

## Article

# Comparison of Artificial Intelligence and Machine Learning Methods Used in Electric Power System Operation

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**Abstract:** The methods of artificial intelligence (AI) have been used in the planning and operation of electric power systems for more than 40 years. In recent years, due to the development of microprocessor and data storage technologies, the effectiveness of this use has greatly increased. This paper provides a systematic overview of the application of AI, including the use of machine learning (ML) in the electric power system. The potential application areas are divided into four blocks and the classification matrix has been used for clustering the AI application tasks. Furthermore, the data acquisition methods for setting the parameters of AI and ML algorithms are presented and discussed in a systematic way, considering the supervised and unsupervised learning methods. Based on this, three complex application examples, being wind power generation forecasting, smart grid security assessment (using two methods), and automatic system fault detection are presented and discussed in detail. A summary and outlook conclude the paper.

**Keywords:** electric power system; smart grid; artificial intelligence; machine learning; digitalization; sector coupling



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## 1. Introduction

Electric power system providers are quite conservative regarding the introduction of technology because of very high requirements concerning the safe and reliable delivery of electric energy. The new hardware and software application must be also extremely reliable before implementation into the electric power system's operation.

The application of artificial intelligence algorithms in the electric power systems has been an intensively discussed topic since the 1970s and 1980s. In 1986, the CIGRE established a working Group 38.06 Expert System in an electric power system which could be fixed as the starting point of the first applications in the scope of international cooperation in this field [1]. Today, applications of AI have gained a new dimension and perspective, on the one hand, through advancing computer hardware, computational technology, and the technologies for processing large datasets like Big Data. On the other hand, the complexity of the planning and operation of modern, decentralized electric power systems (especially with high generation from renewable sources) requires new, fast, intelligent and adaptive operation algorithms, also based on continuously measured real data. This evolutionary process is substantiated using older sources that highlight the longstanding existence of AI methods [2,3].

The machine learning (ML) used extensively in previous years is often associated with AI (artificial intelligence) and a lot of such algorithms have already been successfully implemented, not only in the energy system. AI and ML can also be found in other economic sectors. For example, it is used in medicine to diagnose diseases, in finance to analyze

markets, in the automotive industry for autonomous driving, and even in agriculture to optimize crop yields [4]. In the energy sector, AI is systematically used to improve the flexibility of the power grid, maximize transmission efficiency, optimize communication protocols, and control distribution networks. Applications such as neural networks and fuzzy logic are used to recognize complex patterns in the data and make predictions about energy consumption and grid stability [5].

This paper therefore aims to provide four application examples for the use of AI in the electric power system. A distinction is made here with regard to the area of application in combination with a suitable ML method.

Following the decentralization and digitalization of the power grid, the current trend in research is to use data to improve electricity transmission, distribution and make it more reliable and efficient. These data (measurements) include consumption data collected using electricity meters at various consumption points such as households, businesses or industrial plants. Generation data, on the other hand, record the amount of energy from power plants, solar and wind installations, typically via monitoring systems or SCADA systems. Grid data, such as voltage, current and phase angle, are collected using sensors and monitoring devices in the electricity grid. Market data, including electricity prices and demand forecasts, come from market platforms or specialized data providers. Planning data, on the other hand, include load and generation forecasts that estimate future electricity consumption and energy generation based on historical data and weather forecasts. Grid capacity planning documents contain information on planned expansion projects and infrastructure changes in the electricity grid. Market analyses, in turn, provide insights into future market conditions and price developments in the electricity sector. Smart grids are an application area that not only transmit electricity, but also realize data transfer between different actuators. For example, data can be exchanged between electrical generation and load units as well as directly with a control system [5–7]. The data originating from smart grids consist of information management, control technologies, digital sensing, communication technologies, and field devices, used to coordinate multiple electrical processes. Since conventional modeling techniques have significant limitations in calculating such amounts of data, the use of AI algorithms is becoming increasingly obvious [4,8,9]. The increasing significance of AI goes hand in hand with the availability of cost-effective computers. This is relevant for several reasons: Firstly, AI algorithms, particularly in the realm of machine learning and neural networks, demand substantial computational power. Thanks to affordable hardware and cloud computing, it is now possible to scale these resources affordably, facilitating the implementation of AI solutions across various application domains. Secondly, accessible technology lowers entry barriers, enabling businesses and developers to embrace AI more readily, promoting its widespread use in diverse industries. Thirdly, the availability of cost-effective computers fosters research and innovation in the field of AI. Developers can conduct experimental projects, explore new models, and contribute to the continuous development and enhancement of AI technology [10]. The most essential prerequisite for the increased use of AI throughout electric power systems is the digitization of the energy sector, as well as the availability of the necessary large data sets which could be quickly analyzed from different points of view [11]. This all is necessary because of increased system dynamics, e.g., through the higher integration of renewable energies, higher load flexibility, and fast response storage integrations. By analyzing and evaluating the large data sets, the processes in the energy industry can be made more sustainable and secure. Some of the challenges that can be derived from this for an intelligent power grid are the forecasting of load profiles, the evaluation of the stability of the power grid, fault detection and grid security. These challenges can be addressed through multi-dimensional and multi-layered data collection about the operation of the power grid. However, traditional technologies such as modeling, optimization and control technologies can only solve these challenges to a limited extent. Therefore, the use of AI methods in the electric power grid is becoming more justified. AI techniques use vast amounts of data to create intelligent machines that can handle tasks

that require human intelligence. However, ML is not the only way to implement AI systems. Other possibilities of AI systems include neural networks [12], robotics, expert systems (ES), fuzzy logic (FL) [13] and natural language processing [14]. Overall, AI technologies enable fast and accurate decision-making due to processing large amounts of structured and unstructured data. In smart grid applications, AI can be defined as computers mimicking the cognitive functions of grid operators to achieve self-healing capabilities. However, AI cannot replace the grid operator in some cases, as is presented in [11].

The subdivision of AI in the power grid can be of two types: virtual AI and physical AI. Virtual AI systems include informatics that assist grid operators in performing their tasks. Physical AI systems include self-learning AI systems that can optimize and control a specific grid part with or without human intervention. AI systems in the smart grid can be divided into two categories: artificial narrow intelligence (ANI) and artificial general intelligence (AGI) [11]. ANI refers to AI systems developed for specific tasks with specific requirements and constraints, such as an AI system that performs load forecasting based on different data sets. AGI refers to AI systems that have been developed to learn and develop autonomously [11]. AGI can therefore learn and develop independently, just like humans [11]. The development of AGI systems could help realize true smart grid systems in the future. The amount of AI research for smart grid applications has increased in the last decade [11].

The research questions/objectives of this study include a comprehensive analysis of the use of machine learning (ML) in the energy sector. First, it examines how the use of ML has developed in recent years. Based on this, successful areas of application of ML algorithms in the energy sector are identified and their impact on various areas such as electricity transmission, distribution and efficiency is analyzed. It also focuses on the role of artificial intelligence (AI) and ML in optimizing these processes. Furthermore, new areas of application for ML algorithms in the energy sector and ways in which the use of ML and AI can be further expanded to meet future challenges will be identified. The importance of the digitalization and decentralization of the power grid for the development and use of ML and AI technologies will also be examined. Particular attention will be paid to the opportunities offered by smart grids to use ML and AI to improve grid stability and security. Finally, ML methods that have not yet been fully analyzed and evaluated are identified in order to uncover potential research gaps and outline further research directions.

Section 2 describes potential application areas for artificial intelligence in the electric power system, considering the power grid, energy market, and energy consumers. In Section 3, the ML methods are classified in the systematic way that can be useful for feeding the optimal setting of AI algorithms. In Section 4, based on specific use cases, the implementation of AI methods for the following four important electric power system areas: forecasting, grid stability, fault detection, and smart grid security, is discussed. Section 5 compares the methodologies presented and summarizes them.

Articles were selected based on a search of Google Scholar, Scopus and IEEE Explore databases. The search of the databases consisted of finding keywords of interest and their connections in the article title, keywords and abstract. Each selected article discusses a selected topic, important to the modeling process, on the use of AI in power grid management.

## 2. Application Potential

Artificial intelligence applications in the field of electric power systems offer the advantage of being able to process large amounts of data in real time, which enables a more precise prediction and optimization of energy flows. Compared to traditional methods, AI applications can also identify complex patterns and correlations in the data in order to make more efficient decisions and optimize energy consumption.

The electric power system can be traditionally divided into four areas, for each of the potential topics that artificial intelligence methods can be used, which are visualized in Figure 1. These four groups consider AI in the power grid operation control and

sector coupling (monitoring, maintenance, optimal operation, etc.), AI in distribution grid operations (virtual power plants (VPP), distribution management system (DMS), etc.), in energy market trading (prices forecasting, trading control and supervising), and AI on the consumer side (energy management system (EMS), optimal operation, forecasting load profiles, etc.) [6].

