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Artificial Intelligence in Electrical Power Systems: A Comprehensive Review of Machine Learning Techniques and Applications

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Abstract

The electrical power system is undergoing a significant transformation through the use of Artificial Intelligence (AI) and Machine Learning (ML) for advanced forecasting, monitoring, optimization, fault detection and intelligent control of electrical power systems. It reviews the broadly used ML methods such as regression, decision trees, support vector machines, neural networks, deep learning, ensemble methods, and reinforcement learning, and their implementations in the field of load forecasting, renewable energy integration, stability assessment, predictive maintenance, and smart grids. The review also addresses issues of data quality, computational complexity, cybersecurity, interpretability and model generalization. The future directions of intelligent power systems are highlighted to be promising with emerging approaches such as explainable AI, physics-informed learning, federated learning, digital twins, edge AI and autonomous operation.

Key words

Artificial Intelligence, Machine Learning, Electrical Power Systems, Renewable Energy, Deep Learning, Power System Optimization.

Introduction

Rapid evolution in Electrical Power Systems has introduced new opportunities and challenges for integrating Artificial Intelligence (AI) and Machine Learning (ML). The traditional electrical power systems were built around a central generation, known demand and deterministic operating conditions [1]. But, as more renewable energy resources, distributed generation, EVs, energy storage, smart meters and demand-side management technologies are brought into power networks, they are becoming more complex. The developments create vast amounts of data from sensors, intelligent electronic devices, pharos measurement units, supervisory control and data acquisition systems, and smart meters [2]. The ability to harness AI and ML techniques to handle this data, uncover intricate patterns, forecast future operating scenarios, and aid in automated decision-making makes them potent tools in the process.

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AI has seen significant growth in its application to electrical power systems, including load forecasting, renewable energy prediction, fault diagnosis, power quality assessment, voltage stability analysis, optimal power flow, energy management, and predictive maintenance [3]. Unlike traditional analytical methods, which may rely on mathematical models and assumptions regarding system behavior, ML methods can learn relationships directly from historical and real-time data. This is especially useful for contemporary power systems, where uncertainty and non-linearity play an increasing role [4]. Deepening the intelligence and autonomy of the power system operation has even more potential through advanced methods such as deep learning, reinforcement learning, ensemble learning, and hybrid models of artificial intelligence [5].

Electrical networks are becoming more and more complex and that is one of the key drivers for AI based approaches. Renewable energy systems like solar PV and wind power add variability (and uncertainty) to electricity generation. Meanwhile, consumer behavior is shifting and the rise in the number of EVs makes for more variable and less consistent demand. Thus, traditional forecasting, control and optimization methods might have challenges in handling large scale, nonlinear and highly variable power system data [6].

In electrical engineering, intelligent computational techniques have progressed from basic expert systems and artificial neural networks to more complex deep learning and reinforcement learning algorithms. In the beginning, AI applications were limited to classification, prediction and decision support problems [7]. Advancements in computing power, sensor technology, data accessibility, and cloud-based systems have led to the emergence of AI applications that facilitate real-time monitoring, autonomous control, and optimization. Smart grids have been a significant platform for AI development in recent years [8]. Advanced communication technology and electrical networks being integrated allows for real-time data collection and intelligent decision-making. AI is thus being recognized as a prediction tool, and a significant part of the future autonomous and adaptive power systems [9].

This review covers the principles, applications, benefits, limitations, and recent advancement of machine learning techniques in electrical power systems. It also explores various methods of

artificial intelligence and the issues of data quality, computational demands, interpretability, cybersecurity and deployment. Lastly, the review highlights key research needs and future directions such as Explainable AI, Physics-informed Machine Learning, Federated Learning, Digital Twins, Edge Intelligence, and Generative AI.

Artificial Intelligence and Machine Learning to solve real-world problems

Artificial Intelligence (AI) is the ability of computational systems to learn, reason, decide, recognize patterns, predict and solve problems that normally require human intelligence. AI has emerged as a pivotal technology in electrical power systems to solve more complex operational and planning challenges [10]. Power networks nowadays create vast amounts of data from smart meters, pharos measurement units, supervisory control and data acquisition systems, intelligent electronic devices and renewable energy resources. The AI offers ways to convert this data to valuable information for monitoring, forecasting, optimization, control, and decision making [11]. A significant subset of AI is called Machine Learning (ML), where the goal is to have computational models learn patterns from data and develop more effective solutions with an increasing amount of data without being explicitly programmed to do so for every specific task [12].

