observed in the area of computational and infrastructural deficiencies. For better efficiency, large deep learning models require a substantial amount of memory, power, and training time, which are often unavailable in distribution substations or remote installations. Also, these studies rarely considered cyber-induced anomalies, which mimic normal patterns of

operation and may require more sophisticated detection frameworks. The lack of explainability noticed in some of the studies reviewed is also a limitation to practical deployment. This is because utility operators must understand why a system flags an event as abnormal, and without transparent decision pathways, operators may not fully trust the model's output, thereby reducing the possibility of adoption. Though

most studies have improved anomaly detection capabilities, the real-time validation of these techniques remains the most important next step.

4 Optimization

Optimization in power systems focuses on achieving the best operating conditions for an electrical network [51]. This process involves strategically managing power generation, transmission, and distribution, to lower operational costs, ensure a stable power supply, reduce energy losses, and improve overall system performance, ultimately creating a more economical power system [52]-[57]. The application of AI in power optimization has seen substantial advancements, with various techniques being employed to address different aspects of power system management in which a machine learning technique to handle the high nonlinearity and computational costs of traditional methods as seen in Figure 2 was presented [58], [59]. Additionally, an improved Analytical Hierarchy Process method for optimized load shedding distribution, prioritizing the continuity of power supply based on load types [60].

Moreover, a robust approach focused on minimizing power generation costs and mitigating damages associated with load shedding while a novel approach that prioritized load-shedding, thereby preserving voltage stability [61], [62].

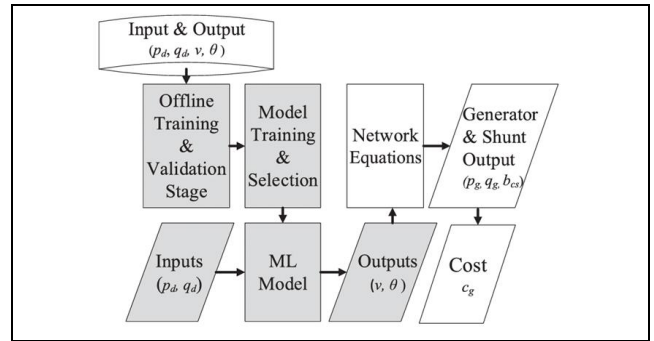


Figure 2. Proposed learning-augmented AC OPF algorithm in [59] is shown, with the shaded area highlighting the machine learning domain.

Furthermore, considering residential communities proposed a Demand-Side Management (DSM) methodology that made use of optimization algorithms to boost the efficacy of smart grids by reducing peak energy demand through strategic load-shifting techniques and integrating on-site renewable energy resources was proposed [63]. Achieving further advancements requires a focus on developing scalable approaches and implementing a robust data collection system to enhance optimization processes. Table 3, presented below, summarizes the findings from these reviewed studies on the use of Artificial Intelligence in power optimization.

Table 3. Key findings in the application of AI in optimization of power generation and distribution [59]-[63].

Related Works	Applications in Power Systems	AI Techniques Used	Case Studies	Advantages over common traditional methods	Limitations of the AI technique used	Proposed Recommendations
[59]	Provides solution for AC optimal power flow (OPF) with machine learning (ML) techniques.	Three ML models: Random Forest, Multi-target decision tree, Extreme learning machine	The case studies involve two test networks: a 500-bus and a 4918-bus system.	The learning-augmented method leverages ML models to predict key variables, thereby reducing the need for extensive numerical iterations and enhancing computational efficiency.	Potential for overfitting and the need for large amounts of training data.	Incorporation of advanced ML techniques such as deep learning or ensemble methods to enhance prediction accuracy and robustness.
[60]	Optimization model for load shedding.	AHP	The efficacy of the planned method is demonstrated using the IEEE 30 bus system.	The results are more reliable and consistent for load prioritization and shedding decisions, which are crucial for effective power system management.	There is a dependency on continuous and accurate data collection.	Developing vigorous data collection and monitoring schemes to guarantee continuous and accurate parameter updates
[61]	Optimization of operational parameters and control of power systems to reduce cost of generation costs and the destruction costs caused by the shedding of loads.	PSO CSA	The IEEE 30-bus test system was used for simulation.	PSO and CSA use probabilistic and bio-inspired approaches to explore a larger solution space and find optimal solutions more effectively	The reliance on specific algorithm parameters can affect the consistency and reliability of the results.	There is a need for comparative studies involving more diverse AI techniques and exploration of hybrid approaches combining multiple AI algorithms to enhance optimization performance

Table 3. Continued.

Related Works	Applications in Power Systems	AI Techniques Used	Case Studies	Advantages over common traditional methods	Limitations of the AI technique used	Proposed Recommendations
[62]	Enhancement of grid shedding optimization.	CSA	The proposed methodology was tested on the IEEE-37 bus system, which includes 9 generators and 26 load buses.	The CS algorithm's use of Lévy flights enhances its ability to discover global optima, making it more effective than traditional methods	The methodology may require fine-tuning of parameters for different scenarios.	Developing scalable AI approaches that can efficiently handle larger and more complex power systems is essential.
		Backpropagation				
		Neural Network				
[63]	Efficient Optimization Algorithm-Based methodology for Demand-Side Management	BOSA	The case study was conducted in a residential community and the simulation model incorporated smart meters, data centers, communication networks, and an Energy Internet platform for real-time energy management.	These AI techniques offer higher robustness and lower standard deviation in energy cost optimization.	The proposed DSM system is focused on controllable appliances, leaving non-controllable appliances outside the optimization process.	Future research should explore the integration of an optimal peak-clipping DSM program alongside the load-shifting technique to manage both controllable and non-controllable appliances more effectively.
		CSO				
		SSA				

Based on the analysis of the works in this section, metaheuristic techniques like PSO, HSA, CA, and MOEA proved to have better search capabilities and lesser power across the different test systems, making them a good choice for power systems optimization. However, these techniques were majorly tested and evaluated with IEEE benchmark networks under ideal and static conditions and do not capture the complexities of real-world grids, like uncertain renewable output, equipment failures, and fluctuating load conditions.

The AI-based OPF approximations was an innovative technique that reduced computation time. However, it also introduced approximate errors that could cause operational constraints like voltage limits and thermal ratings. Another limitation in some of the studies is the assumption of perfect forecasts and demand, which is unrealistic. If these uncertainties are not addressed, optimization models may propose set points that are not achievable and unsafe. Additionally, many suggested techniques for optimization require retraining the whole optimization process when the grid topology changes, thereby making it inefficient for systems undergoing rapid modernization. Real-world deployment of optimization techniques requires algorithms that guarantee both good and safe solutions, and this can be achieved if there is a stronger grounding in operational feasibility and real-time performance guarantees.

5 Predictive maintenance

Predictive maintenance involves monitoring the condition of equipment and systems to predict potential failures, thereby enabling maintenance to be scheduled proactively and efficiently [64]-[66]. Maintenance is made easy. This approach minimizes unexpected breakdowns, reduces operational downtime, and improves the consistency and efficiency of power systems [67],[68]. Unlike routine or reactive maintenance, predictive maintenance makes use of a better strategy. It harnesses data from sensors, historical records, and instantaneous monitoring to evaluate the critical power system components' conditions, such as transformers, generators, and circuit breakers [69]-[71]. The incorporation of AI into predictive maintenance has considerably advanced

this field by enabling the processing of vast datasets, to identify patterns and generate precise forecasts [72],[73]. For example, an investigation on the use of deep learning prototypes in enhancing the diagnostic correctness of dry power transformers in microgrids was done [74]. Again, research on multi-agent system designed for the prognostic health administration of smart transformers within smart grids was conducted by [75]. These models reduced the risk of critical failures, by enabling more accurate health assessments and maintenance scheduling. Additionally, there was a demonstration on how the Health Index of gas-insulated switchgear (GIS) bays could be leveraged to prioritize maintenance tasks and optimize resource allocation [76]. Also, the application of deep learning advanced pattern recognition capabilities to the classification of winding faults using Frequency Response Analysis was carried out by [77]. Furthermore, the introduction of an optimized approach to defect recognition in transmission lines using aerial images was done by [78]. The method with structural diagram in Figure 3 utilizes a coarse-to-fine recognition process that incorporates CNNs and connected domain algorithms. Table 4 summarizes the findings in the studies reviewed in the application of AI in Predictive maintenance and condition monitoring. The AI-based predictive maintenance models achieve impressive diagnostic accuracy for transformers, GIS, circuit breakers, and transmission assets; however, many rely on synthetic or laboratory-generated datasets, which do not capture real noise, aging patterns, or environmental impacts.

Deep learning models trained on such data may fail when confronted with actual field measurements that include sensor drift, environmental interference, or mixed fault signatures. A second issue is the lack of standardized health indicators. Different papers define asset health using incompatible metrics, making cross-study comparison difficult and limiting practical adoption by utilities. A typical example of this problem is the fact that models that will work well for transformers most of the times cannot be transferred to other parts of the power systems, like overhead lines, without a major redesign.

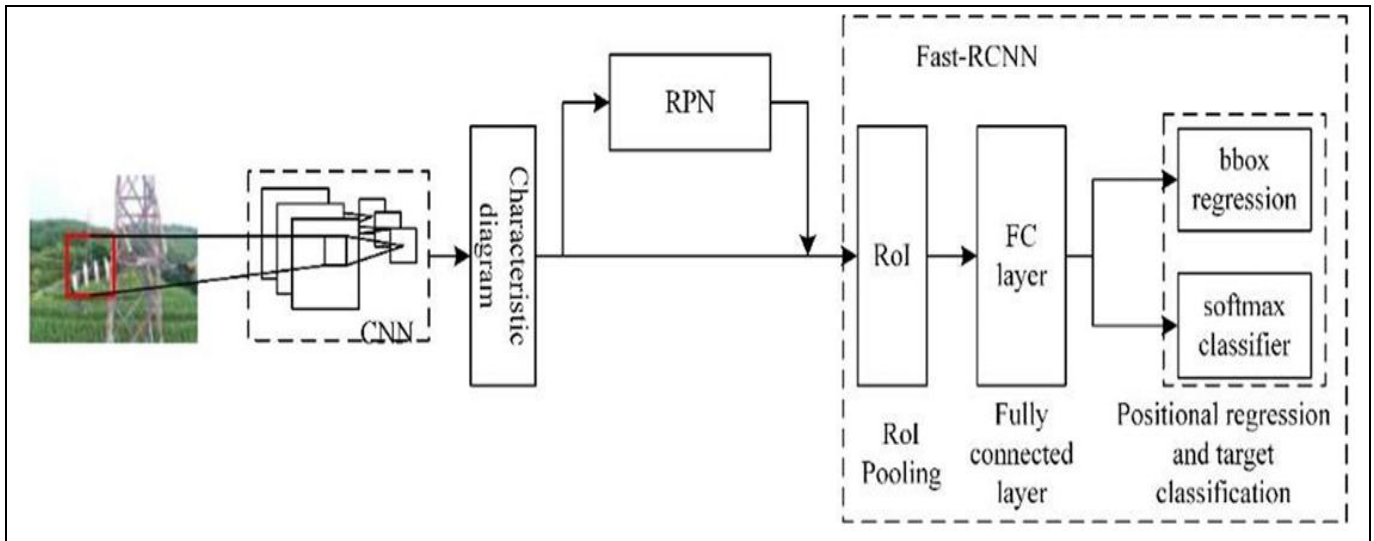


Figure 3. Diagram showing the structure of the faster R-CNN model introduced in [78].