Artificial Intelligence in Power System			
<b>AI in the power grid operation control and sector coupling</b> <ul style="list-style-type: none"> <li>• Dynamic State Estimation</li> <li>• Predictive Analytics for Grid Dynamics</li> <li>• Wide-Area Monitoring Systems</li> <li>• Control of Power System Stabilizers</li> <li>• Optimal Power Flow (OPF) and Control</li> <li>• Fault Detection and Diagnosis</li> <li>• Adaptive Protection Systems</li> <li>• Emergency Control and Remedial Action Plans</li> <li>• Training Simulators and Operator Assistance</li> <li>• Cybersecurity for Grid Stability</li> </ul>	<b>AI in distribution grid operations</b> <ul style="list-style-type: none"> <li>• Demand Forecasting</li> <li>• Load Management and Optimization</li> <li>• Fault Detection and Diagnostics</li> <li>• Voltage Control and Regulation</li> <li>• Distribution Automation</li> <li>• Predictive Maintenance</li> <li>• Renewable Energy Integration</li> <li>• Grid Resilience and Reliability</li> <li>• Outage Management</li> <li>• Cybersecurity</li> <li>• Grid Planning and Expansion</li> </ul>	<b>AI in energy market trading</b> <ul style="list-style-type: none"> <li>• Market Analysis and Prediction</li> <li>• Algorithmic Trading</li> <li>• Portfolio Optimization</li> <li>• Risk Management</li> <li>• Market Sentiment Analysis</li> <li>• Demand and Supply Forecasting</li> <li>• Renewable Energy Forecasting</li> <li>• Automated Settlement and Clearing</li> <li>• Market Simulation and Scenario Analysis</li> <li>• Optimizing Trading Strategies</li> <li>• Blockchain for Smart Contracts</li> <li>• Market Surveillance and Compliance</li> </ul>	<b>AI in energy consumer side</b> <ul style="list-style-type: none"> <li>• Energy Consumption Forecasting</li> <li>• Smart Home Automation</li> <li>• Energy Management Apps</li> <li>• Appliance-Level Energy Monitoring</li> <li>• Predictive Maintenance for Appliances</li> <li>• Energy Billing and Tariff Optimization</li> <li>• Electric Vehicle (EV) Charging Optimization</li> <li>• Virtual Assistants for Energy Advice</li> <li>• Grid Interaction and Demand Response</li> <li>• Energy Efficiency Incentives and Gamification</li> <li>• Home Energy Audits</li> </ul>

**Figure 1.** Overview of potential areas of application of AI systems in the electric power system [6].

The specified areas of electric power systems, as shown in Figure 1, are described below:

- **AI in the power grid operation control and sector coupling:** Due to the transformation process of the power grid, the increasing share of renewable energies, controllable loads and electrical energy storage at the low- and medium-voltage level, as well as the increasing digitalization of the power grid, the operation, and the resulting management of grid stability have become more complex. In addition, there is a high volume of multi-layered data, which are necessary for the operation of smart grid that must be transported, evaluated and analyzed. The results of these data analyses are a reaction of control algorithms which should be intelligent and fast, as well as having an efficient consumption on the feed-in side. Thus, AI can help analyze and control data through linking different participants (loads, generators and storage) as well as different sectors (electricity, heat, gas, and transport). One of the focuses here is on the integration of electric vehicles (EV) [15]. During the time that they are connected to the charging station, they represent electrical energy storage in the grid. The charging/discharging processes must be coordinated with the smart grid needs. AI can help coordinate maintenance work and determine optimal scheduling from the networks, as well as from the individual storage (EV) point of view. This can minimize costs and losses of profits, as well as disruptions to grid operations [16].
- **AI in distribution grid operations:** Incorporating AI into distribution grid operations delivers a myriad of advantages, profoundly enhancing the efficiency, reliability, and sustainability of the electrical distribution system. AI addresses key areas such as predictive maintenance, swiftly detecting faults, optimizing grid operations in real-time, managing renewable energy integration, minimizing energy losses, bolstering grid resilience during extreme events, providing data-driven decision-making through analytics, improving load forecasting accuracy, enhancing cybersecurity, and enabling remote monitoring and control. This comprehensive integration of AI stands as a transformative approach to modernize and elevate the overall performance of the electrical distribution grid [10].
- **Use of AI in energy market trading:** This can help to optimize electricity trading by improving, e.g., the forecast of weather and energy price data. AI can help correlate large amounts of historical weather data with the current data of a location and thus systematically evaluate them. The optimized forecast data can increase grid stability

and thus supply security. ML systems and neural networks (NN) are already in use for this application. The improvement in forecast quality has shown in recent years that the need for balancing energy has increased, despite the growing share of volatile renewable generators in the grid. In the meantime, AI algorithms have become so sophisticated that they can trade independently. This is also called algorithmic trading, algo trading or automated trading.

- **Use of AI in energy consumer side:** The consumers of the electrical grid (private households or industry) will also contribute to stabilization in the power grid in the smart grid concept. These applications are already being implemented with smart meters and smart home automation solutions. For example, a smart home can react to price developments on the electricity market. This can be realized by means of demand-side management (DSM) and demand-side response (DSR). DSM refers to strategies, technologies, and actions aimed at managing and optimizing electricity demand in an electric power system. DSM aims to modulate end-user energy consumption to achieve a better match between supply and demand. This can be achieved through load shifting, peak load reduction, energy storage, consumption reduction at times of high demand (peak shaving), and similar approaches. DSM helps relieve congestion on the electric grid, can reduce the cost of electricity generation, and can facilitate the integration of renewable energy sources. DSR refers to the ability of end users to actively match their electricity demand to available electricity generation. During periods of low electricity generation or high demand, consumers may be asked to reduce or defer their electricity use until a later time when more energy is available. DSR can be implemented by households, businesses, industries, and other electricity consumers. This flexibility helps keep the power grid stable, avoid congestion, and reduce the need for expensive peak generation. Both DSM and DSR are important approaches to energy efficiency and renewable energy integration [17]. They help smooth the demand for energy and match demand to periods of low power supply, making the electric power system more sustainable and resilient. One example of this is air conditioners that increase their output when electricity is cheaply available on the grid. By analyzing user data, user preferences and time windows can be automatically determined and taken into account [18].

Another method for the systematization of use of AI methods in electric power systems is the classifications matrix technique. With regard to the implementation of AI methods in the electric power system, various fields of application can be identified. The basis for this is provided using the following five criteria: (1) integration of renewable energy systems, (2) increased reliability in supply, (3) increase in system efficiency, (4) increase in acceptance and (5) participation in the energy transition [19]. A classification of the fields of application can be made with regard to the energy industry value chain of generation, trade and consumption. In order to better illustrate this, Figure 2 classifies the application areas in relation to the value chain in the matrix into three clusters. These clusters are the general decision-making basis, maintenance and safety, and sales and consumption services [19].

The cluster “General decision bases” addresses various actors (e.g., producers, traders) who have to make investment decisions, increase the utilization of the grid and opt for the forecasts of consumption and generation. For this purpose, the AI methods in this cluster primarily use general data analyses. Therefore, this cluster includes the following application areas [19]:

1. Forecasting;
2. Operation optimization;
3. Inventory optimization and other strategic business decisions.

The “Maintenance and Safety” cluster contributes to minimizing the downtime of power generation plants as well as the grid. In addition, the applications for ensuring safe plant operation were grouped. With regard to the value chain, the application fields of generation and transport are summarized here [19]:

1. Predictive maintenance;
2. Maintenance, repair and dismantling;
3. Security measures.

In the third cluster, the “Sales and Consumption Service”, the services that serve to improve the customer relationship are summarized. Accordingly, they are assigned to consumption. This cluster therefore includes the following use cases [19]:

1. Simplified participation of active consumers;
2. Individualization of products and marketing measures;
3. Process automation for measurements, billing and general sales business.

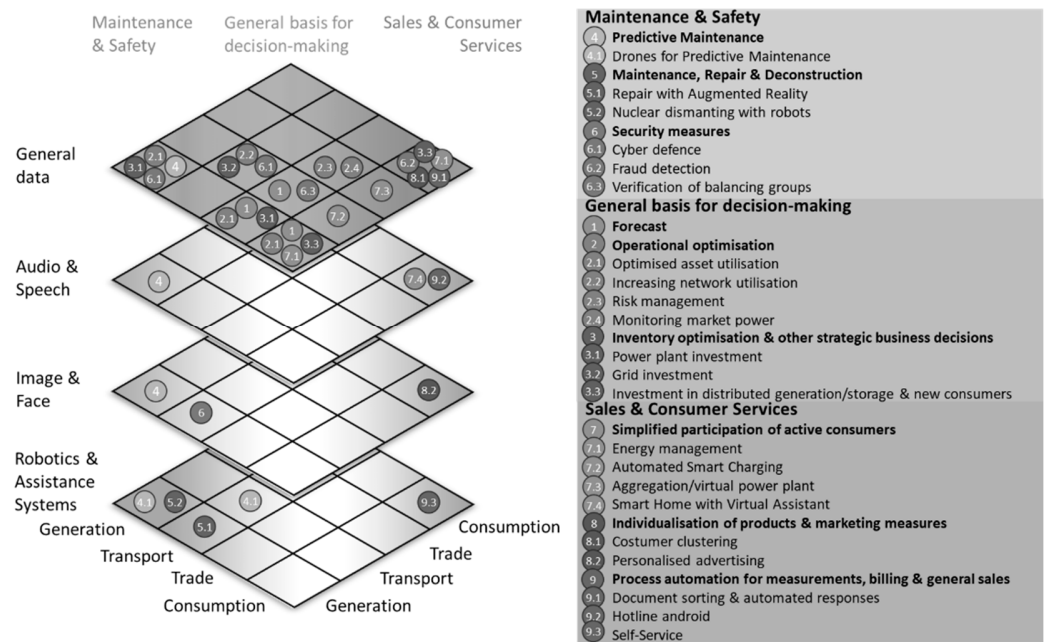


Figure 2. Classification matrix of the application fields of AI in the energy industry [19].