AI is a wide spectrum of techniques for creating intelligent computational behavior. These technologies are knowledge-based systems, fuzzy logic, evolutionary algorithms, neural networks, machine learning, deep learning, and reinforcement learning [13]. AI can be applied in electrical power systems to detect abnormal operating conditions, forecast power demand, detect faults, optimize power system operation, and assist in the automatic control of power systems. The power of AI is highly dependent on the availability and quality of the data, the right model, computational power, and the capacity of the model created to be generalizable to new situations [14]. There are in general four forms of machine learning: supervised learning, unsupervised learning, semi-supervised learning, and reinforcement learning. There are a number of electrical power system problems which are solved by using different paradigms [15].

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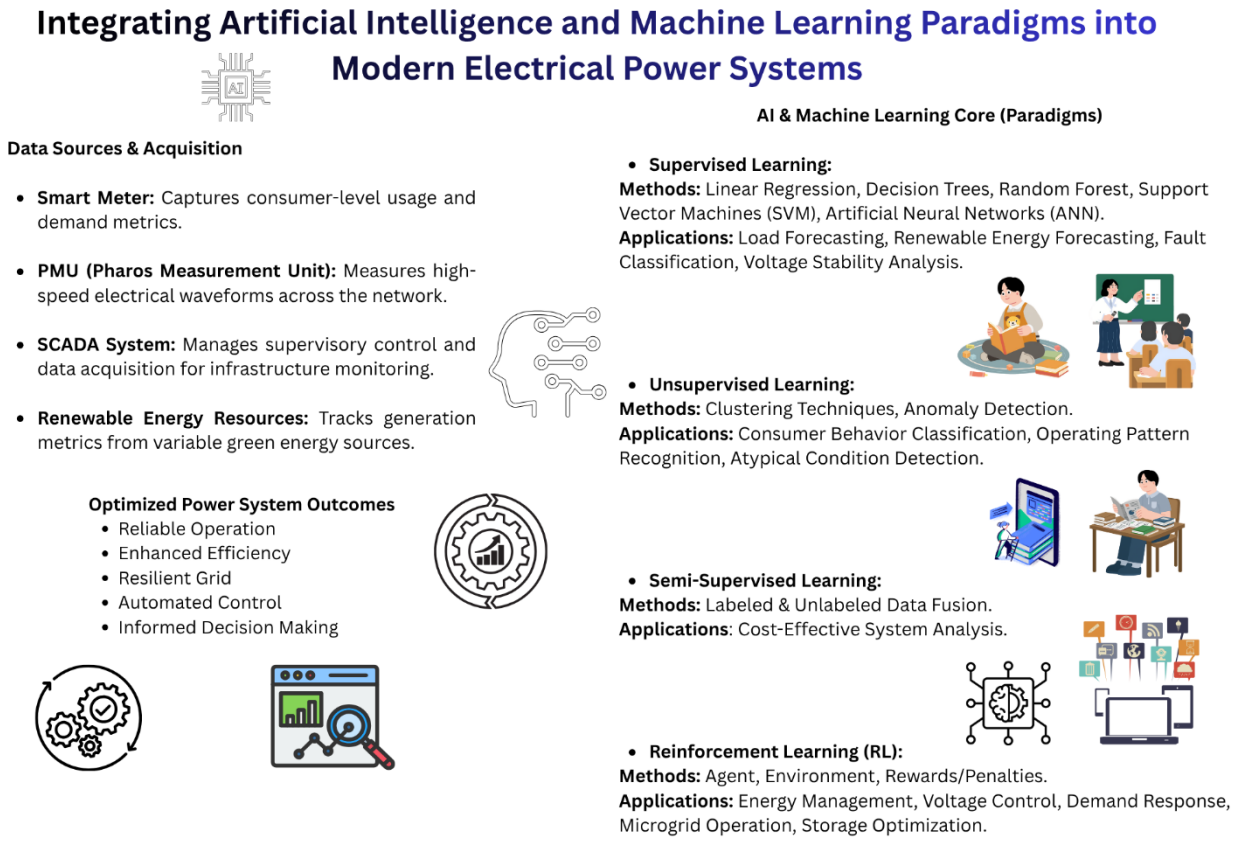


Figure 1. From Smart Grid Data to Autonomous Control: The Role of AI and Machine Learning in Power Networks

Supervised learning is when the input variables and outputs are known from a set of labelled data. The algorithm is trained to map the relationship between these variables and then is used to predict the outputs of the variables from new inputs. Examples of supervised learning methods are linear regression, decision trees, random forest models, support vector machines, and artificial neural networks [16]. These techniques are commonly used in load forecasting, renewable energy forecasting, fault classification, and voltage stability analysis.

Unsupervised learning is used when there is no set output label for the data. Rather, algorithms are used to find the underlying structures, groups, and relationships in the data. For example, consumer behavior can be classified by clustering techniques, and operating patterns and atypical conditions

in electrical networks can be detected [17]. The main idea of semi-supervised learning is to fuse labeled and unlabeled data. This method can be especially helpful when obtaining a high volume of detailed electrical system information that needs to be precisely labeled is problematic or costly [18].