Table 4. Key findings in the application of AI in predictive maintenance and condition monitoring [74]-[78].

Related Works	Applications in Power Systems	AI Techniques Used	Case Studies	Advantages over common traditional methods	Limitations of the AI technique used	Proposed Recommendations
[74]	diagnosing and defect classification of power transformer	CNN	This study was tested in a microgrid environment where dry power transformers are critical components. The microgrid in question serves a small industrial area.	This case study offers automated, precise, and faster diagnostics.	The study's primary weakness is the limited dataset, which could lead to over-fitting and reduce the model's effectiveness in diverse real-world scenarios.	Subsequent studies should expand the dataset and integrating additional data types, such as sensor readings, to enhance the models' robustness and generalization capabilities.
[75]	Prognostic health management (PHM) of smart transformers within smart grids.	Machine learning models, including: Evolutionary support vector machines, Random forests, K-nearest neighbors, Linear regression.	Smart grid-ready energy management system.	Offers significant improvements in predictive accuracy, real-time monitoring, and automated decision-making.	Its primary weakness lies in its dependence on human agents and variability in model performance due to data dependency.	Integration of advanced deep learning techniques and improving data collection processes.
[76]	Determination of the health index of gas-insulated switch gear bays and their components.	Fuzzy Logic	This methodology was applied to a 175 GIS bays in Thailand.	The fuzzy logic model incorporates real-time operational data and adjusts Health index based on both visible and invisible aging. This can be used to prioritize maintenance activities and optimize resource allocation.	Its dependency on comprehensive and high-quality data is a significant weakness.	Integration of more sophisticated AI techniques, such as machine learning, to automate the development of fuzzy rules and improve the model's predictive capabilities.

Table 4. Continued.

Related Works	Applications in Power Systems	AI Techniques Used	Case Studies	Advantages over common traditional methods	Limitations of the AI technique used	Proposed Recommendations
[77]	Classification of faults in power transformer windings	CNN	Simulated various winding faults for Frequency Response Analysis classification in transformers.	Enables the detection of faults across the entire frequency spectrum, reducing the subjectivity and potential errors associated with human analysis to improve accuracy and reliability.	The study's reliance on simulated data and the exclusion of phase measurements limits the direct applicability of its findings to real-world scenarios.	Bridging the gap between simulation and practical application and enhancing the reliability of predictive maintenance in power systems.
[78]	Defect recognition in transmission lines using aerial images	CNN Knowledge distillation Connected domain algorithms.	The model was tested on a power inspection dataset.	Automatically extract and learn features in a hierarchical manner, which improves both the efficiency and effectiveness of defect detection	The study does not thoroughly explore the potential for overfitting or the generalizability of the model to other datasets or types of defects	Mitigation of computational complexity, by exploring the use of more lightweight distillation techniques or hybrid models

Additionally, most studies did not address the interdependent nature of failures across different components. For instance, there may be a correlation between transformer overheating and line congestion, yet the techniques analyzed rarely captured these relationships. From an operational point of view, rule-based systems like fuzzy logic offer interpretability but have a limitation in the area of expert-defined thresholds that may not generalize across different operating conditions. Therefore, AI-based predictive maintenance is mature technically; progress in the deployment of systems that are scalable has been slow.

6 Energy management

Energy management is a very critical feature in power systems that involves controlling, optimizing, and monitoring the generation, distribution, and consumption [79]-[81]. The primary aim is to ensure efficient energy use while preserving system reliability and minimizing operational costs [82],[83]. Artificial Intelligence integration in Energy Management Systems (EMS) for power systems is increasingly important as the demand for efficient and reliable energy distribution grows [84], [85].

The introduction of an ANN-based approach that ensured data reliability for energy management, by tackling problems like missing values, outliers, and redundancy, using the Tracebase dataset was studied [86]. Moreover, the utilization of an AI-driven "Adaptive Neuro-Fuzzy Inference System (ANFIS)" to optimize energy management in microgrids, by minimizing power transfers from the main grid was presented by [87]. Additionally, a proposal on a load scheduling optimization model based on the Cuckoo Optimization Algorithm that effectively accounted for diverse operating conditions and scheduling criteria while integrating distributed renewable energy systems, as illustrated in Figure 4 was presented by [88].

Detailed development and deployment of an EMS for residential electricity consumption, through the use of fuzzy logic to optimize energy consumption control, ensuring more efficient usage of available power resources were done as presented by [89], [90]. Table 5 summarizes the studies

discussed herein. Based on the reviewed works in this section, the AI-based techniques for energy management outperformed the conventional rule-based control because of their ability to enable dynamic load scheduling, improve DER coordination, and offer efficient power distribution. Nevertheless, many models in this domain assumed an ideal operational condition, stable communication, known load profiles, and predictable renewable energy output, but in reality, EMS operate with incomplete data, inverter-level disturbances, and fluctuating loads. In real-world application, actual EMS decisions usually involve trade-offs among emissions, cost, battery longevity, user comfort, and reliability. However, the majority of the reviewed works were oversimplified to optimize only one or two objectives at a time, thereby reducing the real-world applicability of these techniques. Like in other domains, computation is also a major challenge in the application of AI-based techniques in EMS, because most EMS models rely on ANN, ANFIS, or hybrid optimization techniques that require heavy computation, making it difficult to deploy them on low-power embedded controllers that are usually used in microgrids.

Most studies also failed to consider user behavior, tariff variability, and the uncertainty of demand, which are strong influences for energy consumption. Additionally, issues like compatibility and interoperability with already existing EMS, DER controllers, and SCADA systems were not addressed sufficiently, and without considering these compatibility constraints, even high-performing models may be unusable. To solve some of the aforementioned challenges, there's a need for future systems to focus on real-time adaptability and hardware-level optimization if significant adoption is to be seen.

7 Renewable energy inclusion

The incorporation of renewable energies like solar, wind, hydropower, and biomass, into the existing electricity grid is an innovation that has experienced encouraging adoption [91]-[94].

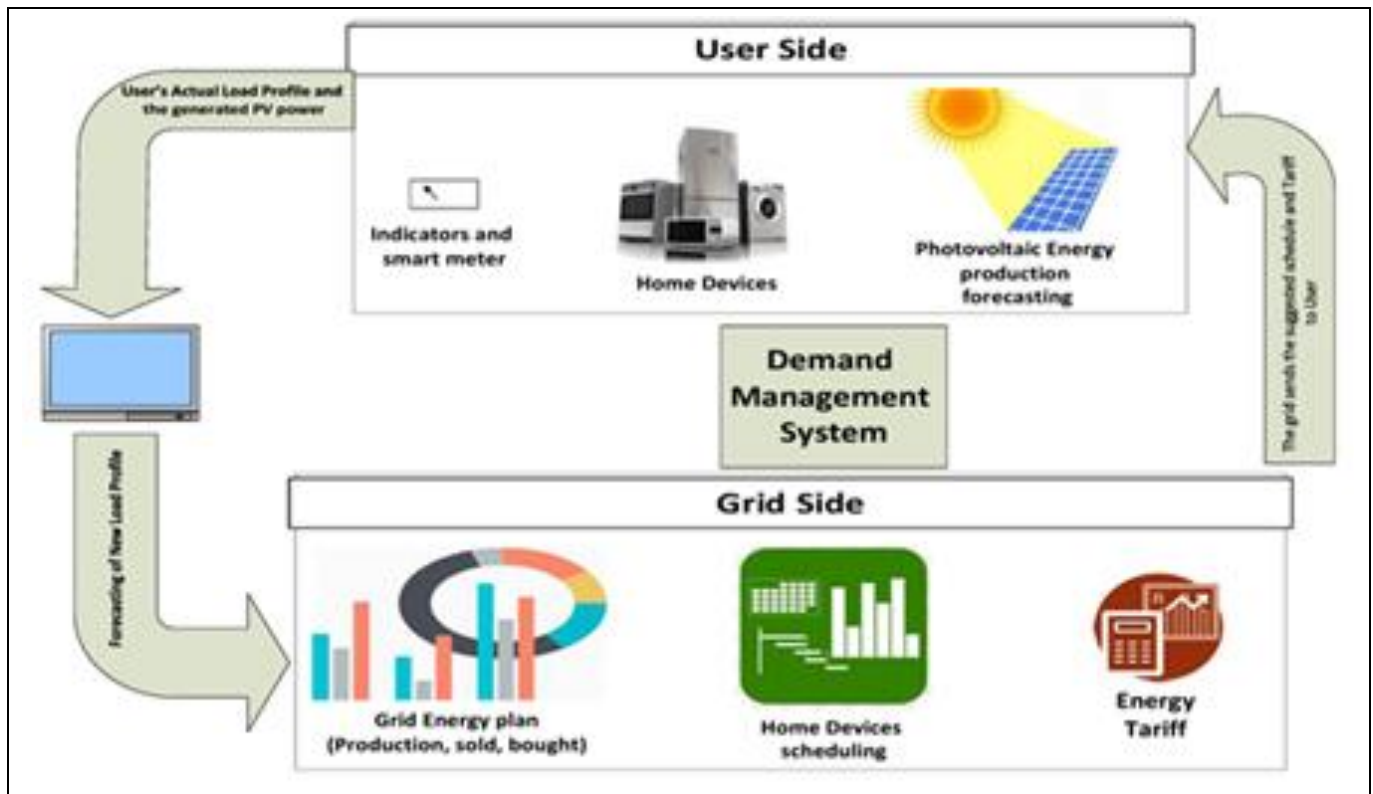


Figure 4. Diagram illustrating the structure of the energy management system modelled in [88].