### 3. Overview of Methods

As shown in Figure 3, artificial intelligence (AI) is the concept of developing machines that have human-like intelligence to solve complex tasks. Machine learning (ML) is a subset of AI that uses algorithms to learn from data and recognize patterns without being explicitly programmed.

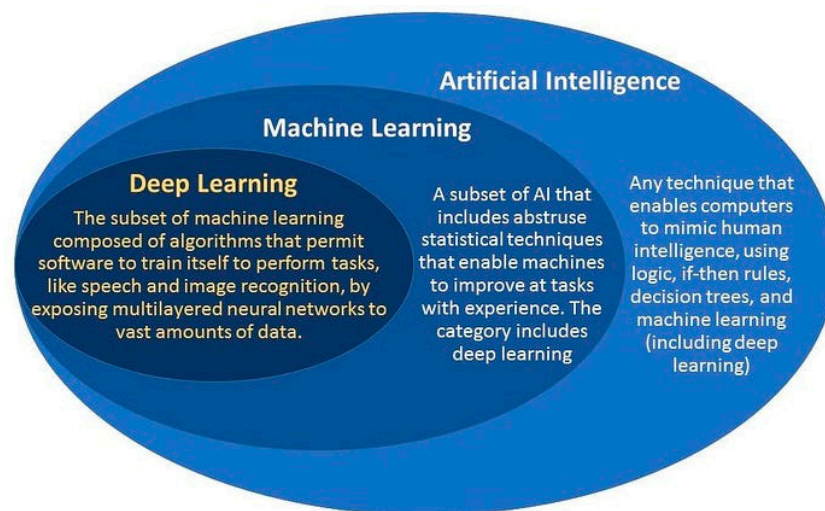


Figure 3. Context of artificial intelligence, machine learning and deep learning [20].

Within machine learning falls deep learning, which focuses on neural networks with many layers and can recognize complex patterns in large datasets. These techniques are applied in various fields, from image recognition and natural language processing to robotics and autonomous driving [20]. Machine learning is an important branch of artificial intelligence. It focused on setting or adaptive setting of computer programs (also used AI methods) from stored or/and constantly improving real time data. In this paper, we will focus on machine learning as a sub-field of artificial intelligence, since it can be used to formalize the problems which could be solved in power engineering. ML has experienced a rapid development in recent decades and has become a central field of artificial intelligence technology [21]. This fascinating discipline, mentioned above, enables feeding in computer programs via the data from real (very often real-time) measurements for the recognition of patterns (e.g., networks emergency states) and the solving of complex problems (suggesting the emergency measure) without having to be explicitly programmed [22]. Machine learning has a wide range of applications, through recognizing such complex patterns in language or images and processing them in areas such as medicine and business process optimization. This chapter takes an in-depth look at machine learning and its various sub-groups. It presents the general view, methods and applications that have made this field a cornerstone of modern information technology. With a focus on the different subgroups of machine learning, the specific approaches and techniques used in each area are explained. In Figure 4, we visualize a general overview of the methods of machine learning, without going into further groups [23].



Figure 4. Overview of machine learning Methods [23].

Furthermore, the methods can use different techniques for learning (see Figure 5). This can be classified into four sections as follows:

- (1) Unsupervised learning (Figure 5a):

This section focuses on learning, where the algorithm recognizes patterns and structures on its own from the input data, without being given any output. Clustering and dimension reduction are just some of the discussed topics [21].

(2) Supervised learning (Figure 5b):

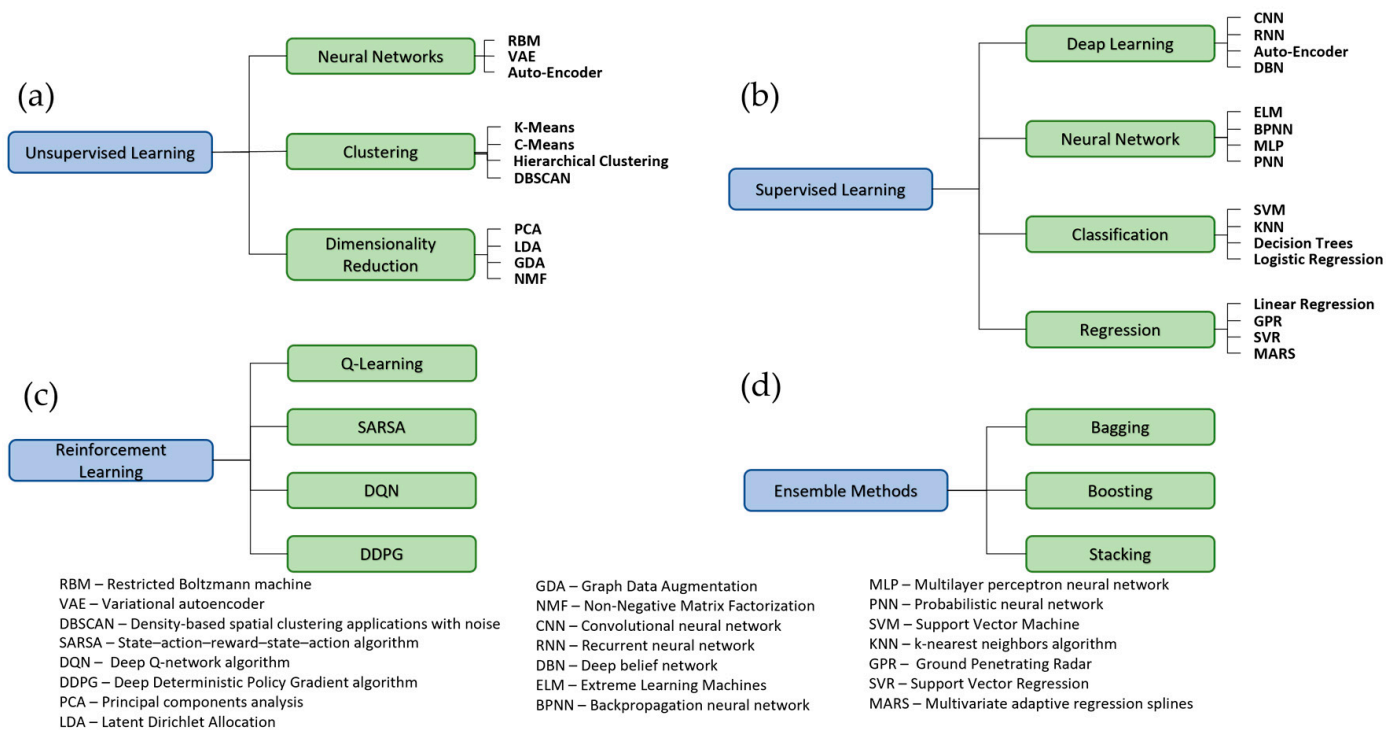
This section deals with learning from input/output data, as long as the output error has been minimized. Examples of applications such as classification and regression are presented [21].

(3) Reinforcement learning (Figure 5c):

Reinforcement learning is another important subset of machine learning in which an agent performs actions in an environment and learns which actions are best through rewards or punishments. Applications in robotics and game strategies are highlighted [24].

(4) Ensemble Methods (Figure 5d):

The main idea behind ensemble learning is that the combination of several models can compensate for the errors and weaknesses of individual models, leading to better and more robust predictions. By combining different models, they can learn from each other and use their respective strengths [25].



**Figure 5.** Subdivision of ML methods [11]. (a) Unsupervised Learning; (b) Supervised Learning; (c) Reinforcement Learning; (d) Ensemble Methods.

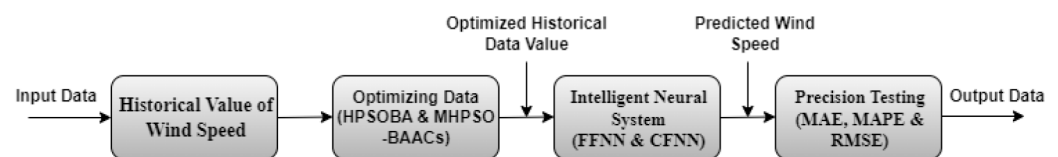
Overall, this comprehensive review provides a basic introduction to machine learning and a detailed insight into its diverse subsets. From the basics to advanced applications, machine learning is undoubtedly an important driver of technological advances and a source of countless innovative approaches [11].

## 4. Application Examples and New Approaches

### 4.1. Wind Generation Forecasting

A big area of AI methods implementation in electric power systems is the forecasting. This topic has been especially developed after the wide implementation of renewable energy in the electric power system, due to the weather-dependent in-feed of this energy. This volatile in-feed influences the electric power system stability and security of energy supply and energy prices via energy trading, as well as via the planning and the electric power system operation. The AI-based forecasting of various values in the above-mentioned topics

have been practically implemented for many years in electric power system companies. In the following, an example for the prediction of wind speed and the related wind power using neural networks and the supervised learning technique will be given. In this case, we are talking about the use of AI and ML in the form of deep learning. This will be assigned to the application area of forecasts (see Figure 2) from the cluster “General decision bases”. The methods used feedforward and cascaded-forward neural networks (FFNNs and CFNNs) with a novel metaheuristic optimization algorithm, i.e., a Hybrid Particle Swarm Optimization (PSO) and a Bat algorithm (BA) called HPSOBA, as well as a modified hybrid PSO and BA with parameter-inspired acceleration coefficients (MHPSO-BAAC) [26]. The mentioned optimization algorithms are used in both FFNN and CFNN to optimize the parameters of the network. These parameters include weights of neurons input and bias values that are adjusted during training to improve network performance. By applying optimization techniques, FFNN and CFNN can be effectively trained to recognize complex patterns in data and accurately perform their respective tasks such as classification or regression [27]. The Bat algorithm is a metaheuristic algorithm for global optimization. It was inspired by the echolocation behavior of microbats with different emission pulse rates and volumes [28]. This method can be used to predict wind speed and power to determine and calculate the design parameters of a wind turbine for a suitable region. It can also be used in the operational phase of a wind turbine, as it can estimate the amount of electrical energy that can be drawn from a wind-based system in a given period of time. This optimizes grid planning and lowers the operating costs of power plants by reducing the need for reserve capacity [10]. The structural block diagram of the wind speed prediction method used in this method is shown in Figure 6.