Reinforcement learning (RL) is a learning paradigm that leverages an agent to interact with an environment and learn an optimal strategy based on the rewards and penalties it receives from the environment. In the power systems, RL can be used for energy management, voltage control, demand response, micro grid operation, and storage optimization [19].

Machine Learning Techniques for Electrical Power Systems

Machine Learning (ML) has become one of the key enablers of Artificial Intelligence (AI) for current electrical power systems. A lot of data is now available for smart meters, phasor measurement units (PMUs), supervisory control and data acquisition (SCADA) systems, intelligent electronic devices and renewable energy plants, which have given rise to new opportunities in data-driven decision making and modeling [20]. Electrical power systems are highly nonlinear, dynamic and uncertain processes and for some applications, traditional mathematical and numerical methods lead to computational challenges. ML techniques can identify the relationships based on past and present data and make accurate predictions, classifications and control decisions. Each of the ML methods has its own strengths based on the nature of the EE problem [21].

One of the easiest methods of supervised learning is linear regression, which is used to set up relationships of dependent variables to independent variables. It can be used in power systems for forecasting electricity demand, estimation of electricity generation, and analysis of relationships between various system parameters [22]. Logistic regression is mostly utilized for classification problems, e.g., normal operating condition versus abnormal operating condition. These methods are relatively simple and cheap to compute, but may not be able to model very nonlinear power system behavior [23].

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Decision Trees are a series of decision rules that classify or predict the outcome. They can be relatively easily understood and can work with numerical and categorical data. Random forests are an ensemble of decision trees, built on random data, and whose predictions are aggregated. Various applications of these methods include fault classification, identification of power quality disturbances, load forecasting, and stability assessment [24]. They are attractive for practical use in power systems due to their robustness and relatively good interpretability.

Supervised learning techniques, called Support Vector Machines (SVMs) search for an optimum decision boundary between the various classes. SVMs can also solve nonlinear classification problems in the framework of kernel functions. SVMs have been applied to power systems research in the areas of fault detection, fault classification, transient stability assessment, power quality monitoring, and electricity demand prediction. They are extremely effective when using fairly small amounts of data [25]. Artificial Neural Networks (ANNs) are a collection of interconnected computational units capable of learning complex relationships between the input and the output variables. ANNs have been applied in various applications such as the prediction of renewables, power system identification, fault diagnosis, voltage stability assessment, and load forecasting [26]. They are good for modeling nonlinear relationships, which is why they are particularly well suited for use with complex electrical systems.

Deep learning is a type of neural networking that uses multiple layers to automatically learn increasingly complex features from massively large data sets. For sequential data, Recurrent Neural Networks (RNNs) can be employed and for pattern recognition, Convolutional Neural Networks (CNNs) can be used, and for classification of Power Quality Disturbances (PQD) [27]. Specialized Recurrent Neural Networks (RNNs), known as Long Short-Term Memory (LSTM) networks, are well suited to the problem of load and renewable energy forecasting because they are able to learn longer-term temporal relationships. Clustering is a data-driven technique that can divide the data based on similarities and similarities in operation or in consumer behavior without using supervision data, such as the K-means clustering algorithm [28]. These methods can be used to assist in Customer Segmentation, Identifying operating state and Anomaly Detection.