Table 5. Key findings in the application of AI-Driven energy management and demand response [86]-[90].

Related Works	Applications in Power Systems	AI Techniques Used	Case Studies	Advantages over common traditional methods	Limitations of the AI technique used	Proposed Recommendations
[86]	Improvement of data quality in smart home energy management systems	ANN NARX-SCG	Tracebase dataset, which contains real-world smart home energy consumption data. The dataset includes timestamped energy consumption records for various appliances over multiple days.	Maintaining data integrity in smart home energy systems by detecting and removing anomalies such as garbage data, outliers, and redundant records.	The technique is limited to numerical data, and the danger of over-fitting during the training process must be carefully managed by adjusting the number of training epochs based on dataset size	It is recommended to explore its applicability to more diverse datasets beyond numerical data. Additionally, the model's scalability could be improved by leveraging distributed computing techniques, ensuring that the ANN can handle larger and more complex datasets with varying degrees of anomaly.
[87]	Optimization of power distribution in renewable energy, battery energy storage systems (BESS), and the main grid.	ANFIS Fuzzy logic.	A microgrid composed of solar PV systems, wind turbines, and a BESS, interconnected with the main grid.	The ANFIS-based Energy Management System effectively manages nonlinear loads, optimizes battery usage to prevent overcharging or deep discharge, and provides voltage support to the microgrid	The complexity in designing and tuning the ANFIS controller, coupled with scalability concerns, presents challenges.	Integrating real-time data streams into the ANFIS framework could enhance its responsiveness to sudden changes in load or generation and improve scalability

Table 5. Continued.

Related Works	Applications in Power Systems	AI Techniques Used	Case Studies	Advantages over common traditional methods	Limitations of the AI technique used	Proposed Recommendations
[88]	Generic load scheduling optimization model tailored for smart grid systems.	Cuckoo optimization algorithm	The study was conducted using factual load data from an Egyptian building. This structure, which includes diverse facilities such as lecture halls, administrative rooms, and laboratories, served as the basis for testing the scheduling approach.	The model handles challenges with computational intensity and scalability more effectively, making it a preferable choice for smart grid applications.	The approach might need further validation across different types of buildings and energy systems.	The algorithm's applicability could be tested and optimized for different distributed renewable energy systems, such as wind energy and hybrid systems, to validate its effectiveness across diverse energy sources.
[89]	Development and practical implementation of an Energy Management System	Fuzzy Logic	The model was designed with fuzzy logic and implemented using object-oriented programming in C++, was tested both in simulation and laboratory environments.	Provides flexibility by handling uncertainty and imprecision in input data, such as varying energy consumption patterns and weather conditions affecting PV output.	Its reliance on weather conditions for renewable energy, limited control over low-power devices, and lack of remote-control capabilities are notable weaknesses.	Improving remote control functionalities, expanding control to low-power devices, and testing the system in diverse real-world.
[90]	Optimization of residential electricity consumption by scheduling household appliances	fuzzy logic	The study was conducted in a South African residential area where electricity prices fluctuate based on TOU tariffs.	The model dynamically adjusts the operation of household appliances based on real-time inputs and TOU tariffs, providing a more flexible and efficient way to manage energy usage.	When the remaining daily electricity limit is low, it automatically shuts off appliances, which may inconvenience users.	Future work should consider integrating user preferences into the fuzzy logic controller, allowing for prioritization of critical appliances even when electricity is low.

The mass adoption is enormous. The application of AI in optimizing the integration of renewable energy sources (RES) into power systems has also seen significant advancements [95],[96]. Various studies presenting innovative methods for the integration goal of energy share increment and improvement of cleaner energy in the overall energy mix have been done in [97]-[99]. The Exploration of the importance of Ai in the optimum hybrid sizing that ensures reliable power in off-grid and remote areas.

Optimal allocation of distributed generators and BESS in power grids were analyzed in [102]. A study conducted on the techno-economic optimization of hybrid energy systems, comparing various battery technologies, thereby improving grid performance and revealing the most cost-effective solution, particularly in small-scale applications was done by [103]. Furthermore, for effective optimization of power systems through renewable energy integration, a proposal on a fuzzy multi-objective upgraded Kepler optimizer algorithm (MOIKOA) for a hybrid microgrid optimization as illustrated in Figure 5. Summary of the review is shown in Table 6 below was presented [104].

AI has made impressive contributions to renewable energy planning and integration, especially in areas like system sizing, hybrid design, DG and BESS placement, and techno-economic analysis. Algorithms such as IHS, mOPA with Lévy flights, IMFO, and MOIKOA often outperform traditional methods in simulations. But even with these gains, real-world deployment still faces noticeable gaps. A major issue is that many studies

focus on single-objective optimization, usually around cost or energy loss. In reality, integrating solar, wind, and storage into the grid requires balancing several factors at once including reliability, uncertainty, environmental concerns, grid stability, battery degradation, and fluctuating demand. Some papers provide strong cost insights, but they still fall short of capturing the multi-layered trade-offs utilities deal with.

There is also the challenge of handling binary decisions such as which components should be active at a given time. Although variants of mOPA offer strong global search performance, they do not always translate well to real operating decisions. Meanwhile, models like IMFO that perform well in DG and BESS allocation often fail to capture the instant and unpredictable fluctuations of solar and wind, which can disrupt whatever optimal plan the model produces. Even techno-economic studies, though useful, tend to overlook real-world obstacles. Few papers discuss battery degradation, supply chain issues, regulatory barriers, or financial limitations in developing regions. Capital and maintenance costs remain major hurdles, especially for small-scale or rural installations.

8 Cybersecurity

AI technologies have become more vulnerable to cyberattacks [105]-[107]. However, a notable improvement in cybersecurity has been witnessed, as seen in the various advanced AI techniques applied to enhance cybersecurity and resilience in power systems, addressing significant threats

such as unauthorized access, cyberattacks, and data breaches [108]-[110].

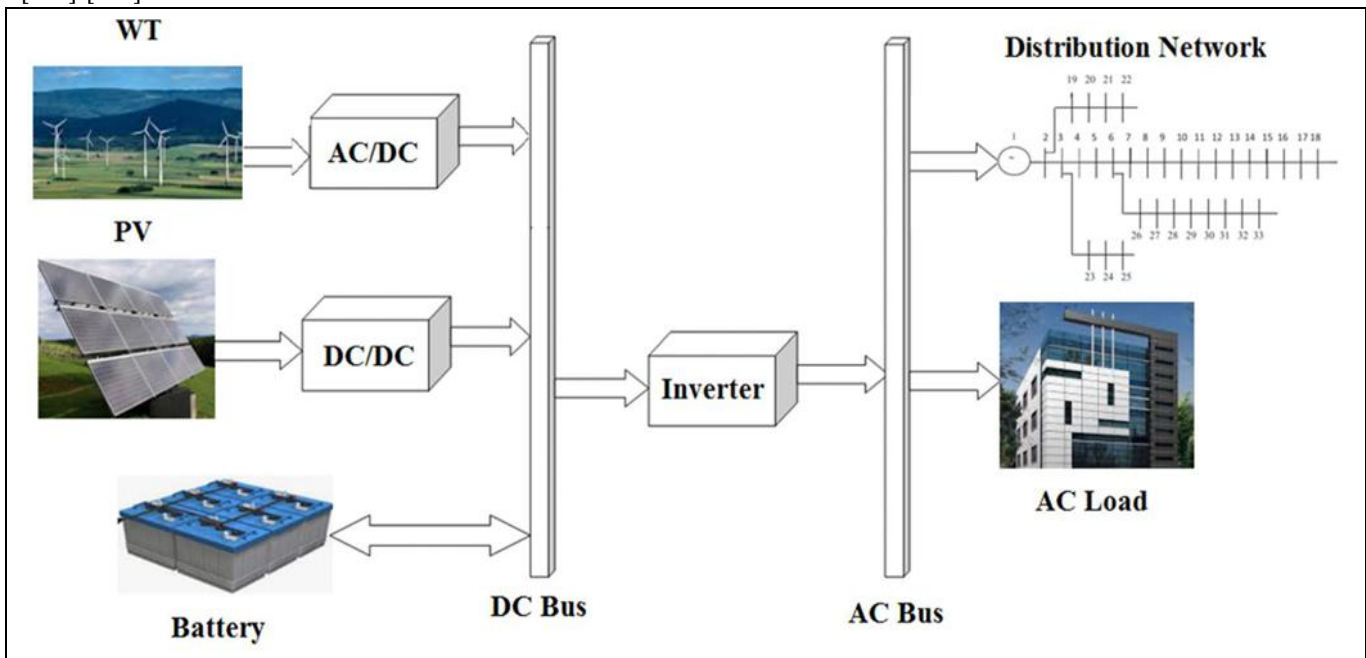


Figure 5. Diagram of the PV/WT/BES microgrid system proposed in [104].

Table 6. Key Findings in the Integration of AI in Renewable Energy [100]-[104].

Related Works	Applications in Power Systems	AI Techniques Used	Case Studies	Advantages over common traditional methods	Limitations of the AI technique used	Proposed Recommendations
[100]	Optimal sizing of hybrid energy systems	IHS	A remote area in Davarzan, Iran.	Effectively minimizes TLCC while ensuring reliable power supply.	It has a narrow focus on TLCC as the sole optimization objective	Incorporation of multi-objective optimization approaches.
[101]	Minimization of energy costs, loss of power supply probability, and excess energy in the system	mOPA Lévy flight OBL	The mOPA algorithm on isolated hybrid power system in Egypt to optimize its size, aiming to meet load demands at the lowest energy cost	By incorporating LF and OBL strategies, mOPA improves search efficiency and reduces the likelihood of getting stuck in local optima.	Its performance in binary optimization problems has not been fully explored	Developing binary versions of the algorithm and exploring it.
[102]	Addresses the problems caused by the unpredictable nature of renewable energy sources, by optimizing the deployment of distributed generators (DGs) in power grids	IMFO Gaussian barebones Quasi-opposite-based learning	Two IEEE standard distribution networks: the 69-bus and 118-bus systems	Improved precision and robustness as a result of its enhanced exploitation capability and global convergence rate.	The study does not explore the effect of immediate fluctuations in renewable energy on the optimization process.	The effect of instantaneous fluctuations in renewable energy should be incorporated into the optimization process to enhance applicability of the algorithm in dynamic power grid environments.
[103]	Techno-economic analysis of hybrid systems	FPA PSO	The study made use of different battery energy storage technologies and went further to compare three hybrid power system configurations: PV/BESS/BESS, WT/BESS, and a combination of both PV/WT/BESS	The model offers more sophisticated solutions by simulating natural processes and swarm behavior, leading to better optimization results and improved cost efficiency	A notable weakness of this model is the higher initial cost, which may hinder widespread adoption.	There is need for more extensive optimization studies to further reduce energy costs and enhance the economic feasibility of small-scale renewable energy systems.