**Figure 6.** Block diagram of the presented system FFNNs and CFNNs [26].

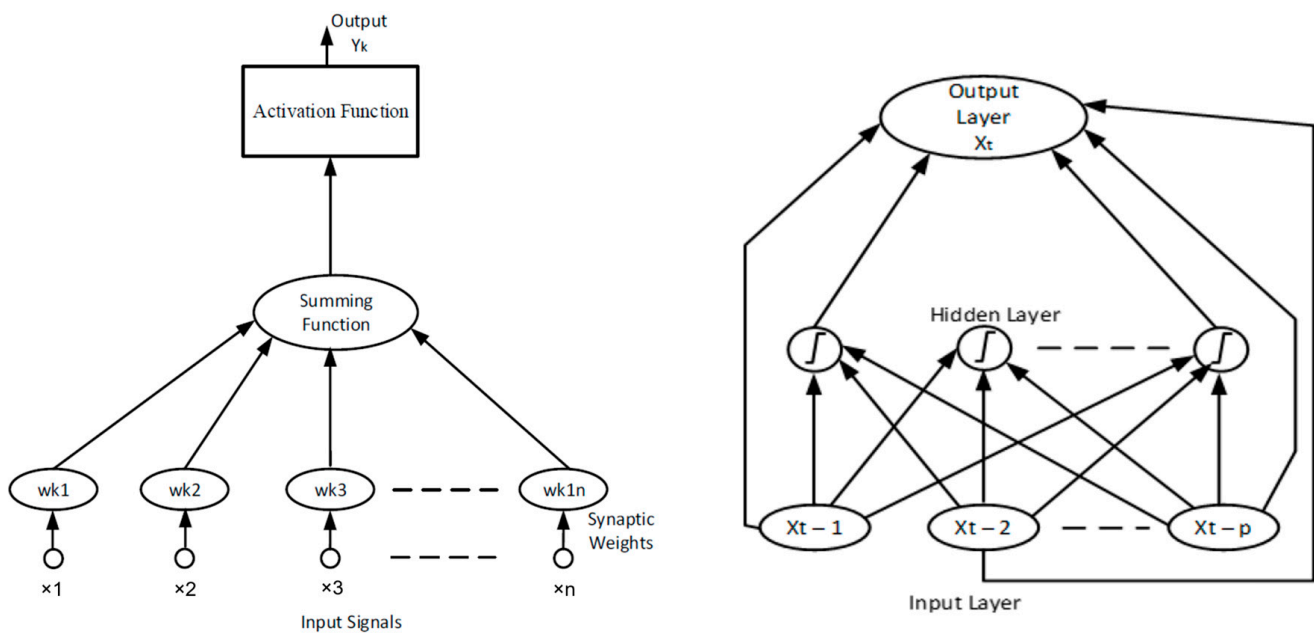
The main instances of this method consist of (1) the historical wind speed data of a region, (2) the optimization procedure needed to train the neural networks (HPSOBA- and MHPSO-BAAC), the (3) neural networks and (4) the accuracy of the predicted values (MAE, MAPE, RMSE) [26].

The neural network is trained using a training technique called Backpropagation, based on gradient descent. During training, the network was fed input data (e.g., historical wind data of wind speed) from 150 days of the year 2019, and the network’s outputs (e.g., predictions for wind speed or energy) were compared with the actual output values. Subsequently, the errors between the predictions and the actual values were calculated, and the gradient of this error function was backpropagated to adjust the weights in the network and minimize the error. This process was iteratively performed until the network converged and provided acceptable predictions.

HPSOBA (Hybrid Particle Swarm Optimization with Bat algorithm) and MHPSO-BAAC (Modified Hybrid Particle Swarm Optimization–Bat algorithm with Adaptive Crossover) are optimization algorithms used during the training process to adjust the weights and biases in the neural network. These algorithms are metaheuristics, aiming to improve the performance of the neural network by finding an appropriate configuration of the weights. They work by exploring and evaluating various weight combinations to identify those that minimize the error function most effectively. By applying these optimization algorithms during the training process, the neural network can be trained faster and more efficiently, potentially leading to better predictions for wind speed and energy. Particle Swarm Optimization (PSO) is a metaheuristic optimization technique, from the class of optimization algorithms used to solve complex optimization problems for which conventional methods may not be efficient or effective. HPSOBAs and MHPSO-BAACs are

extensions of PSO and are used for this use case to optimize the historical wind speed and power data for a site.

HPSOBA demonstrated the smallest MAE (0.0673) and thus predicted the best performance for wind power and wind speed. This was followed by the MHPSO-BAAC training technique with an MAE of 0.0737. The poorest predictions were achieved using PSO with an MAE of 0.0876. The FFNN, which is shown schematically in Figure 7 on the left, is a biologically stimulated classification algorithm. It consists of neurons that act as processing units and are structured in layers, where each neuron in the layer is connected to all units in the previous layers [29]. Data are input and travel through the layers in the network until they arrive at the output layer. In FFNN's standard procedure, it works as a classifier and has no feedback between layers, which earns it the name of a feedforward neural network [26].

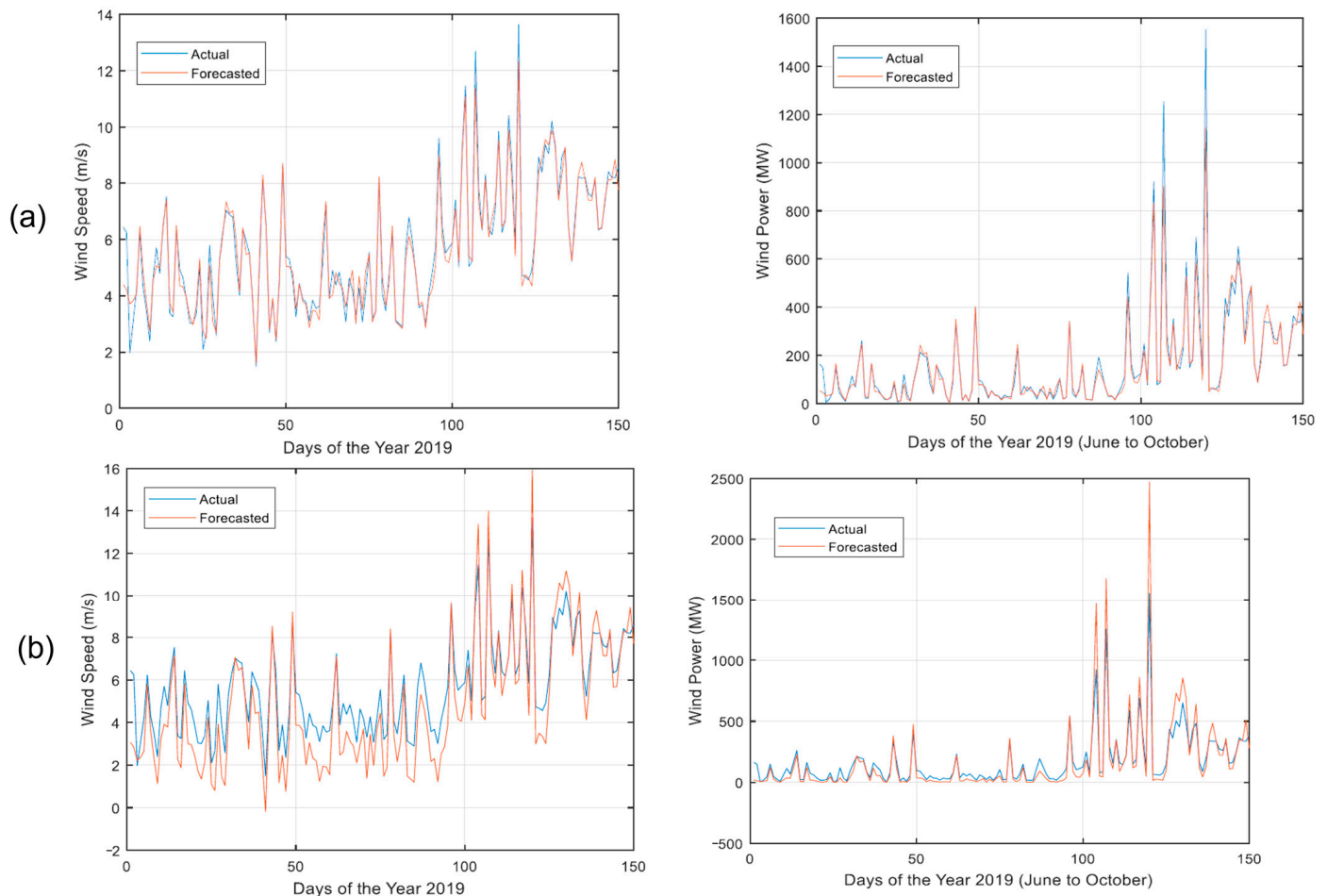


**Figure 7.** The architecture of the feedforward neural network (FFNN, left) and the architecture of the cascade forward neural Network (CFNN, right) [26].