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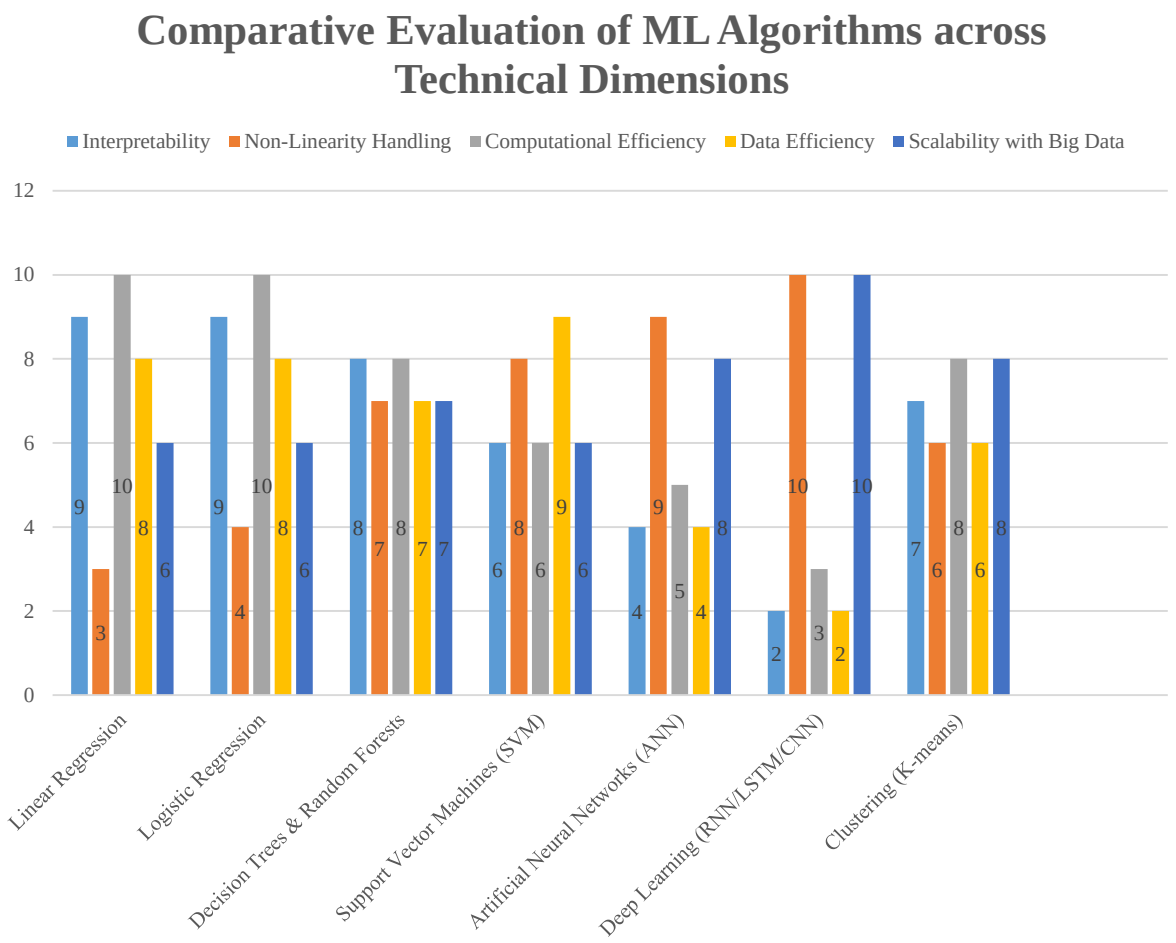


Figure 2. Comparative Evaluation of ML Algorithms across Technical Dimensions

AI Applications in Electrical Power Systems

To manage the complexity, uncertainty and volume of information generated by today's power systems, Artificial Intelligence (AI) and Machine Learning (ML) are increasingly relevant tools. The advent of renewable energy resources, distributed generation, electric vehicles, energy storage, and smart grid technologies has driven a need for advanced analytical and decision-making tools to meet the challenges of today's rapidly changing energy landscape [29]. AI-powered approaches can uncover intricate patterns in electrical system data, make precise forecasts, classifications, and optimization recommendations. This has led to the deployment of AI in virtually every aspect of

power system operation, from forecasting and monitoring, to protection, maintenance, and energy management [30].

Load forecasting is a well-established use of machine learning for electrical power systems. Electricity demand forecast is critical for the generation scheduling, economic dispatch, unit commitment and system planning. Normal forecasting techniques might struggle to determine the nonlinear relationships due to weather, consumer activity, holidays and economic activity [31]. Historical consumption, temperature, humidity and other data, with the help of ML techniques like artificial neural networks, support vector machines, random forests, and LSTM networks, can be used to increase the accuracy of the forecast [32].

Solar and wind power generation are highly variable, causing difficulties for power system operators. Historical data on renewable production, weather conditions, solar radiation, wind speed, temperature, and atmospheric conditions can be used to predict the renewable generation using AI models. Recently, LSTM networks and other recurrent networks have been employed to learn temporal patterns, typically using deep learning models [33]. Better renewable forecasting enables operators to better balance their renewable generation and demand, and lowers the uncertainty of integrating renewable energy. The state estimation computes useful variables of the system like bus voltage magnitudes, voltage angles, power flows, etc., from the available measurements. AI based state estimation can be used to supplement traditional methods, which can help to uncover nonlinear relationships and to deal with incomplete or noisy measurements [34]. Another area where ML models can help is in identifying abnormal measurements and enhancing the accuracy of the grid monitoring system.

Properly identifying and diagnosing faults is critical for electrical system reliability and avoiding equipment damage. Using voltage, current, frequency and waveform characteristics, AI models can detect faults like short circuit, line to ground, and phase to phase faults. Neural networks, decision trees, support vector machines and deep learning models have shown great promise in the field of fast fault identification and classification [35]. Power quality can be poor in modern electrical networks, due to voltage sags, voltage swells, power failures, harmonics, transients, and

other power quality issues. Different types of these disturbances can be automatically classified using measured electrical signals with the use of AI techniques [36]. CNNs and other pattern recognition techniques are especially effective for studying the complex characteristics of the waveforms as well as the various types of disturbances.