Table 6. Continued

Related Works	Applications in Power Systems	AI Techniques Used	Case Studies	Advantagee over common traditional methods	Limitations of the AI technique used	Proposed Recommendations
[104]	Optimization of hybrid microgrids	MOIKOA Fuzzy Logic	The optimization of the hybrid system was performed within a 33-bus distribution network	This model outperforms traditional methods in terms of minimizing energy losses.	The reliance on forecasted data, can lead to increased costs and deviations in network performance.	Development of more robust multi-objective optimization frameworks that incorporate real-time data and adaptive optimization techniques.

A recommendation of an unsubstantiated anomaly detection framework, demonstrated in Figure 6, for large-scale smart grids, focusing on distinguishing between faults, disturbances, and intelligent cyber-attacks was presented by [111]. A study on a tremendously randomized tree-based pattern was introduced to detect sneaky cyber-attacks in grids [112]. [113], while focusing on global feature relationships, a research on a secure federated learning approach for detecting false data detection was carried out [113]. Also, a proposal on a method combining Grey-Wolf Optimization with deep learning for invasion recognition in smart power grids was done [114]. A study on hybrid semi-supervised system to improve cybersecurity in smart grids by effectively identifying temporal patterns in network traffic, facilitating precise anomaly detection was done [115]. A detailed summary of case studies showcasing AI applications in cybersecurity is presented in Table 7.

The studies reviewed reveal hat techniques like Sparse Detection Frameworks, Kernel PCA, Extra Trees, transformers, GWO enhanced neural networks, and GRU AE models are show strong performance in identifying false data injection attacks, stealthy manipulation, and unusual communication behavior. In addition, the numerous tests on IEEE bus systems and specialized cybersecurity datasets highlight how much progress has been made. Still, several challenges stand in the way of real-world application. Many models depend on fixed thresholds, hand-picked parameters, and static training data - meaning they work well against the types of attacks they were trained on but struggle when attackers change their strategies.

Another problem is the narrow focus on specific attack types. Most studies emphasize false data injection attacks, leaving out other serious risks like denial-of-service attacks, spoofing, topology manipulation, or coordinated multi-layer attacks. Very few studies explore how these models behave during packet loss, communication failures, or unstable network conditions that commonly occur in real SCADA environments. Additionally, most models are tested on clean and structured datasets that do not reflect the irregular environments of actual power utilities. As a result, even high-performing models may experience significant performance drops once deployed in real networks. Scalability adds another concern. Techniques like CNNs or GRUs require substantial computational power, and many studies do not evaluate how well these models perform when thousands of grid devices generate high-frequency data.

9 Artificial intelligence in battery energy storage and power quality monitoring

Battery Energy Storage Systems (BESS) and power quality (PQ) monitoring have recently gained attention as important application areas for artificial intelligence, mainly due to the increasing penetration of renewable energy sources and power electronic devices in modern power systems. These developments introduce operating conditions that are difficult to model accurately using conventional analytical methods alone.

9.1 AI applications in battery energy storage systems

Recently, the use of AI techniques in BESS tasks has increased significantly. Typical examples of its usage in BESS systems are in tasks like state-of-charge and state-of-health estimation, degradation forecasting, and operational scheduling. Deep learning models like LSTM and CNN have shown improved accuracy in capturing nonlinear behaviour of batteries and long-term degradation trends when compared to machine learning techniques [116]. The performance gains of deep learning models most time comes at the expense of high data requirements and computational effort. Machine learning techniques like SVMs and random forests are still widely used because of their computational simplicity and in applications where faster inferences are required [117]. Even though these machine learning models may not achieve the same level of accuracy as the deep learning techniques, they are generally easier to deploy and interpret, which makes it important in utility-scale BESS operations. Hybrid techniques that make use of physics-based battery models with a combination of data-driven learning have been proposed to improve the robustness and reduce the data dependency of these techniques [118].

Also, metaheuristic optimization techniques have been integrated with predictive models to support charge-discharge scheduling and cost optimization. Despite their effectiveness in simulation studies, such approaches often introduce additional complexity and are mostly suitable for offline planning rather than real-time control. Existing studies have a major challenge, which has to do with the fact that most models are trained on controlled datasets This raises concern about their generalizability to large-scale, real-world BESS deployments. Another issue that has not been properly addressed has to do model transparency and operational risks.

9.2 AI Applications in power quality monitoring

Power quality disturbances like voltage sags, harmonics, and transient events continue to pose serious challenges for grid

operators, especially in networks with high converter-based generation. AI-based techniques have been largely explored to

automate PQ disturbance detection and classification.

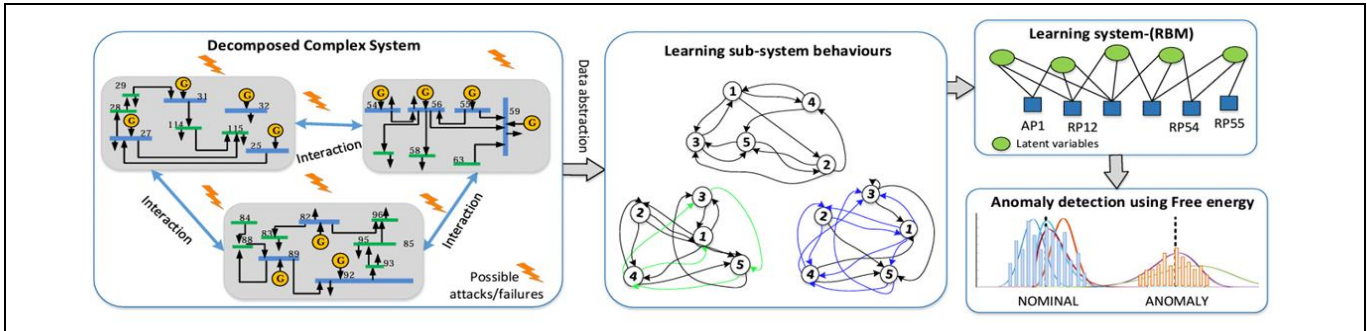


Figure 6. Proposed method in [111], for detecting cyber-attacks using unsupervised learning.

Table 7. Key findings in the application of AI in cybersecurity and resilience [111]-[115].

Related Works	Applications in Power Systems	AI Techniques Used	Case Studies	Advantages over common traditional methods	Limitations of the AI technique used	Proposed Recommendations
[111]	Large-scale cyberattack detection for smart grids	SDF	The framework was tested on IEEE 39, 118, and 2848 bus systems	offers enhanced detection capabilities, especially against sophisticated FDA that might bypass traditional residual-based detectors.	dependence on predefined thresholds and parameters, which might not generalize well across different smart grid environments.	future research could explore adaptive thresholding and dynamic parameter tuning to enhance the method's generalizability.
		DBN				
[112]	detection of sophisticated cyber-attacks in smart grids by reducing the dimensionality of the data	KPCA	The IEEE 57-bus and 118-bus systems	Provides a more reliable detection mechanism for sophisticated cyber-attacks	Historical active power flow measurements were used. lack of real-world validation,	Integration other machine learning techniques to improve adaptability and resilience.
		Extra-Trees algorithm				
[113]	Detection of false data injection attacks (FDIAs) in grids	SDF	Experiments were conducted on IEEE 14-bus and 118-bus systems	Does not rely on sequential data processing	Focuses solely on FDIA detection and does not address other types of cyber-attacks or incorporate solutions for packet loss.	Incorporation of solutions for communication packet loss and expanding the detection capabilities to include other types of cyber-attacks.
		Transformer deep learning models Paillier cryptosystem				
[114]	Intrusion detection in smart power grids.	GWO	Datasets from Mississippi State University and Oak Ridge National Laboratory	Ability to achieve high classification accuracy and effectively manage complex, noisy data	There may be scalability issues when applying the model to larger or more diverse datasets,	Enhancing the prototype's scalability to handle larger and varied datasets.
		CNN				
		MLP				
[115]	detection of complex anomalies, recognizing temporal patterns, and adapting to various types of cyberattacks in smart grids	GRU	The IEC 60870-5-104 dataset	Offers a more sophisticated approach by leveraging deep learning's ability to manage complex, high-dimensional data	Quality and quantity of the training data can influence performance potentially limiting its applicability in diverse scenarios.	Combination of transfer and ensemble learning approaches to improve the model's adaptability and reliability in varied smart grid
		AE-GRU				

Machine learning models, when combined with engineered features extracted from voltage and current waveforms, have demonstrated reliable performance with relatively low computational cost [119]. More recent work has focused on deep learning models, especially CNNs and CNN-LSTM hybrids, which are capable of learning directly from raw waveform data and identifying complex disturbance patterns without extensive feature engineering [120]. Although these models often report high classification accuracy, their reliance on large, labeled datasets limits their applicability in real grid environments, where disturbance data are noisy, overlapping, and sometimes poorly labeled. Another practical concern is deployment. Deep learning models for PQ analysis are computationally demanding and difficult to implement on edge devices such as PQ meters and intelligent electronic devices. As a result, their use is often restricted to offline analysis or centralized monitoring systems. Additionally, unsupervised and semi-supervised learning approaches have been proposed as alternatives in data-scarce scenarios, but these methods can suffer from high false alarm rates, particularly under changing operating conditions [121].

10 Cross-domain synthesis of AI techniques in power systems

The adoption of AI techniques in power systems as already seen in this review spans across forecasting, anomaly detection, optimization, renewable energy and so on. While these domains present unique challenges, so many overwhelming patterns emerge when comparing deep learning, machine learning, and hybrid or metaheuristic approaches. This section of this review synthesizes the insights from the different reviewed studies in order to highlight the trade-offs that shape the performance deployment feasibility of AI techniques:

10.1 Accuracy versus data requirements

In almost all domains that were considered in these studies, deep learning techniques like LSTM, GRU, CNN, and Transformer-based models achieve the highest accuracy in the aspect of prediction, particularly in load forecasting, and anomaly detection. This high predictive accuracy is as a result of their ability to learn nonlinear and temporal patterns directly from raw signals. Despite the impressive capabilities of DL models, they have a major drawback because of their dependence on large high-quality data, which is usually unavailable in developing grids or SCADA environments.