In Figure 7, on the right, is the schematic structure of the CFNN. The CFNN has a connection of a hidden layer and an integrated multi-layer network, and the system has a direct linkage where the input and output layers are formed. The perceptron has a linkage directly connected between the input and output layers of the CFNN. Unlike the FFNN, the connection between the input and output layers is made through an indirect link. At the end of the model, the mean absolute error (MAE), mean absolute percentage error (MAPE) and root mean square error (RMSE) are applied to check the accuracy of the predicted values. The results of these forecasts, as well as the forecast prediction for wind speed and power, are visualized in Figure 8 below. In the upper area, (a) are the forecast data for the analysis of the wind energy prediction (power and speed) using the FFNN, which was trained using HPSOBA. In the lower area, (b) are the forecast data for the analysis of the wind energy prediction (power and speed) using the CFNN, which was trained using HPSOBA [26].

Historical data from one and a half years (January 2018 to May 2019) have provided input data for the multi-layer NN [26]. The performance is analyzed by evaluating the predicted wind speed and power compared to the actual values during the same period and error calculation techniques to check the accuracy using MAE, MAPE and RMSE [10]. The analysis considers the comparison of the performance of the training methods, with HPSOBA outperforming the other training algorithms, followed by MHPSO-BAAC. However, the overall comparative analysis confirms the superior performance of the developed

metaheuristic optimization algorithms of HPSOBA and MHP SO-BAACs for the prediction mechanisms. This justifies the versatility, flexibility and applicability of the developed algorithms. The presented system predicts the daily wind speed for the mentioned period of months. This will ultimately lead to efficient power generation and thus better energy yield and cost savings.



**Figure 8.** (a) Comparative analysis of wind power and speed forecasting using the FFNN trained through HPSOBA, (b) comparative analysis of wind power and speed forecasting using the CFNN trained through HPSOBA [26].

The field of application of the forecasts is not limited to weather forecasting (WP). Rather, the load profiles for short-term load profile forecasts (STLF), medium-term load profile forecasts (MTLF) and long-term load profile forecasts (LTLF) can also be made [30]:

- LTLF among 3-year and 50-year energy consumption is predicted;
- MTLF ranges from 2 weeks to 3-year;
- STLF refers to hour, day, or week ahead predictions.

The listed example of weather forecast is only one example of the application of forecasts. The paper [11] has already provided an overview of the applied methods, which will be extended by this work. Therefore, the following Table 1 lists further scientific articles on the subject of forecasting in the energy sector.

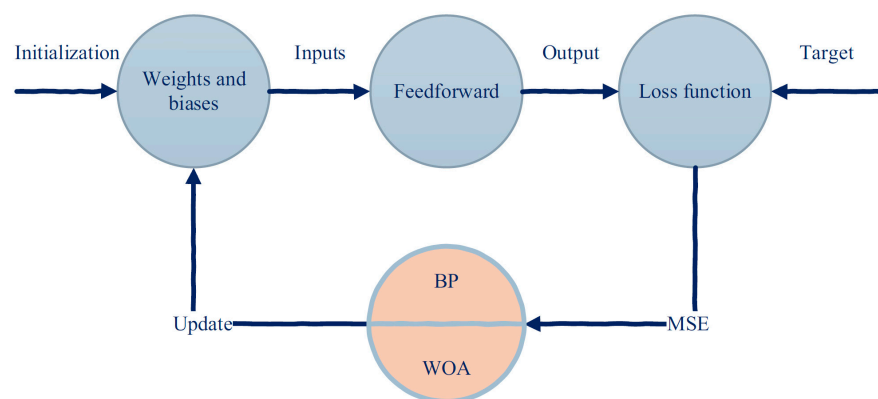
**Table 1.** Summary of approaches for prediction techniques.

Authors and Reference	Year	Objective	Techniques
Ellahi et al. [26]	2022	WP (wind power)	FFNN, CFNN
Elsaraiti et al. [31]	2022	WP (solar power)	Deep Learning (DL)
Kuzlu et al. [32]	2020	WP (solar power)	Random Forest Regression (RFR)
Mustaqeem et al. [33]	2021	STLF	Ensemble DL
Timur et al. [30]	2020	MTLF	ANN, Support Vector Machines (SVM)
Ayub et al. [34]	2020	STLF, MTLF	Hybrid of Random Forest (RF) and Extreme Gradient Boosting (XGB)
Almalaq et al. [35]	2017	STLF, LTLF	autoregressive (AR), fuzzy inference system (ANFIS), Support Vector Machines (SVM)

#### 4.2. Smart Grid Security

The smart grid describes generally the next-generation intelligent energy system. As this includes complex and interconnected cyber infrastructure, it must be able to accurately detect potential cyber attacks and take appropriate action in time. This example describes a new intrusion detection model that is able to classify cyberattacks and incidents in the power grid into two, three and more classes. The intrusion detection model is based on an artificial neural network (ANN) trained with the Whale Optimization Algorithm (WOA). The WOA is applied to initialize and adjust the weight vector of the ANN to achieve the minimum mean square error. The proposed WOA-ANN model can detect the challenges of attacks, fault prediction and fault detection in a stream. The WOA is thereby used to train the ANN and to find the optimal weights [36].

In the described work [36], two multi-layer perceptron (MLP) networks have been implemented. Each of these MLPs includes an input layer, a hidden layer and an output layer, as shown in Figure 9. The numbers of input, hidden and output nodes are  $m$ ,  $h$  and  $k$ , respectively. These numbers are different for binary, triple and multi-class problems. It takes the inputs and generates the outputs based on the weights and biases present. The computed output from the feedforward path is compared to the target result using the loss function. In the traditional MLP network, the Levenberg–Marquardt back propagation algorithm is then determined to update the weights and biases for the next iteration. In the MLP network, the WOA algorithm is used to update the weights for the next iteration [36].



**Figure 9.** The training process of the multi-layer perceptron [36].

Figure 10 shows the applied architecture of the electric power system of this example [36]. This system contains two generators, G1 and G2, two transmission lines, L1 and L2, three busbars, B1 to B3 and four circuit breakers, CB1 to CB4, controlled via four relays, R1 to R4. These relays communicate with the higher-level data acquisition system via a substation switch and router. The relays use a distance protection system to trip the circuit breakers when faults are detected, regardless of whether the faults are real or fake, as they have no internal validation to tell the difference. Operators can also manually issue

commands to these smart relays to manually trip the breakers. The attack scenarios assume that an attacker has already gained access to the substation network and poses an inside threat by issuing commands from the switchgear. The Power Distribution Center (PDC) is an electrical system that controls the distribution of electrical power to various devices. The control system at the bottom of Figure 10 includes several intelligent electronic devices, such as Snort, Syslog and, a control panel to monitor the entire network [36].

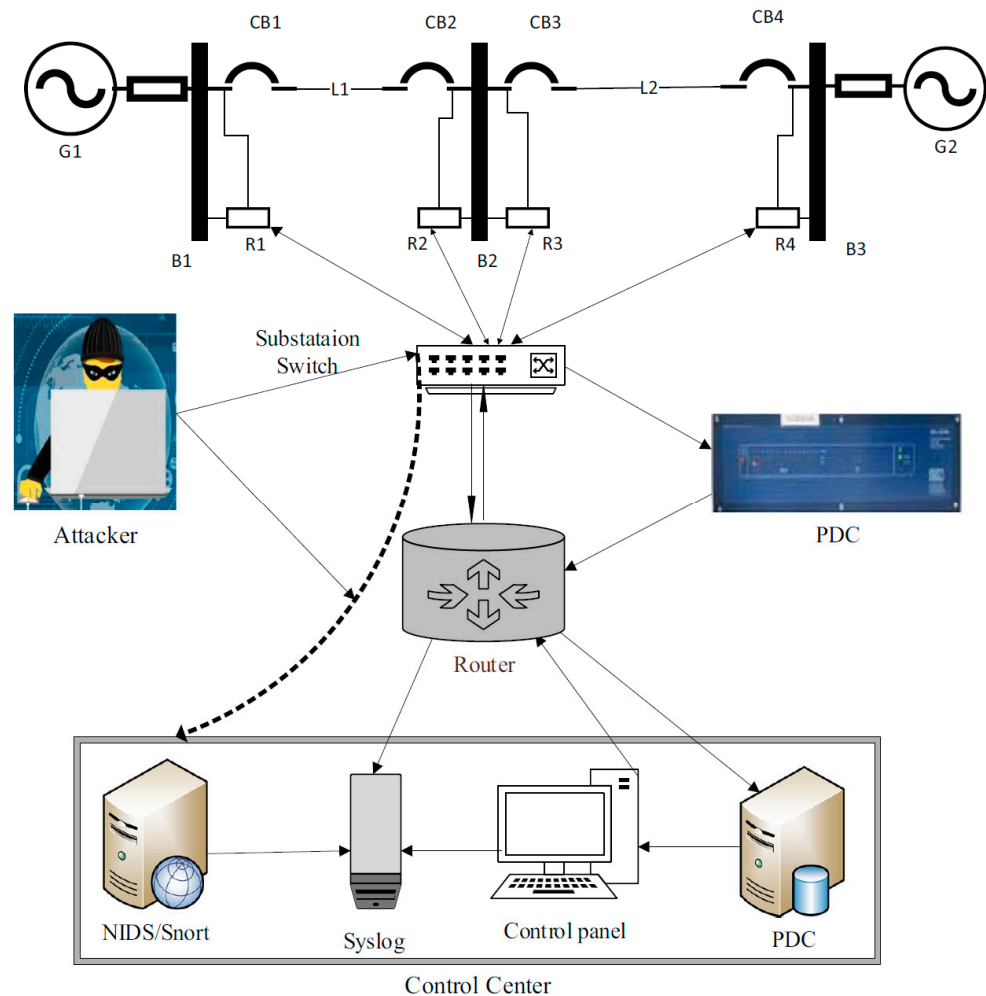


Figure 10. Power-system architecture [36].