AI can aid in voltage stability and transient stability assessment by forecasting system behaviour after disturbances and loading changes and determining if the system will operate in the acceptable range. By rapidly identifying the operating states and supplying stability indicators, the burden of repeated conventional simulations can be reduced using the ML models [37]. Optimal power flow provides optimal operating conditions subject to electrical and operational constraints. Likewise, economic dispatch is to dispatch generation in an economic manner while keeping the system balanced. AI and optimization based ML methods can model efficient solutions to complex nonlinear problems. As the number of distributed resources grows, and operational conditions become more complex, these methods are highly beneficial [38].

Artificial Intelligence in Smart Grids

Smart grids are a fundamental change in the conventional electric power grid. Smart grids are different from traditional power networks, which primarily rely on centralized generation and unidirectional electricity flow, and feature sophisticated communication, sensing, automation, distributed energy resources, and bidirectional power flow [39]. These qualities create a massive amount of data from smart meters, sensors, renewable energy devices and equipment, electric vehicles, energy storage units, and intelligent electronic equipment. Artificial Intelligence (AI) and Machine Learning (ML) offer valuable means to analyze that data and enable smart monitoring, forecasting, optimization, and control [40]. As a result, AI has emerged as a crucial technology to enhance the efficiency, reliability, flexibility and resilience of smart grids.

Some key challenges for the stability and reliability of smart grids is the need for continuous monitoring. AI algorithms are capable of analyzing real-time data from sensors, Phasor Measurement Units (PMUs), SCADA systems and smart meters to detect abnormal operating conditions [41]. The machine learning models can identify patterns related to voltage violations,

equipment failures, overloads, and other disturbances. AI-based control systems can then help the operator to make suitable corrective actions. This can help to reduce response times and enhance grid stability [42].

Demand response is changing electricity demand to adjust to changing electricity prices, changing system conditions, or changing electricity grid requirements. By studying consumer behavior, historical electricity usage, weather data, and electricity pricing, AI can forecast electricity demand. Intelligent algorithms can then determine suitable demand response strategies [43]. For instance, flexible loads can be moved away from the high energy cost hours of the day, thus decreasing peak loading and possibly reducing energy costs. Automated demand response can also be enabled by reinforcement learning, which learns appropriate control strategies from the interaction with the grid [44].

Distributed energy resources (DERs), such as rooftop solar photovoltaic, small wind turbines, and fuel cells and other local generation resources, are becoming a major part of smart grids. These are variable and decentralized resources, which pose operational difficulties. AI can predict their performance, manage their use and fine-tune their role in the grid. Intelligent coordination of DERs can enhance voltage management, minimize power losses and enable reliable integration of renewable generation [45].

Micro grids are small-scale electrical systems that can be used to power local communities or businesses, either on their own or in conjunction with the larger power grid. AI can assist microgrid operators in managing generation, loads, storage systems, and renewable energy resources. Machine learning and reinforcement learning techniques can be used to optimize power exchanges between components and guarantee reliability [46]. AI-based control can be used to decide on an operating strategy to keep critical loads and then switch from grid connected to island mode during grid disturbances. Variable renewable energy (VRE) sources and electricity demand require energy storage systems. AI algorithms can calculate optimum charging and discharging patterns according to the terms of the electricity market, forecasts for renewables, demand, battery state,

and grid needs. Along with these, battery state of charge and state of health can be estimated by predictive models for enhancing the battery life and operational efficiency [47].

The increasing adoption of electric vehicles (EVs) introduces both challenges and opportunities for smart grids. Uncoordinated charging can lead to a higher peak demand and stress distribution networks. AI can forecast EV charging patterns and plan charging timetables. AI can also manage the process of releasing stored energy from EV batteries into the grid when needed, as part of vehicle-to-grid applications [48]. AI can be used to assist in decentralized energy markets where consumers and producers are able to directly trade electricity. Machine learning algorithms can predict energy availability, demand and market prices, and intelligent optimization methods can identify appropriate trading strategies. This can promote the use of local energy and enhance the economic value of distributed RE generation [49].

Fusion of Renewable Energy and Artificial Intelligence

Increasingly, renewables are becoming a significant part of the transition to sustainable, low carbon electrical power systems. Application of solar photovoltaic (PV), wind, small hydro and other renewable energy can help limit reliance on fossil fuel and lower GHG emissions. Renewables, however, pose a significant operational challenge as many renewables are variable, weather dependent and are geographically distributed [50]. Solar power depends on the solar radiation, cloud cover and temperature, whereas the wind power is significantly dependent on the wind speed and atmospheric conditions. Artificial Intelligence (AI) and Machine Learning (ML) offer sophisticated solutions to renewable energy forecasting, uncertainty management, optimization of energy resources and a balance of the grid. So, AI is becoming more important to include high amounts of renewables in modern electrical power systems [51].