On the other hand, machine learning models like SVM, K-NN, random forest, and decision trees require fewer data points and when compared to DL models, can be quite efficient in tasks like classification-based anomaly detection and short-term predictive maintenance. Because of their requirements for lesser amounts of data, they are more suitable for small utilities and environments with low sensing infrastructure. Just like the ML techniques, hybrid and metaheuristic models, such as PSO, GA, and CSA-based optimization, do not require large amount of data. However, they need extensive simulations, and the computational burden that comes with these simulations can sometimes limit their real-time application.

10.2 Computational complexity and real-time applicability

Deep learning models are highly accurate, but they often come with a heavy computational price. Large networks require significant processing power, long training periods, and substantial memory, which makes real-time use difficult in many real-world power-system settings. This becomes especially noticeable in places like substations that still rely on low-power PLCs, microgrids running on compact embedded controllers, or remote sites where even data bandwidth is limited. In contrast, ML models tend to be lighter and faster. Their quick training and inference times make them a better fit for applications that demand quick decisions, such as real-time cybersecurity detection, lightweight energy-management algorithms, or predictive-maintenance tools running on constrained hardware. Metaheuristic techniques sit somewhere else entirely: they're great for offline tasks like sizing distributed generation or planning grid configurations. However, their slow and sometimes unpredictable convergence makes them a poor match for systems that need responses within milliseconds like rapid cybersecurity incident handling.

10.3 Interpretability and operator trust

For utility operators, trust in AI techniques highly depends on whether they can understand why a model is making a particular decision. DL models, despite their strong performance, provide the least transparency. When dealing with issues like fault identification, cyber-intrusion alerts, or EMS decisions, operators often struggle to justify actions based on "black-box" outputs. ML-based models, on the other hand, offer a more comfortable middle ground. Tools such as feature importance rankings, decision trees, or rule-based splits give operators something concrete to interpret. Hybrid rule-based systems go even further in terms of clarity. Because their decision processes are clearly defined, they remain popular in energy-management setups and protection schemes where explainability is essential. This ongoing interpretability gap is one of the main reasons deep learning - despite its accuracy, still sees limited deployment in safety-critical areas like protection coordination, system-stability decisions, and intrusion detection.

10.4 Robustness to non-stationarity and concept drift

Non-stationary behavior shows up throughout power systems, whether from changing loads, fluctuating DER output, or evolving cyber threats. A consistent pattern in the reviewed studies is that deep learning models perform very well when data conditions are stable but tend to lose reliability once the underlying distribution begins to drift. Many of these models need frequent retraining to stay effective. Machine learning methods degrade more gradually; ensemble approaches like Random Forests, for instance, usually remain usable for longer, though they still need updates when system conditions change significantly. Unsupervised models like autoencoders or clustering models help reduce dependence on labeled data but are often quite sensitive to shifts in the data distribution. Only very few works incorporate mechanisms like online learning or adaptive retraining, suggesting that the field still lacks robust drift-handling strategies.

Figures 7 and 8 summarize the fundamental trade-offs among deep learning, machine learning, and hybrid/metaheuristic

models in power systems application. The quadrant diagram in Figure 7 shows how each model balances accuracy and computational complexity. Deep learning has output the highest accuracy but needs a significant amount of computation resources. Machine learning on the other hand

provides moderate-high accuracy with a much lower computational cost when compared with deep learning. Hybrid and metaheuristic models deliver moderate accuracy with higher computational overhead, which makes them better for offline optimization than real-time use.

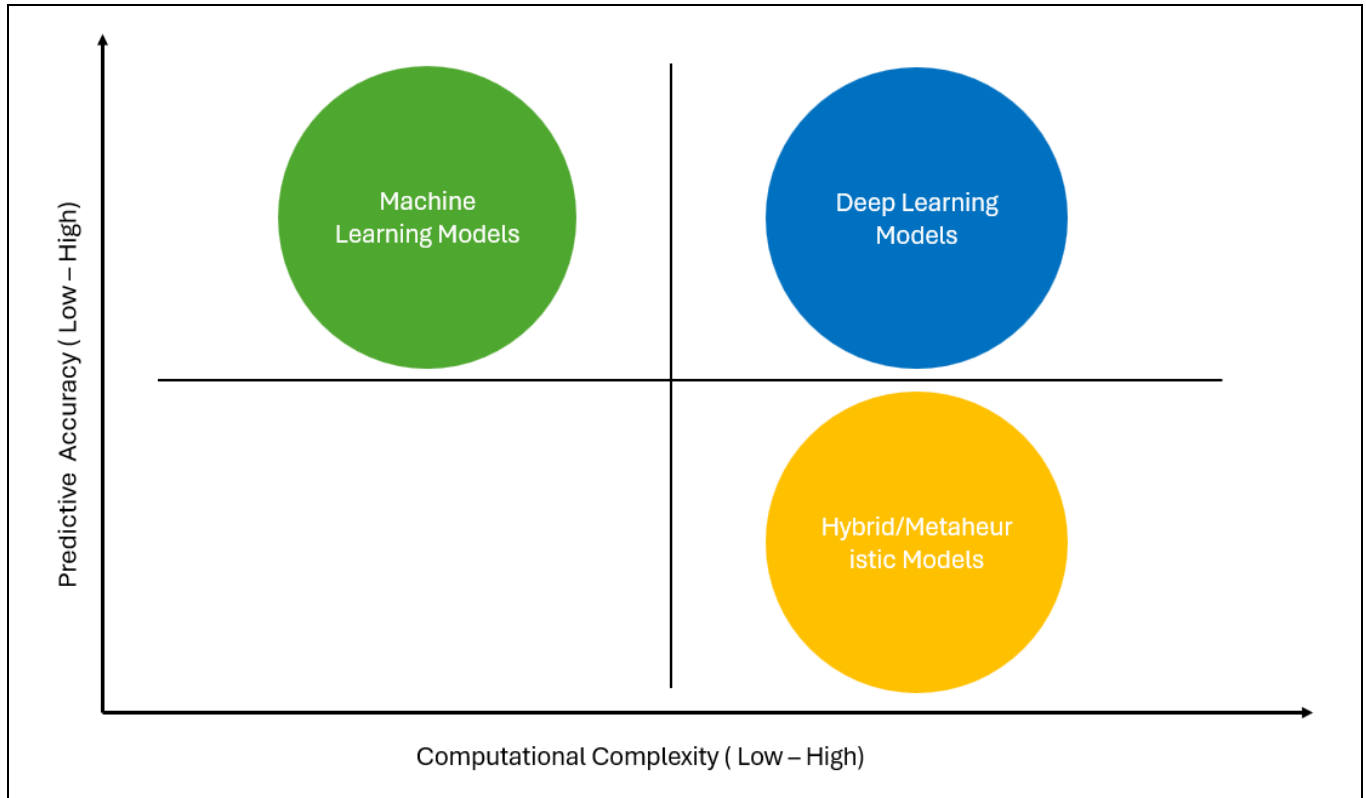


Figure 7. Trade-off landscape of AI techniques in power systems.

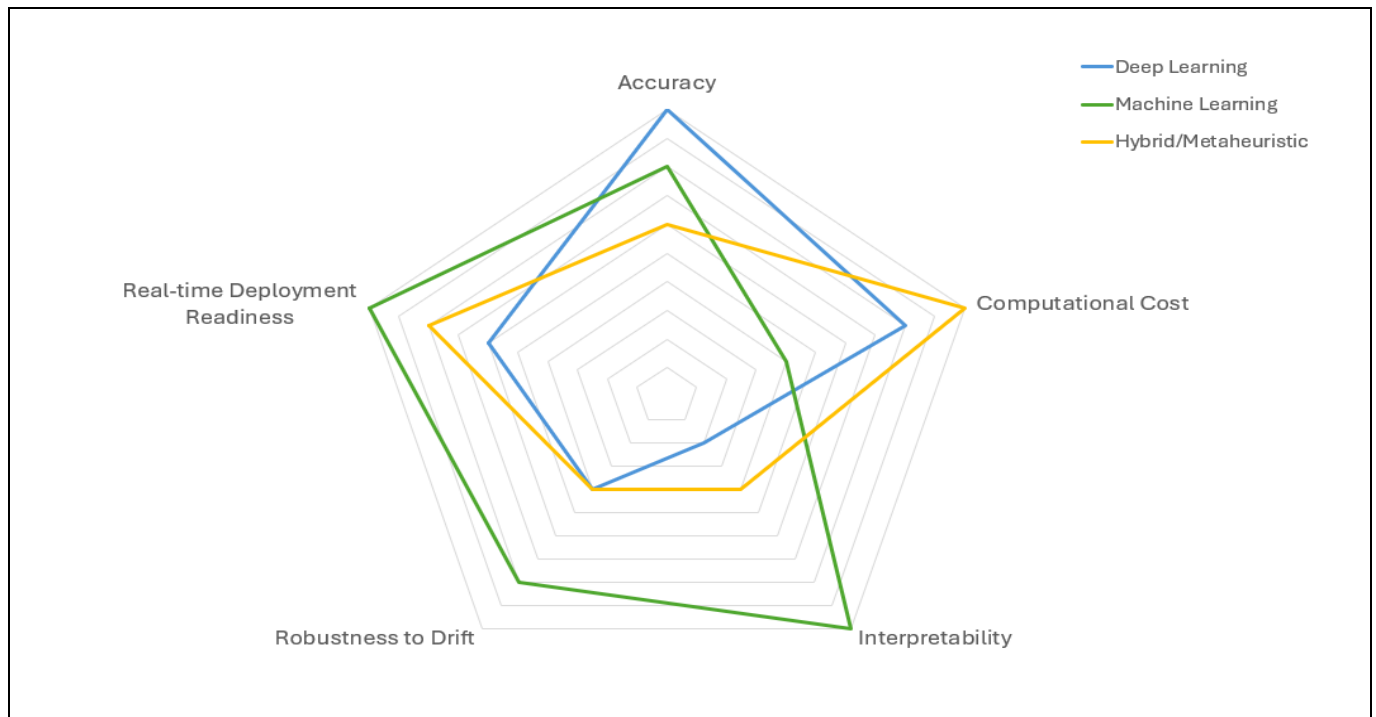


Figure 8. AI model trade-offs across power system requirements.