Generally, with the growth of the use of smart grid technologies which are strongly information-dependent, special attention comes to criminal activity such as energy fraud and cyber attacks [37]. Therefore, the following Table 2 shows current applications as an extension to paper [11].

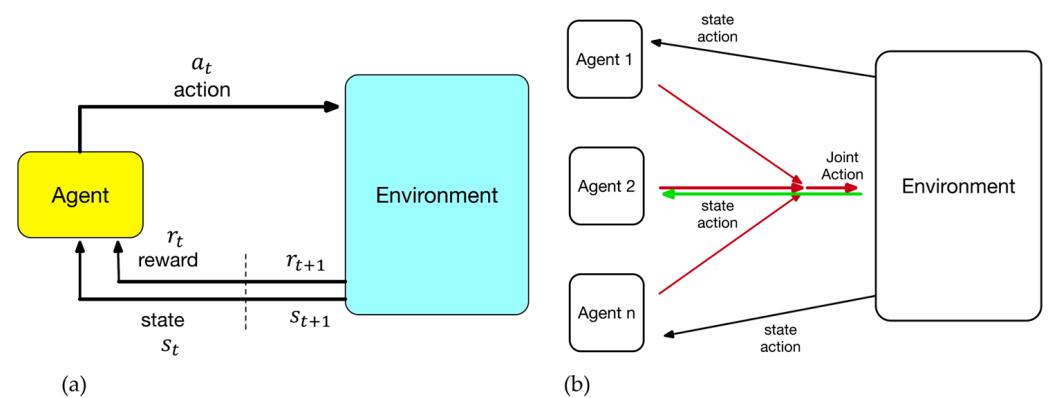
Table 2. Summary of approaches for smart grid security techniques.

Authors and Reference	Year	Objective	Techniques
Ni et al. [38]	2019	Attack detection	Reinforcement learning
Mirzaee et al. [39]	2022	Attack detection and threat analysis	Adversarial ML (AML)
Hu et al. [40]	2020	Detecting electricity fraud	DL with multitask feature extracting fraud detector (MFEFD).
Punmiya et al. [41]	2019	Detecting electricity fraud	Ensemble learning with gradient boosting theft detector (GBTD)

### 4.3. Grid Stability

Another application example addresses the compensation of line losses, which do not have to be coordinated within a balancing group by human intervention but are mechanically compensated by the balancing capacity. This method for power balancing in the electrical grid thus addresses grid stability and thus also the cluster “General decision-making principles”, as well as the application area of operational optimization. It is implemented using reinforcement learning (RL). In this method, single or multiple agents (multi-agent system) are used, as shown in Figure 11. In RL, for the single agent-system, the agent learns by interacting with the dynamic environment through a trial-and-error process, as visualized in Figure 11a. The agent’s goal is to learn an optimal strategy by finding the expected value of the cumulative sum of rewards. The basic framework of reinforcement learning is the Markov decision process, i.e., a random process represented by the tuple  $(S, A, R, P)$  [42].

- (1)  $S$  presents the state space,  $s_t \in S$  is the state the agent is in at time step  $t$ .
- (2)  $A$  presents the action space,  $a_t \in A$  is the action performed by the agent at time step  $t$ .
- (3)  $R$  is the reward,  $r_t \sim \rho(s_t, a_t)$  is the immediate reward value that the agent has in state  $s_t$  when performing the action  $a_t$ .
- (4)  $P$  presents the state transition probability,  $p[s_{t+1} | s_t, a_t]$  represents the probability that the agent will performs an action  $a_t$  and changes from the state  $s_t$  to the next state  $s_{t+1}$ .



**Figure 11.** (a) A single agent interacting with its environment, (b) Multi-agents interacting with the environment [42].

The multi-agent RL framework (Figure 11b) is a stochastic approach based on a Markov decision process represented by the tuple  $S, A_1 \dots A_n, R_1 \dots R_n, P$ . Here,  $n$  denotes the number of agents,  $A = A_1 \times \dots \times A_n$  is the joint action space of all agents,  $R_n: S \times A \times S \rightarrow R$  is the reward function of each agent,  $P: S \times A \times S \rightarrow [0, 1]$  is the state transition function, assuming that the reward function is bounded. In the case of multi-agent settings, state transitions are the result of the joint action of all agents.

This approach of a multi-agent RL system was implemented in a project called DEZENT [13]. The DEZENT project was dedicated to decentralized and adaptive electrical energy management through a distributed real-time multi-agent architecture. The energy management system focuses on a regional grid in which mainly renewable energy sources are used. The grid architecture (Figure 12) is divided into four levels. The first level (0.4 kV) is a low-voltage grid covering sub-areas (a neighborhood). The second level (10 kV) is an area network of medium-range covering a suburb (regional network). The third level (110 kV) is a long-range energy transport network. Finally, the fourth level (380 kV) is where electricity is generated using large power plants (coal, gas or nuclear). The electricity demand of prosumers is covered by alternative energy sources within the first two levels and the additional electricity demand is provided on the fourth level at the latest. At the negotiation levels, the balancing of supply and demand between the participants is carried out by balancing group managers (BGM), who are located at different network levels and

work in parallel in each network. A BGM is a financial instrument that balances the electricity supply and demand between a producer and a consumer who have placed a similar bid. A day is discretized, resulting in a series of consecutive time slots, and negotiation takes place in each slot. The duration of the time window must be longer than the time needed to stabilize the flow. The latter time depends on the size of the balancing groups. Negotiation is carried out independently for the groups at the lowest level for the smallest subdivision. If a balance cannot be found for all account managers in a group, the dissatisfied customers are forwarded to the next higher BGM and the negotiation area is extended to this new customer group. In addition, a slot in SDC consists of three negotiation cycles and the sale or purchase of electricity (at a fixed price) to/from the main production facilities. Each cycle consists of 10 negotiation rounds in which the bids and offers of the customer agents are adjusted according to their own negotiation strategies [43,44].

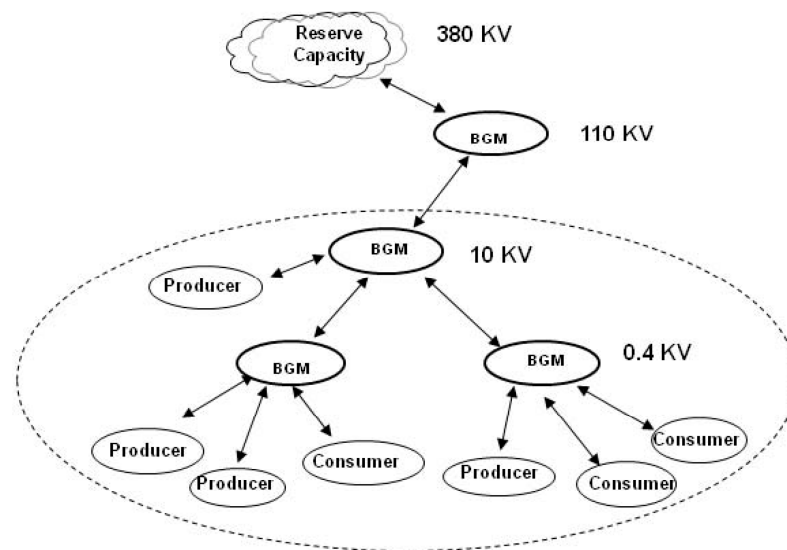


Figure 12. Power grid architecture [43].

The negotiation architecture takes place with regard to the electrical power between the consumers and producers of the electrical grid. Here, different urgent energy needs in generation and consumption are related to individual price expectations and adequately allocated to each other using the algorithm. The result of the negotiation algorithm is an allocation of power input or output at negotiated remuneration costs or energy prices, a so-called supply configuration. The algorithm translates the inputs and demands of all actors into a stable supply configuration [42,43]. In the course of negotiations, consumers increase their bids, while producers decrease their offers. The speed with which individual agents adjust their asking prices depends on individual negotiation parameters, so-called negotiation strategies (see Figure 13). The factor by which price frames are reduced is called the shrinking factor  $S_r$  [43].

An example (Figure 13) shows the adjustment of the price frames for  $S_r = \text{EUR } 0.002$  and  $S_r = \text{EUR } 0.004$  and marginal costs  $A = \text{EUR } 0.05$ ,  $B = \text{EUR } 0.21$ . The shrinkage factor is intended to create an incentive to conclude contracts as early as possible and thus regionally (to minimize transmission losses). The selection of  $S_r$  is chosen in such a way that as little control and balancing energy as possible is incurred. At the same time, the number of cycles per period remains as small as possible.