One of the key applications of AI in power generation is solar forecasting, as solar generation is highly variable and dynamic depending on weather conditions. Historical PV generation data, solar irradiance, weather conditions (temperature, humidity, cloud cover) and weather forecasts can be used to predict PV generation using machine learning models [52]. Complex relationships between weather conditions and solar generation can be detected using Artificial Neural Networks (ANNs),

Support Vector Machines (SVMs), Random Forests, as well as deep learning models like Long Short-Term Memory networks (LSTM). Forecasting is essential for helping system operators to manage conventional generation, energy storage, and supply and demand imbalances [53].

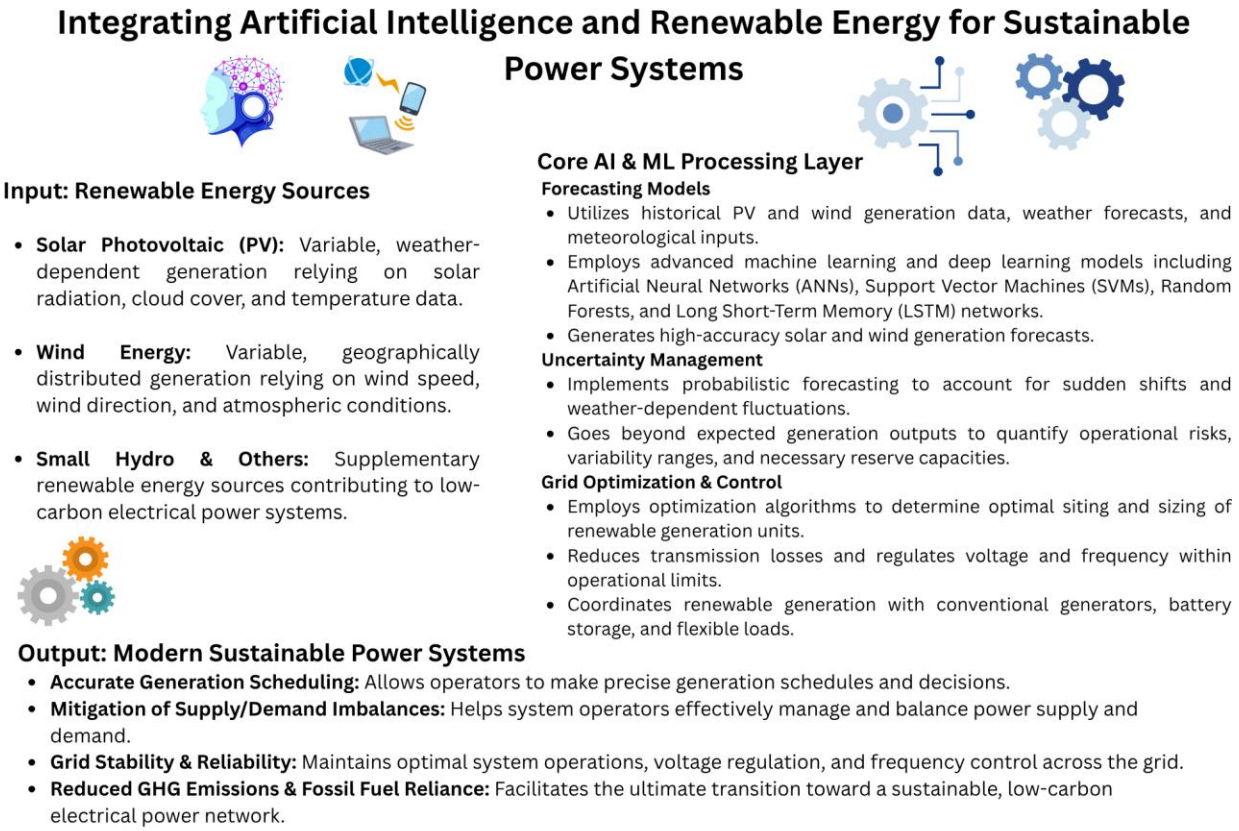


Figure 3. Integration and Fusion of Renewable Energy Sources and Artificial Intelligence for Smart Grids.

For wind energy forecasting, too, it is crucial that wind speed varies considerably over small time scales. AI models can process past wind production data and meteorological data like wind speed, wind direction, temperature and atmospheric pressure. Non-linear and temporal relationships exist in wind power data, and can be captured using machine learning and deep learning techniques. Better forecasts allows operators to make better generation scheduling decisions and diminish the operational risk of wind farms [54]. One of the significant challenges of integrating renewable energy is uncertainty. The conventional forecasting approaches are not entirely able to account for

sudden shifts in renewable generation. The use of AI can enhance probabilistic forecasting by not just forecasting expected renewable generation, but also the range of generation that may occur [55]. This knowledge will assist operators in their preparation for and response to unexpected changes, including reserve capacity.