The radar chart in Figure 8 expands the comparison across some additional requirements, which includes: interpretability, deployment readiness, and robustness to concept drift. Though deep learning models have a high level of accuracy, they perform poorly in other aforementioned requirements. Across different studies, machine learning remains the most balanced option, with strong interpretability and a reliable deployment performance. Hybrid/metaheuristic models has a significant computational burden and lower robustness. This limits their suitability for environments that are dynamic. Summarily, no single method possesses all requirements, and AI model selection must align with practical constraints and system-level objectives.

11 Conclusion

This review has highlighted the transformative impact of AI across several key areas of power systems: load forecasting, anomaly detection, predictive maintenance, energy management, cybersecurity, and renewable energy integration. Our analysis of real-world case studies demonstrates that AI-driven solutions consistently outperform traditional methods by significantly improving system reliability and efficiency. These advancements have led to more effective power generation, distribution, and consumption strategies, ultimately resulting in faster data processing, higher data quality, reduced energy loss and costs, and enhanced security. Despite these clear benefits, significant challenges remain that hinder the widespread implementation of AI in the power sector. A primary issue is the over-reliance on historical or forecasted data rather than real-time data, which limits the scalability and adaptability of many AI techniques. Additionally, the substantial computational resources required for training and deploying complex models, along with the inherent complexities of the models themselves, continue to be major barriers to broader adoption.

12 Future research directions and recommendations

1. Future research should focus on developing more robust data collection methods that can capture and utilize real-time data effectively. It is also crucial to explore diverse datasets to improve model training and create resource-efficient algorithms that can be deployed without prohibitive computational costs,
2. Researchers and practitioners can work towards creating standardized real-world datasets and benchmarks, in order to establish open datasets for forecasting, anomaly detection, cyberattacks, and other domains with unified metrics,
3. There should also be works focused on the design of advanced real-time and edge-deployable lightweight AI techniques like pruned DL, quantized networks, efficient transformers that will be suitable for SCADA, microgrid controllers, and embedded devices,
4. Development of Adaptive, online-learning models that update with changing load patterns, renewable penetration, and cyber-threat behaviors would be a huge step forward in addressing issues like concept drift and the ever-evolving system conditions,
5. Issues with uncertainty handling is another critical area that should be addressed through the

Incorporation of probabilistic forecasting, uncertainty quantification, and adversarial robustness for both operational and cybersecurity tasks,

6. Future studies should also build coordinated frameworks that link forecasting, EMS, optimization, BESS control, anomaly detection, and cybersecurity into unified decision systems, instead of having independent techniques across multiple domains,
7. New AI techniques should be validated using pilot-scale and hardware-in-the-loop experiments, in order to move beyond simulations by testing models in real field devices,
8. Further studies should consider developing physics-informed and constraint-aware AI models that can integrate grid physics, protection limits, and stability constraints directly into ML/DL models to reduce infeasible outputs.

13 Author contribution statements

Benjamin O. Ezurike: Conceptualization, Investigation, Writing original draft. Chibuzor Chuks. Rewriting original draft, writing review & editing. Onwewuchi Ezurike. Methodology, Writing original draft. Stephen A. Ajah. Writing original draft. Daniel Nmadu. Methodology, Writing original draft. Udora N. Nwawelu: Investigation, rewriting original draft, writing review & editing. Chukwunneve A. Okoronkwo: Writing original draft, Writing review & editing. All the authors read and unanimously approved the final manuscript.

14 Ethics committee approval and conflict of interest statement

"There is no need for ethics committee approval for the prepared article". "There is no conflict of interest with any person/institution in the prepared article".

15 References

- [1] Jiang Y, Li X, Luo H, Yin S, Kaynak O. "Quo vadis artificial intelligence?". *Discover Artificial Intelligence*, 2(4), 2022.
- [2] Hassani H, Silva ES, Unger S, TajMazinani M, Mac Feely S. "Artificial intelligence (AI) or intelligence augmentation (IA): What Is the future?". *AI*, 1(2), 143-155, 2020.
- [3] Xu Y, Liu X, Cao X, Huang C, Liu E, Qian S, Liu X, Wu Y, Dong F, Qiu C, Qiu J, Hua K, Su W, Wu J, Xu H, Han Y, Fu C, Yin Z, Liu M, Roepman R, Dietmann S, Virta M, Kengara F, Zhang Z, Zhang L, Zhao T, Dai J, Yang J, Lan L, Luo M, Liu Z, An T, Zhang B, He X, Cong S, Liu X, Zhang W, Lewis JP, Tiedje JM, Wang Q, An Z, Wang F, Zhang L, Huang T, Lu C, Cai Z, Wang F, Zhang J. "Artificial intelligence: A powerful paradigm for scientific research". *The Innovation*, 2(4), 100179, 2021.
- [4] Nivedhaa NA. "A Comprehensive review of AI's dependence on data". *International Journal of Artificial Intelligence and Data Science*, 1(1), 1-11, 2024.
- [5] Sarker IH. "AI-based modeling: Techniques, applications and research issues towards automation, intelligent and smart systems". *SN Comput. Sci.*, 3,158, 2022.
- [6] Rashidi HH, Tran NK, Betts EV, Howell LP, Green R. "Artificial intelligence and machine learning in pathology: The present landscape of supervised methods". *Academic Pathology*, 6, 2019.

- [7] Mahato R. *Artificial Intelligence, what is It?* Editors: Sundari SP, Chong ST, Prabu M. Outcomes of Best Practices in Classroom Research, 197-202, New Delhi, India, L' Ordine Nuovo Publication, 2022.
- [8] Prakash N, Atiq A, Shahid M, Rani J, Dikshit S. "Merging minds and machines: The role of advancing AI in robotics". *EAI Endorsed Transactions on Internet of Things*, 10, 2023.
- [9] Saleh Z. "Artificial Intelligence Definition, Ethics, and Standards". Electronics and Communication Law, Standard and Practice. The British University in Egypt, 2019.
- [10] Zhang C, Lu Y. "Study on artificial intelligence: The State of the art and future prospects". *Journal of Industrial Information Integration*, 23, 100224, 2021.
- [11] Balbaa M, Abdurashidova M. "The impact of artificial intelligence in decision making: A comprehensive review". *EPRA International Journal of Economics, Business and Management Studies*, 11(2), 27-38, 2024.
- [12] Chennupati A. "The evolution of AI: What does the future hold in the next two years". *World Journal of Advanced Engineering Technology and Sciences*, 12(1), 22-28, 2024.
- [13] Pothen A. *Artificial Intelligence and its Increasing Importance*. Editors: Karthikeyan J, Hie TS, Jin NY. Learning Outcomes of Classroom Research, 74-81, New Delhi, India, L' Ordine Nuovo Publication, 2022.
- [14] Younesi A, Shayeghi H, Wang Z, Siano P, Sani AM, Safari A. "Trends in modern power systems resilience: State-of-the-art review". *Renewable and Sustainable Energy Reviews*, 162, 112397, 2022.
- [15] Kuriakose E, Aziz A, Qays MO, Hossain ML, Hasan R, Sohan MR. "Resiliency measurement framework for distributed energy resource integrated distribution networks". *Int. Conf. on Advances in Computing, Communication, Electrical, and Smart Systems*, Dhaka, Bangladesh, 8-9 March 2024.
- [16] Zohuri B, Mossavar-Rahmani F, Behgounia F. "Global electricity demand and clean energy source growth scenario". *J. Energy Power Eng.*, 16, 156-165, 2022.
- [17] Khan W, Ishrat M. *Unveiling the depths of explainable AI: A comprehensive review*. Editors: Sharma S, Prakash A, Sugumaran V. Technological Advancements in Data Processing for Next Generation Intelligent Systems, 78-106, Hershey, Pennsylvania, USA, IGI Global, 2024.
- [18] Abdalla AN, Nazir MS, Tao H, Cao S, Ji R, Jiang M, Yao L. "Integration of energy storage system and renewable energy sources based on artificial intelligence: An overview". *Journal Energy Storage*, 40, 102811, 2021.
- [19] Rodrigues L, Faria D, Coelho F, Mello J, Saraiva JT, Villar J, Bessa RJ. "Analysis of flexibility-centric energy and cross-sector business models". *19th Int. Conf. Eur. Energy Market*, Lappeenranta, Finland, 6-8 June 2023.
- [20] Lyu W, Liu J. "Artificial intelligence and emerging digital technologies in the energy sector". *Appl. Energy*, 303, 117615, 2021.
- [21] Liu Z, Sun Y, Xing C, Liu J, He Y, Zhou Y, Zhang G. "Artificial intelligence powered large-scale renewable integrations in multi-energy systems for carbon neutrality transition: Challenges and future perspectives". *Energy and AI*, 10, 100195, 2022.
- [22] Huawei Technologies. "Artificial Intelligence Technology". Hangzhou, China. Springer, 2021.
- [23] Arrieta AB, Díaz-Rodríguez N, Del SJ, Bennetot A, Tabik S, Barbado A, Garcia S, Gil-Lopez S, Molina D, Benjamins R, Chatila R, Herrera F. "Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI". *Information Fusion*, 58, 82-115, 2020.
- [24] Vasudevan K, Pub I. "Applications of artificial intelligence in power electronics and drives systems: A comprehensive review". *Journal of Power Electronics*, 1(1), 1-14, 2023.
- [25] Emmert-Streib F, Yli-Harja O, Dehmer M. "Artificial intelligence: A clarification of misconceptions, myths and desired status". *Frontiers in Artificial Intelligence*, 3, 524339, 2020.
- [26] Stock S, Babazadeh D, Becker C. "Applications of artificial intelligence in distribution power system operation". *IEEE Access*, 9, 150098-150119, 2021.
- [27] Pandey U, Pathak A, Kumar A, Mondal S. "Applications of artificial intelligence in power system operation, control and planning: A review". *Clean Energy*, 7(6), 1199-1218, 2023.
- [28] Barja-Martinez S, Aragüés-Peñalba M, Munné-Collado I, Lloret-Gallego P, Bullich-Massagué E, Villafafila-Robles R. "Artificial intelligence techniques for enabling Big Data services in distribution networks: A review". *Renewable and Sustainable Energy Reviews*, 150, 111459, 2021.
- [29] Heymann F, Quest H, Lopez-Garcia T, Ballif C, Galus M. "Reviewing 40 years of artificial intelligence applied to power systems - A taxonomic perspective". *Energy and AI*, 15, 100322, 2024.
- [30] Hussain S, Alammari R, Iqbal A, Shikfa A. "Application of artificial intelligence in electrical power systems". *IEEE International Conference on Informatics, IoT, and Enabling Technologies*, Doha, Qatar, 2-5 March 2020.
- [31] Chinda FE. "The impact of artificial intelligence on engineering innovations". *Int. J. Appl. Res. Technol.*, 12(7), 22-28, 2023.
- [32] Khaleel M, Ahmed AA, Alsharif A. "Artificial intelligence in engineering". *Brilliance*, 3(1), 32-42, 2023.
- [33] Ahmad N, Ghadi Y, Adnan M, Ali M. "Load forecasting techniques for power system: Research challenges and survey". *IEEE Access*, 10, 71054-71090, 2022.
- [34] Habbak H, Mahmoud M, Metwally K, Fouda MM, Ibrahim, MI. "Load forecasting techniques and their applications in smart grids". *Energies*, 16(3), 1480, 2023.
- [35] Patel R, Patel M, Patel R. "A review: Introduction and understanding of load forecasting". *Journal of Applied Science and Computations*, 6, 1449-1457, 2019.
- [36] Tang X, Dai Y, Wang T, Chen Y. "Short-term power load forecasting based on multi-layer bidirectional recurrent neural network". *IET Generation, Transmission & Distribution*, 13(17), 3847-3854, 2019.
- [37] Rafi SH, Al-Masood N, Deebe SR, Hossain E. "A short-term load forecasting method using integrated CNN and LSTM network". *IEEE Access*, 9, 32436-32448, 2021.
- [38] Yadav M, Jamil M, Rizwan M, Kapoor R. "Application of Fuzzy-RBF-CNN ensemble model for short-term load forecasting". *Journal of Electrical and Computer Engineering*, 2023(1), 669796, 2023.
- [39] Zaboli A, Tuyet-Doan VN, Kim YH, Hong J, Su W. "An LSTM-SAE-based behind-the-meter load forecasting method". *IEEE Access*, 11, 49378- 49392, 2023.