This means that consumers select their starting bids from the lower half of the price range and generators select their starting bids from the upper half of the price range. The procedure within a negotiation cycle is identical at each negotiation level. All agents involved in grid operation submit bids or offers for energy quantities they require or offer in their balancing group managers, ordered according to Figure 14's illustration of the adjustment of bids and offers. At the end of each of the 10 negotiation rounds, these bids

and offers are coordinated by the BGM agent. The BGM agent allocates bids and offers at the end of each of the 10 negotiation rounds according to individual strategies and price expectations. The BGM agent coordinates these bids and offers within his balancing group and concludes contracts between the agents with “similar” bids or offers. This “similarity” is expressed by a system-wide similarity parameter. A producer bid P (price) and a consumer bid C (costs) are similar if  $|bid P - bid C| \leq similarity$  applies. At the beginning of each bargaining round, consumers and producers are sorted according to their current bids and offers. The process takes place from top to bottom, starting with the highest bidding consumer and the highest bidding similar producer. If the demand of individual agents cannot be satisfied within their balancing group, the needs are moved to the next higher (tension/negotiation) level. At this higher level, they meet dissatisfied agents from other balancing groups.

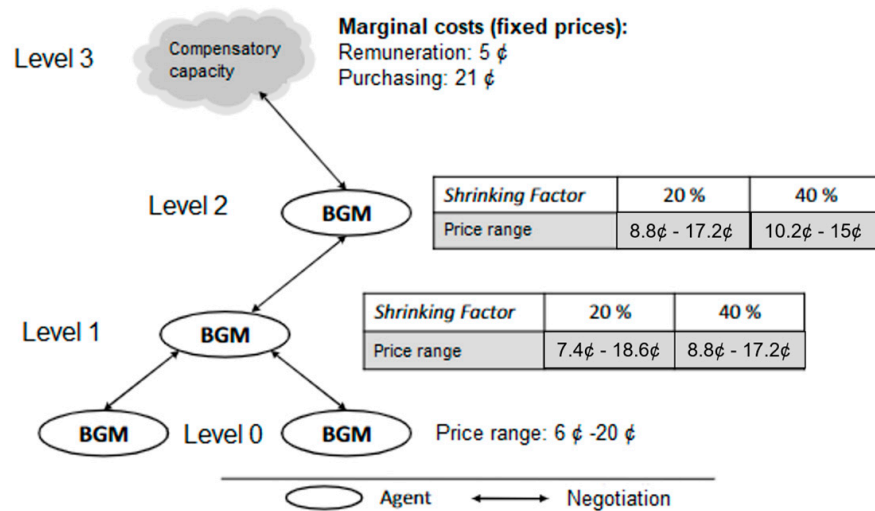


Figure 13. Process of price negotiation between agents [43].

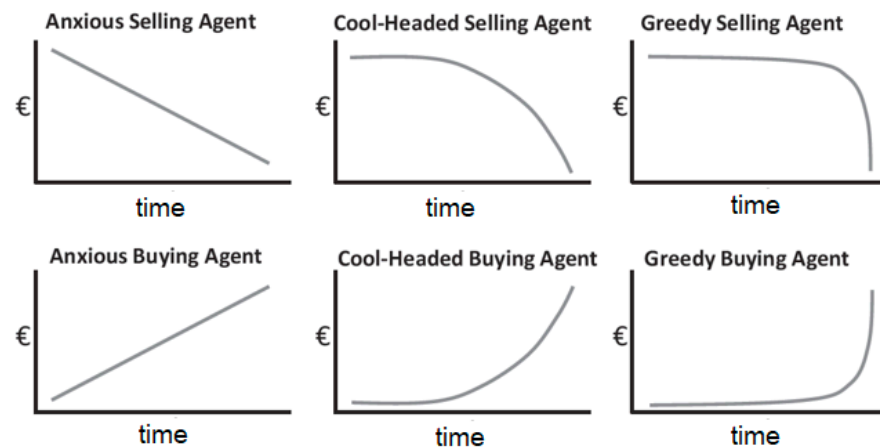


Figure 14. Discreet negotiation strategies for consumers or producers [43].

In Figure 14, according to studies on realistic bidding behavior, three fixed strategies are specified for both consumers and producers (for market-based negotiations of electrical power), which are chosen for the agents depending on the situation (Anxious Selling/Buying Agent, Cool-Headed Selling/Buying Agent or Greedy Selling/Frugal Buying Agent). In Figure 14, these forms of adaptation are chosen because they intuitively reflect real observable bidding behavior in auctions under extreme behavior (anxious, greedy and frugal respectively). Producers who are “anxious” i.e., more anxious to sell their energy, lower their prices faster than producers who pursue strategies of the “cool-headed” or

“greedy” type. In this case, the prices never fall below the minimum prices set by the producers. Analogous considerations are made with regard to consumer behavior [43].

The result of integrating BGM as aggregators into the grid management system is to reduce peak energy consumption and electricity costs for the population of prosumers. In practice, scalability issues will be crucial factors. For example, the distributed view of BGM as aggregators in the DECENT approach can be quite advantageous. The corresponding system design could be extended and optimized with the help of self-learning and self-adaptive autonomous components [44].

The following Table 3 lists other recent scientific work on artificial intelligence methods complementary to [11], with respect to grid stability [45].

**Table 3.** Summary of approaches for grid stability techniques.

Authors and Reference	Year	Objective	Techniques
Cai et al. [46]	2022	Voltage stability	3D Convolutional Neural Network (3D-CNN)
Pinzón et al. [47]	2019	Voltage stability	Random Forest (RF)
Zhong et al. [48]	2022	Voltage stability	Heterogeneous graph attention deep network (HGAT)
Wang et al. [49]	2019	Frequency stability	Frequency response (SFR) model and the extreme learning machine (ELM)
Xie et al. [50]	2021	Frequency stability	CNN and long short-term memory (LSTM) network
Shahzad et al. [51]	2022	Transient stability	ANN
Huang et al. [52]	2022	Transient stability	NN with Neural Lyapunov function (LNLF)
Wang et al. [53]	2021	Transient stability	SVM
	2021	Transient stability	ELM

#### 4.4. Grid Protection-Fault Detection

By automatically monitoring large amounts of data, potential failures, safety risks or inefficient operating conditions can be quickly identified. As a result, timely maintenance actions can be taken and operating costs can be reduced, leading to more reliable and efficient power generation and distribution [22]. Therefore, the following example will be used to explain the use of ensemble methods for the improved fault diagnosis of wind turbines based on the sine–cosine algorithm to identify the potential weak points of a wind turbine, which are mainly the generator, the gearbox, the power electronics and the blades [54]. The following example is assigned to the cluster “Maintenance and Safety”, and thus addresses the application area of predictive maintenance (Figure 2).

In the paper [54], an improved and effective ensemble learning approach for fault detection and diagnosis in wind turbines is presented. As shown in Figure 15, the developed strategy includes three main steps. The first phase starts with data processing, feature optimization and selection, and fault detection and diagnosis (FDD). The main objective of the proposed method, which is based on the ensemble-learning-based sine–cosine optimization algorithm (EL-SCOA), is to improve fault diagnosis in order to improve the performance and efficiency of wind turbines. Unlike conventional diagnostic methods that use the raw data directly, the presented method extracts and selects the most influential features from the original dataset and outputs them as the input to the classifier for diagnostic purposes. The classifier uses bagging and boosting algorithms as ensemble techniques and ANN as a base classifier. Thus, the different states of a wind turbine can be identified and classified [54].

Boosting algorithm is an ensemble technique in which weak learning models (also known as weak classifiers or base algorithms) are gradually combined to create a strong learning model. The idea behind boosting is that each weak learner reacts to the errors of the previous learners and focuses on the cases that were poorly classified by the previous models. This reduces the errors and improves the prediction accuracy of the combined model. A well-known algorithm that uses the boosting strategy is AdaBoost (Adaptive Boosting). AdaBoost works through assigning a weighting factor to each data point to

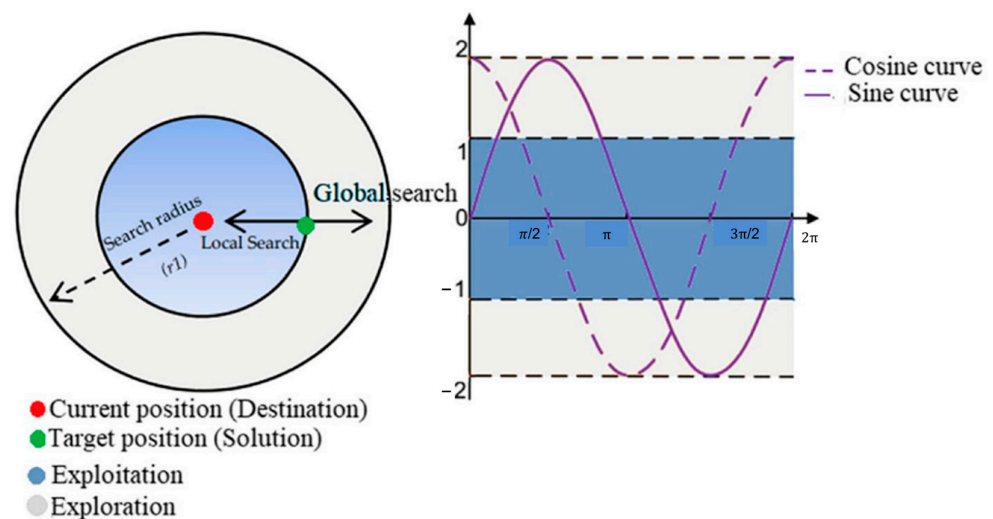
increase the importance of misclassifications and focus the algorithm on correcting these errors [55,56].