By using AI to optimize the use of renewable resources and meet technical and operational requirements, we can create a more efficient and sustainable electrical grid. Optimizing the use of renewable resources within electrical networks using AI can help reduce the impact of renewables on the grid and achieve greater efficiency and sustainability [56]. Using machine learning and optimization algorithms, one can identify optimal deployment sites and sizes of renewable generation, reduce transmission losses, and keep voltage and frequency within the set limits. AI can also help with coordinating the renewable generation with the conventional generators and flexible loads [57].

Explainable and Trustworthy AI in Power Systems

With the proliferation of Artificial Intelligence (AI) and Machine Learning (ML) in electrical power systems, there is great potential to enhance forecasting, monitoring, optimization, fault detection and automated control. But the use of AI in critical infrastructure raises other key issues of transparency, reliability, safety and accountability [58]. Indeed, many cutting-edge ML models, especially deep neural networks, are “black-box” systems that it may be hard to figure out how a specific prediction or decision is reached. Whether in an electrical power system, where a faulty decision could result in damage to equipment, loss of power, loss of funds, or instability in the system, or any other type of power system, ability and trustworthiness are therefore essential [59].

Explainable Artificial Intelligence (XAI) is a method in understanding the logic behind AI predictions or decisions. For Power Systems, ability provides explanations to engineering questions that might arise about why a model predicted a certain fault, stability condition, load level or equipment failure. When an AI model is predicting that a transmission line is imminent to become unstable, operators need enough information to be able to take corrective action based on

the AI model's prediction [60]. Explainable models can provide operators with a greater degree of confidence and help validate and integrate AI systems into existing operational workflows.

Interpretability is a measure of how easily a human can comprehend the inner workings or results of a model. Deep neural networks are typically more difficult to understand than simpler models like linear regression or decision trees [61]. But for some applications, more complex models can yield better predictive accuracy. Hence, there is a tradeoff between accuracy and interpretability that is often needed. Through the feature importance, sensitivity analysis and visualization methods it is possible to determine which variables of a system most affect an AI prediction [62].

There are a number of XAI techniques that can be applied to interpret complex ML models. Some approaches like Local Interpretable Model-Agnostic Explanations (LIME) or Shapley Additive explanations (SHAP) can give information on the influence that a single input variable has on a prediction. These techniques can be used to analyze factors such as voltage, current, frequency, load demand, temperature, or renewable generation when evaluating power system conditions [63]. The explanations can help engineers determine if an AI model is using physically meaningful information.

Reliability is crucial for trustworthy AI, as it must produce consistent and stable outputs in varying circumstances. Electrical power systems are subjected to varying load, intermittent renewable generation, failures, extreme weather, and communication issues. If a model is trained in a few scenarios, it may not work well in different scenarios [64]. Hence, models need to be thoroughly validated with a wide range of datasets and under realistic operating conditions. Additionally, uncertainty estimation can provide operators with information on how confident they can be about the AI predictions [65].

There are also regulatory, data security, cybersecurity and accountability concerns with AI applications in power systems. When an automated AI system makes an error in an operational decision, there needs to be a clear answer on who is responsible. Moreover, sensitive electricity consumption data from smart meters needs to be safeguarded from unauthorized access [66]. AI

systems need to be developed with proper cybersecurity features, human oversight, transparency, and measures to ensure their operation.

To ensure the safe use of AI-powered technologies in electrical power systems, explainable and trustworthy AI is key. Future studies will need to focus on creating AI models that incorporate high accuracy, interpretability, robustness, uncertainty awareness, cybersecurity and physical consistency [67]. Combining traditional engineering expertise and expertise with explain ability of AI can help develop efficient power systems that are both reliable and transparent and would be acceptable in the real world [68].

Future trends and emerging perspectives

The next few years are predicted to be a dramatic period in the evolution of electrical power systems, especially as Artificial Intelligence (AI), Machine Learning (ML) and digital technologies rapidly mature. The growing market of renewable energy, distributed generation, electric vehicles, energy storage and smart grid technologies is leading to more complex and dynamic operating environments [69]. Meanwhile, the proliferation of large amounts of electrical and operational data is introducing new decision-making opportunities with intelligent applications. AI-driven technologies are consequently shifting from traditional predictions and classifications to autonomous control, real-time optimization, resilience building and intelligent energy management [70].