- [40] Bracale A, Caramia P, De Falco P, Hong T. "A multivariate approach to probabilistic industrial load forecasting". *Electric Power Systems Research*, 187, 106430, 2020.
- [41] Himeur Y, Ghanem K, Alsalemi A, Bensaali F, Amira A. "Artificial intelligence-based anomaly detection of energy consumption in buildings: A review, current trends and new perspectives". *Applied Energy*, 287, 116601, 2021.
- [42] Zhao Y, Zhang C, Zhang Y, Wang Z, Li J. "A review of data mining technologies in building energy systems: Load prediction, pattern identification, fault detection and diagnosis". *Energy and Built Environment*, 1(2), 149-164, 2019.
- [43] Kardi M, AlSkaif T, Tekinerdogan B, Catalão PS. "Anomaly detection in electricity consumption data using deep learning". *Int. Conf. on Environment and Electrical Engineering and 2021 IEEE Industrial and Commercial Power Systems Europe*, Bari, Italy, 7-10 September 2021.
- [44] Park CH, Kim T. "Energy theft detection in advanced metering infrastructure based on anomaly pattern detection". *Energies*, 13(15), 3832, 2020.
- [45] Feng L, Xu S, Zhang L, Wu J, Zhang J, Chu C, Wang Z, Shi H. "Anomaly detection for electricity consumption in cloud computing: framework, methods, applications, and challenges". *EURASIP Journal on Wireless Communications and Networking*, 2020, 194, 2020.
- [46] Da Silva A, Guarany IS, Arruda B, Gurjao EC, Freire RS. "A method for anomaly prediction in power consumption using Long Short-Term Memory and Negative Selection". *IEEE International Symposium on Circuits and Systems*, Sapporo, Japan, 26-29 May 2019.
- [47] Zhang J, Zhang H, Ding, S, Zhang X. "Power consumption predicting and anomaly detection based on Transformer and K-Means". *Frontiers in Energy Research*, 9, 2021.
- [48] Erika S, Antonello R, Gianfranco DL, Massimo P, Rondolfo A. "Systematic review of energy theft practices and autonomous detection through artificial intelligence methods". *Renewable and Sustainable Energy Reviews* 184, 11354. 2023.
- [49] Mascali L, Schiera DS, Eirauda S, Barbierato L, Giannantonio R, Patti E, Bottaccioli L, Lanzini A. "A machine learning-based anomaly detection framework for building electricity consumption data". *Sustain. Energy Grids Netw.*, 36, 101194, 2023.
- [50] Wan Q, Li Y, Yuan R, Meng Q, Li X. "Fault identification and localization of a time-frequency domain joint impedance spectrum of cables based on deep belief Networks". *Sensors*, 23(2), 684, 2023.
- [51] Jaber AS, Kunna MA, Khatir SK. "Power systems optimization challenges and applications: An overview". *International Conference on the Cognitive Computing and Complex Data*, Huaian, China, 21 - 22 October 2023.
- [52] Dulau LI, Bica D. "Optimization of the reliability of power systems through allocation". *56th International Universities Power Engineering Conference, Middlesbrough*, United Kingdom, 31 August-3 September 2021.
- [53] López E, Domínguez-Cruz RF. Salgado-Tránsito I. "Optimization of power generation grids: A case of study in Eastern Mexico". *Mathematics and Computer Applications*, 26(2), 46, 2021.
- [54] Pawar SS, Ingole A, Kadam P, Kadam YV, Atre P, Dhanke J. "Power transmission performance optimization: Intelligent approach needed". *European Chemical Bulletin*, 12(4), 10862-10866, 2023.
- [55] Fan H, Yu K, Li Z, Shahidehpour M. "Optimization of power supply capacity of distribution network considering the participation of power sales companies in spot power trading". *IEEE Access*, 7, 99651-99657, 2019.
- [56] Airoboman AE, EA Ogujor. "Reliability optimization on power systems network using genetic algorithm". *Journal of Electrical, Control and Telecommunication Research*, 2, 18-29, 2020.
- [57] Aneke NE, Ngang NB. "Reduction of power system losses in transmission lines using optimization technique". *International Journal of Engineering Science*, 10(4), 58-66, 2021.
- [58] Kurukuru VSB, Haque A, Khan MA, Sahoo S, Malik A, Blaabjerg F. "A review on artificial intelligence applications for grid-connected solar photovoltaic systems". *Energies*, 14(15), 4690, 2021.
- [59] Rahman J, Feng C, Zhang J. "A learning-augmented approach for AC optimal power flow". *International Journal of Electrical Power & Energy Systems*, 130, 106908, 2021.
- [60] Le TN, Nguyen HNV, Nguyen TA, Phung TT, Phan BD. "Optimization of load ranking and load shedding in a power system using the improved AHP algorithm". *Engineering, Technology & Applied Science Research*, 12(3), 8512-8519, 2022.
- [61] Le THN, Phung TT, Le TN, Nguyen PN. "Load shedding technique for power system using neural network improved by cuckoo search algorithm". *Journal of Technical Education Science*, 78A, 63-72, 2023.
- [62] Le TN, Nguyen HNV, Hoang TT, Nguyen NA. "Optimizing the power system operation problem towards minimizing generation and damage costs due to load shedding". *Engineering, Technology & Applied Science Research*, 13(5), 11643-11648, 2023.
- [63] Jasim AM, Jasim BH, Neagu B, Alhasnawi BN. "Efficient Optimization Algorithm-Based Demand-Side Management Program for Smart Grid Residential Load". *Axioms*, 12(1), 33, 2022.
- [64] Jamarani, A., Haddadi, S., Sarvzadeh, R., Haghi Kashani, M., Akbari, M., Moradi, S.'Big Data and Predictive analytics: A systematic review of applications". *Artificial Intelligence Review* 57, 176. <https://doi.org/10.1007/s10462-024-10811-5>. 2024
- [65] Geng S, Wang X. "Predictive maintenance scheduling for multiple power equipment based on data-driven fault prediction". *Computers & Industrial Engineering*, 164, 107898, 2021.
- [66] Kane AP, Kore AS, Khandale AN, Nigade SS, Joshi PP. "Predictive maintenance using machine learning". *arXiv*, May 2022. <https://arxiv.org/pdf/2205.09402>
- [67] Zonta T, Da Costa CA, Zeiser FA, De Oliveira Ramos G, Kunst R, Da Rosa Righi R. "A predictive maintenance model for optimizing production schedule using deep neural networks". *Journal of Manufacturing Systems*, 62, 450-462, 2022.
- [68] Basit J, Zeb A. "Predictive maintenance using deep learning: Enhancing reliability and reducing electrical system downtime". *International Journal of Innovations in Science & Technology*, 6(3), 1120-1136, 2024.