Physics-informed machine learning is a new paradigm that unites data-driven learning and known physical laws and engineering principles. ML models that are trained using the conventional approach can give incorrect or even unrealistic predictions in environments where their training data does not match their operating conditions [71]. Physics-informed models can enhance the generalization, reliability, and interpretability of the learning process by integrating power system equations and physical constraints into the learning [72]. This method can be used in power flow analysis, state estimation, stability analysis, and system optimization, with great potential.

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Federated learning allows multiple organizations or electrical facilities to train machine learning models together, while not sharing sensitive data directly. This can be especially helpful for utilities that have geographically spread or confidential customer or system data. Distributed learning can help in preserving privacy while still providing models with access to a variety of data sets. Some potential uses are fault detection, load forecasting, cyber security, and predictive maintenance [73].

A digital twin is a virtual version of a physical electrical asset or whole electrical system. By combining real-time sensor data with AI models, digital twins can simulate system behavior and predict potential failures or operational problems [74]. Predictive maintenance, equipment health monitoring, system planning and operator training are all areas that could benefit from the use of AI-powered digital twins. They can represent the actual world under realistic conditions and demonstrate their potential for future intelligent power system management [75].

Edge AI includes handling data at the edge, rather than sending all data to a central cloud system. Edge devices can provide real-time analysis of sensor measurements, smart meters, and intelligent electronic devices in an electrical system. This can facilitate the reduction of communication delays and facilitate quick fault detection, local control and protection applications [76]. This is because specialized hardware is likely to be more widely available in the future, making AI more and more applicable to real-time grid operations. Another field where there is new research is generative AI. Large AI models can help with technical analysis, system documentation, decision support, simulation and knowledge extraction from large volumes of information in the power system [77]. When used in safety-critical applications, though, they must be carefully validated, as outputs can be wrong or physically impractical recommendations.

Conclusion

The introduction of Artificial Intelligence (AI) and Machine Learning (ML) is rapidly revolutionizing electrical power systems with sophisticated features to predict, monitor, optimize, diagnose faults, control, and make decisions. The key concepts, most important machine learning methods, practical applications, integration with smart grids, renewable energy use, and

comparative assessment of results and future trends of AI-driven electrical power systems have been explored in this review. The results show that AI has significant potential to tackle the complexity and uncertainties of today's electricity networks.

The different machine learning methods have their own pros and cons based on the specific application in the power system. Decision trees, random forests, and support vector machines can deliver good classification and forecasting results, and regression techniques can be effective for relatively simple prediction problems. In cases of complex nonlinear relationships and time-dependent data, artificial neural networks and deep learning models are especially useful. In addition, recurrent neural networks, LSTM models have been very promising in the field of load and renewable energy prediction, while reinforcement learning provides potential improvement opportunities in the area of adaptive control and energy management. By leveraging the strengths of various techniques, hybrid and ensemble methods can further enhance accuracy, robustness, and generalization.

There are various areas where applications of Artificial Intelligence (AI) are applicable to electrical power systems. They encompass load forecasting, renewable energy forecast, state estimation of power systems, fault detection, power quality monitoring, system stability evaluation, optimal power flow, economic dispatch, predictive maintenance, electricity price forecasting, etc., and energy management. AI can support smart grid applications like demand response, distributed energy resource coordination, micro grid operations and management, energy storage management, electric vehicle integration, peer to peer energy trading, and grid resiliency. These applications may help enhance reliability, operating efficiency, economic performance, sustainability and flexibility.

AI applications are key for renewable-dominated power systems due to the inherent variability and uncertainty of solar and wind energy sources. Operators can leverage AI-based forecasting and optimization to forecast renewable generation, integrate energy storage, deal with uncertainty, and balance supply and demand. However, reliable results require reliable and representative datasets

to be available. Challenges of data quality, missing values, measurement noise, computational needs, cyber security, model generalization and compatibility with existing infrastructure still exist.

Trustworthiness and explain ability of AI is another key concern. While the predictive accuracy of black-box models can be high, they can be hard for power system operators to interpret. Explainable AI, uncertainty estimation, physics-informed machine learning, and human oversight are thus key to safety and reliability. The expected future developments include federated learning, digital twins, edge AI and generative AI, autonomous grid operation and quantum machine learning.

AI cannot be seen as a replacement for traditional electrical engineering practices; rather, it can be used as a supplemental tool that can improve them. The intelligent electricity system is a future system that will rely on data-driven intelligence, physical knowledge, engineering skills, cybersecurity, and suitable laws and regulations. Ongoing cross-disciplinary research will be crucial to create accurate, explainable, secure, adaptable, and computationally efficient AI systems. AI and ML can be a key enabler in the design of more resilient, sustainable, reliable, and intelligent electrical power systems that can serve the future energy needs. With proper development and effective validation, they can make a major contribution to developing power systems that are more resilient and sustainable.

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