- [69] Arez D, Navas HVG, Gaspar P. The Bridge between Artificial Intelligence and Predictive Maintenance in Industry 4.0: A Systematic Review. *Applied Sciences*. 2026;16(10):4882. <https://doi.org/10.3390/app16104882>
- [70] Lekidis A, Georgakis A, Dalamagkas C, Papageorgiou E. "Predictive maintenance framework for fault detection in remote terminal units". *Forecasting*, 6(2), 239-265, 2024.
- [71] Alves F, Badikyan H, António Moreira HJ, Azevedo J, Moreira PM, Romero L, Leitão P. "Deployment of a smart and predictive maintenance system in an industrial case study". *IEEE international Symposium on Industrial Electronics*, Delft, Netherlands, 17-19 June 2020.
- [72] Onwusinkwue S, Osasona F, Ahmad I, Anyanwu A, Dawodu S, Obi O, Hamdan A. "Artificial intelligence (AI) in renewable energy: A review of predictive maintenance and energy optimization". *World J. Adv. Res. Rev.*, 21(1), 2487-2799, 2024.
- [73] Yousuf H, Zainal AY, Alshurideh M, Salloum SA. *Artificial Intelligence Models in Power System Analysis*. Editors: Hassanien A, Bhatnagar R, Darwish A. Artificial Intelligence for Sustainable Development: Theory, Practice and Future Applications, 231-242. Cham, Switzerland, Springer, 2021.
- [74] Laayati O, Amaziane O, Bouzi M, El Bazi N, El Hadraoui H, Chebak A. "Smart energy management system: Predictive maintenance for dry power transformers using transfer learning". *International Conference on Electrical, Computer, Communications and Mechatronics Engineering*, Tenerife, Canary Islands, Spain, 19-21 July 2023.
- [75] Laayati O, El Hadraoui H, Maghraoui A, El Bazi N, Bouzi M, Chebak A, Guerrero J. "An AI-layered with multi-agent systems architecture for prognostics health management of smart transformers: A novel approach for smart grid-ready energy management systems". *Energies*, 15(19), 7217, 2022.
- [76] Panmala N, Suwanasri T, Suwanasri C. "A fuzzy logic approach to health index determination for a gas-insulated switchgear". *Energies*, 16(18), 6605, 2023.
- [77] Phillip M, Singh A, Ramlal CJ. "Narrow band frequency response analysis of power transformers with deep learning". *Energies*, 16(17), 6347, 2023.
- [78] Li Y, Li Y, Wang Q, Wang W, Liu G, Li Z, Wu H, Jiang S. "Research on defect recognition technology of transmission line based on visual macromodeling". *Appl. Math. Nonlinear Sci.*, 9(1), 1-15, 2024.
- [79] Heydari M, Heydari A, Amini M. "Energy management and energy consumption: A comprehensive study". *World Information Technology and Engineering Journal*, 10(4), 22-28, 2023.
- [80] Zhang J. "Energy management system: The engine for sustainable development and resource optimization". *Highlights in Science, Engineering and Technology*, 76 (2023), 618-624, 2023.
- [81] Akdağ O. "Intermittent earth fault function in electric distribution systems: significance, working principle, and application potential". *Pamukkale University Journal of Engineering Sciences*, 31(1), 67-72, 2025.
- [82] Cooremans C, Schoenenberger A. "Energy management: A key driver of energy-efficiency investment?". *Journal of Cleaner Production*, 230, 264-275, 2019.
- [83] Meliani M, El Barkany A, El Abbassi E, Darcherif AM, Mahmoudi M. "Energy management in the smart grid: State-of-the-art and future trends". *International Journal of Engineering Business Management*, 13, 1-26, 2021.
- [84] Alam MS, Arefifar S. "Energy management in power distribution systems: Review, classification, limitations and challenges". *IEEE Access*, 7, 92979-93001, 2019.
- [85] Kanungo SK. "Future trends in energy management systems: Opportunities and predictions for energy efficiency". [Unpublished manuscript], 2024.
- [86] Hanafi A, Moawed MA, Abdullatif OE. "Advancing sustainable energy management: A comprehensive review of artificial intelligence techniques in building". *Engineering Research Journal*, 53(2), 26-46, 2024.
- [87] Prakash KP, Kumar YVP, Ravindranath K, Reddy GP, Amir M, Khan B. "Artificial neural network-based data imputation for handling anomalous energy consumption readings in smart homes". *Energy Exploration & Exploitation*, 42(4), 1432-1449, 2024.
- [88] Obulareddy S, Ameeruddin RK. "ANFIS-based energy management system for microgrids". *Journal of Electrical Systems*, 20(3), 1673-1682, 2024.
- [89] Shaban A, Maher H, Elbayoumi M, Abdelhady S. "A cuckoo load scheduling optimization approach for smart energy management". *Energy Reports*, 7, 4705-4721, 2021.
- [90] Chojacki A, Rodak M, Ambroziak A, Borkowski P. "Energy management system for residential buildings based on fuzzy logic: Design and implementation in smart meter". *IET Smart Grid*, 3(2), 254-266, 2020.
- [91] Busisiwe RL, Mbuyu S, Reginald NN. "A fuzzy logic based residential electrical energy optimization system based on time of use tariffs". *International Energy Journal*, 21(3), 415-426, 2024.
- [92] Nazarov A, Sulimin V, Shvedov V. "Renewable energy sources: global implementation experience". *E3S Web of Conferences*, 474, 01030, 2024.
- [93] Ilojiyanya V, Umoh AA, Etukudoh EA, Ibekwe K, Hamdan A. "Renewable energy technologies in engineering: A review of current developments and future prospects". *International Journal of Science and Research Archive*, 11(1), 952-964, 2024.
- [94] Çapraz O. "Evaluation of renewable energy sources for Denizli using multi-criteria decision-making methods". *Pamukkale University Journal of Engineering Sciences*, 31(2), 180-198, 2025.
- [95] Umeh CA, Nwankwo AU, Oluoka PO, Umeh CL, Ogbonnaya AL. "The role of renewable energies for sustainable energy governance and environmental policies for the mitigation of climate change in Nigeria". *European Journal of Applied Science, Engineering and Technology*, 2(2), 71-98, 2024.
- [96] Benchikh S, Tarik J, Lamrani R. "Enhancing renewable energy systems with advanced artificial intelligence solutions". *SCT Proceedings in Interdisciplinary Insights and Innovations*, 2, 319, 2024.
- [97] Nassereddine M, Nassereddine G, Arid A, Samad M. *Artificial Intelligence Applications in Renewable Power Systems*. Editors: Samad ME, Nassereddine G, El-chaarani H, Nemat SE. Industrial Applications of Big Data, AI, and Blockchain, 26-57, Hershey, USA, IGI Global, 2024.

- [98] Ukoba K, Olatunji KO, Adeoye E, Jen TC, Madyira D. "Optimizing renewable energy systems through artificial intelligence: Review and future prospects". *Energy & Environment*, 35(7), 3833-3879, 2024.
- [99] Karmich S, Ziani EM, Jamal B, El Malki M. "Impact of integration of renewable energies and energy efficiency on the reliability of the national electricity grid". *International Journal of Power Electronics and Drive Systems*, 14(4), 2433-2446, 2023.
- [100] Rakib MW, Munna AH, Farooq T, Agili B, He M. "Enhancing grid stability and sustainability: Energy-storage-based hybrid systems for seamless renewable integration". *European Journal of Electrical Engineering and Computer Science*, 8(3), 1-8, 2024.
- [101] Maleki A, Nazari MA, Pourfayaz F. "Harmony search optimization for optimum sizing of hybrid solar schemes based on battery storage unit". *Energy Reports*, 6(7), 102-111, 2020.
- [102] Emam MM, El-Sattar HA, Houssein EH, Kamel S. "Modified orca predation algorithm: Developments and perspectives on global optimization and hybrid energy systems". *Neural Computing and Applications*, 35, 15051-15073, 2023.
- [103] Yekini SM, Mathurine G, Onyegbadue IA, Funsho O. "Techno-economic optimization of clean energy hybrid systems in the context of assorted battery storage technologies". *African Journal of Environmental Sciences and Renewable Energy*, 15(1), 170-189, 2024.
- [104] Duan F, Eslami M, Khajehzadeh M, Basem A, Jasim D, Palani S. "Optimization of a photovoltaic/wind/battery energy-based microgrid in distribution network using machine learning and fuzzy multi-objective improved Kepler optimizer algorithms". *Scientific Reports*, 14, 13354, 2024.
- [105] Alsuwian T, Shahid A, Amin AA. "Smart Grid Cyber Security Enhancement: Challenges and Solutions-A Review". *Sustainability*, 14(21), 14226, 2022.
- [106] Tatipatri N, Arun SL. "A comprehensive review on cyber-attacks in power systems: Impact analysis, detection, and cyber security". *IEEE Access*, 12, 18147-18167, 2024.
- [107] Ezurike BO, Nmadu D, Ajah SA, Uma UU, Nwawelu UN, Ogah OE, Osuji CC, Emeh JC, Okoronkwo CA. "Recent advances on the challenges of resilient automation systems of the power grid: Critical review". *Smart Grids and Sustainable Energy*, 9, 42, 2024.
- [108] Meduri K, Nadella G, Gonaygunta H. "Enhancing cybersecurity with artificial intelligence: Predictive techniques and challenges in the age of IoT". *International Journal of Science and Engineering Applications*, 13(4), 30-33, 2024.
- [109] Simoes MG, Elmusrati M, Vartiainen T, Mekkanen M, Karimi M, Diaba S, Anti E, Lopes W. "Enhancing data security against cyberattacks in artificial intelligence-based smart grid systems with crypto agility". *arXiv*, 2023. <https://arxiv.org/abs/2305.11652>
- [110] Mohamed N, Oubelaid A, Almazrouei S. "Staying ahead of threats: A review of AI and cyber security in power generation and distribution". *International Journal of Electrical and Electronics Research*, 11(1), 143-147, 2023.
- [111] Karimipour H, Dehghantanha A, Parizi R, Choo KR, Leung, H. "A deep and scalable unsupervised machine learning system for cyber-attack detection in large-scale smart grids". *IEEE Access*, 7, 80778-80788, 2019.
- [112] Camana MR, Ahmed S, García CE, Koo I. "Extremely randomized trees-based scheme for stealthy cyber-attack detection in smart grid networks". *IEEE Access*, 8, 19921-19933, 2020.
- [113] Li Y, Wei X, Li Y, Dong ZY, Shahidehpour M. "Detection of false data injection attacks in smart grid: A secure federated deep learning approach". *IEEE Transactions on Smart Grid*, 13(6), 4862-4872, 2022.
- [114] Naeem H, Ullah F, Srivastava G. "Classification of intrusion cyber-attacks in smart power grids using deep ensemble learning with metaheuristic-based optimization". *Expert Systems*, 42(1), e13556, 2024.
- [115] Harrou F, Bouyeddou B, Dairi A, Sun Y. "Exploiting autoencoder-based anomaly detection to enhance cybersecurity in power grids". *Future Internet*, 16(6), 184, 2024.
- [116] Ragula ST, Srinivas P. "Predictive battery health management using deep learning in a cloud-integrated web framework". *American Journal of AI Cyber Computing Management*, 5(4), 403-409, 2025.
- [117] Jo S, Jung S, Roh T. "Battery state-of-health estimation using machine learning and preprocessing with relative state-of-charge". *Energies*, 14(21), 7206, 2021.
- [118] Zhang S, Liu Z, Xu Y, Guo J, Su H. "A physics-informed hybrid data-driven approach with generative electrode-level features for lithium-ion battery health prognostics". *IEEE Transactions on Transportation Electrification*, 11(1), 4857-4871, 2025.
- [119] Iturrino Garcia CA, Bindi M, Corti F, Luchetta A, Grasso F, Paolucci L, Piccirilli MC, Aizenberg I. "Power quality analysis based on machine learning methods for low-voltage electrical distribution lines". *Energies*, 16(9), 3627, 2023.
- [120] Chinthaginjala R, Srinivasulu A, Agrawal A, Kim TH, Tera SP, Ahmad S. "Hybrid AI and semiconductor approaches for power quality improvement". *Scientific Reports*, 15, 25640, 2025.
- [121] Almalki AJ. "Unsupervised learning with hybrid models for detecting electricity theft in smart grids". *IEEE Access*, 12, 187027-187040, 2024.