**Figure 15.** The steps of the EL-SCOA approach for fault diagnosis [54].

**Bagging strategy:** Bagging stands for “bootstrap aggregating”. In this approach, multiple instances of the same learning algorithm (or different algorithms) are trained on different subsets of the training data. These subsets are created using drag-and-drop (bootstrap process) from the original training data. Each of the models learns independently and may not agree in its predictions. A well-known algorithm that uses the bagging strategy is Random Forest, where decision trees are trained on different bootstrap samples and then their predictions are combined [56].

SCOA is a swarm-based optimization method. As shown in Figure 16, SCOA is based on periodic behaviors of sine and cosine functions and is motivated by the theory of transcendental functions. Similar to other optimization methods, SCOA performs optimization by using clear mathematical rules. Thus, it is possible and likely that a series of initial coincidences will lead possible solutions either away from or towards the final position (optimal solution) [54].



**Figure 16.** Diagram of the SCOA search mode [54].

In the paper [54], data from a healthy and functioning wind turbine were subjected to different fault scenarios: open circuit (OC), short circuit (SC) and wear. Thus, the system was first examined to see how it behaved in a healthy condition. Then, the different fault scenarios were injected independently, considering how each fault affects and influences the behavior of the system in that situation. For example, the transition state that occurs when moving from a healthy state to a faulty state was not considered. The presented methodology [54] was designed to propose the sine–cosine algorithm to optimize, select and extract the most informative features from the raw data. The retained selected features of the classification technique are fed for diagnostic purposes. The classification method includes bagging and boosting as ensemble methods and an ANN as a base classifier.

The presented fault detection example tries to distinguish between different operating conditions (short circuit, open circuit and wear-out faults) occurring at different connection sides (generator side and grid side). Compared to other existing methods, including ANN, KNN, CFNN, FFNN, GRNN, and SVM, the experimental results of the work [54] show that the proposed method generates very good results.

Automatic fault detection and diagnosis plays a crucial role in monitoring-based operation management as well as in reducing downtime, energy losses, and service costs [57]. Therefore, Table 4 shows the current applications for fault detection and diagnosis as a supplement to paper [11].

**Table 4.** Summary of approaches for fault detection techniques.

Authors and Reference	Year	Objective	Techniques
Wang et al. [58]	2019	Fault diagnosis in electric power systems	Principal component analysis (PCA) and SVM
Wadi et al. [59]	2021	Fault detection in electric power system	PCA and SVM
Veerasamy et al. [60]	2021	Fault detection in solar integrated electric power system	LSTM
Ajagekar et al. [61]	2021	Fault diagnosis in electric power system	Quantum computing (QC) and DL
Shadi et al. [62]	2022	Fault detection in electric power system	DL with Recurrent Neural Network RNN and LSTM

## 5. Discussion and Comparison

The four methods presented in this paper are now compared with regard to various quality characteristics. These characteristics provide information regarding their actuality and applicability. In particular, the data requirements, implementation effort, response time, applicability for grid applications, and security are compared with each other.

### Example 1: Wind Generation Forecasting via Feedforward Neural Network (FFNN) and Convolutional Feedforward Neural Network (CFNN)

The system has moderate- to high-data requirements, making it suitable for applications with clear pattern recognition needs. In terms of implementation effort, it is relatively easy to implement, but meticulous parameter tuning is essential for optimal performance. Response time is fast, making it suitable for real-time applications such as load forecasting in the grid. Its applicability for grid applications is notable, particularly in pattern recognition and load forecasting tasks within the grid infrastructure. However, security is a concern, as it may be vulnerable to attacks such as overfitting, necessitating robust security measures to safeguard its integrity.

### Example 2: Smart Grid Security via WOA-ANN

The data requirements of this system depend on the complexity of the application, spanning from moderate to high, adapting to the specific demands of the task at hand. Implementation effort varies based on the network structure, presenting a variable landscape in terms of complexity and resources required. Response time fluctuates with network size but remains conducive to real-time applications, ensuring timely processing of data. Its applicability for grid applications is versatile, extending to tasks like load forecasting and fault detection, catering to the diverse needs of grid management. However, security remains a concern as the system is vulnerable to attacks, emphasizing the need for robust security measures to safeguard against potential threats and breaches.

### Example 3: Grid stability—via Agent System

The data requirements for this system are contingent upon the complexity of the assigned tasks, adapting accordingly to the intricacies involved. Implementing the system proves to be complex, as it entails the orchestration of multiple autonomous agents working in tandem. Response time varies, contingent upon the level of coordination among agents, with optimal performance achieved through efficient collaboration. In terms of its applicability for grid applications, the system excels in cooperative tasks, particularly in network management and regulation, where coordinated efforts are paramount. While the system

demonstrates robustness against failures of individual agents, it necessitates protection against unauthorized interference to maintain the integrity and security of grid operations.

#### **Example 4: Grid protection—Fault detection via EL-SCOA**

The data requirements for this system range from moderate to high, contingent upon the complexity of the learning tasks it undertakes. As for implementation effort, it is characterized as complex, necessitating the involvement of multiple autonomous agents. Response time varies, potentially being fast for specific applications. In terms of its suitability for grid applications, particularly in complex and dynamic grid environments, it shines, especially within adaptive control systems. Regarding security, the system exhibits greater resilience against failures of individual agents; however, it necessitates protection against unauthorized interference to maintain its integrity.

In conclusion, the choice of method depends on the specific requirements of the grid application. FFNN, CFNN, and ANN are versatile, while EL-SCOA and agent systems excel in complex, adaptive, and cooperative grid scenarios. Security aspects must be considered for all methods, as they exhibit varying vulnerabilities to different types of attacks.

In the following, the methods are compared with each other on the basis of 10 different performance attributes. Since the comparison of these different methods is based on different test procedures with different data sets and different hardware setups, the results from the referenced publications are presented in general terms. This also serves to simplify comprehension. A definition of the following attributes is as follows (Table 5):

- **Architecture:** Describes the structure and complexity of each neural network or algorithm;
- **Application:** Explains the use cases and application domains suitable for each method;
- **Scalability:** Evaluates the ability of each method to adapt to growing data volumes or complex problem scenarios;
- **Computational Cost:** Describes the required computational resources or computational effort for each method;
- **Memory Requirements:** Indicates the amount of memory space needed for training and execution of each method;
- **Training Time:** Describes the time required to train the model or algorithm;
- **Robustness:** Assesses the stability and reliability of each method in processing data or solving problems;
- **Overfitting:** Describes the risk of overfitting, where the model fits too closely to the training data, potentially compromising its performance on new data.

Feedforward Neural Networks (FFNNs) and Convolutional Neural Networks (CNNs) represent two distinct architectures in the field of neural networks. FFNNs are characterized by their simplicity, featuring fully connected layers that make them suitable for processing structured or tabular data. In contrast, CNNs are more complex, incorporating convolutional layers that excel in capturing spatial relationships, making them particularly effective for tasks involving image and video data. Meanwhile, WOA-ANN (Whale Optimization Algorithm-Artificial Neural Network) combines the power of neural networks with the optimization capabilities of the Whale Optimization Algorithm, enhancing the scalability and robustness of FFNNs or CNNs through the optimization of hyperparameters and network weights. On the other hand, agent systems operate with decentralized and autonomous agents, offering versatility across various domains and tasks, with scalability achieved through parallelism and distributed behavior. The EL-SCOA (Elephant Swarm Optimization Algorithm) represents a metaheuristic algorithm designed specifically for optimization tasks, leveraging global search mechanisms for scalability and robustness. Each approach comes with its own computational costs, memory requirements, training times, and levels of robustness, making them suitable for different contexts and problem domains. Understanding the strengths and weaknesses of each approach is crucial for selecting the most appropriate method for a given task or application.

**Table 5.** Comparison of ML methods based on 10 performance attributes.

Attributes	FFNNs and CNNs	WOA-ANN	Agent Systems	EL-SCOA
Architecture	Simple (fully connected for FFNNs), complex (CNNs with convolutional layers) [63]	Combination of FFNNs or CNNs with WOA optimization [64]	Decentralized, autonomous agents [65]	Metaheuristic algorithm [66]
Application	Structured/tabular data (FFNNs), image and video data (CNNs) [63]	Various data types and domains [64]	Versatile applications across domains [65]	Optimization across various contexts [66]
Scalability	Limited scalability due to rapid increase in parameters (FFNNs), high scalability due to parameter sharing (CNNs) [63]	Enhanced scalability through optimization of hyperparameters and network weights [64]	High scalability through parallelism and autonomous behaviour [65]	Good scalability through global search and exploration [66]
Computational Cost	Low to moderate for small models, high for deep and complex models [63]	High due to optimization process [64]	Varies depending on number and complexity of agents [65]	High for large problem sizes and complex search spaces [66]
Memory Requirements	Depends on depth and complexity of model architecture [63]	Varies, often higher due to additional parameters from optimization [64]	Requires efficient communication mechanisms for agent coordination [65]	Varies depending on problem size and complexity [66]
Training Time	Shorter for smaller models, longer for deeper and more complex models [63]	Varies, can be longer due to optimization process [64]	Depends on number and complexity of agents [65]	Can be longer, depending on convergence speed and problem size [66]
Robustness	Less robust due to tendency to overfit (FFNNs), very robust especially for image data (CNNs) [63]	Enhanced robustness through optimization process [64]	Very robust and adaptive to changes [65]	Robust, but depends on parameter settings and problem characteristics [66]
Overfitting	High without regularization techniques [63]	Varies, often lower due to optimization process [64]	Low risk due to decentralized and distributed nature [65]	Low, but convergence-dependent and influenced by exploration-exploitation trade-off [66]

## 6. Summary and Outlook

The application of AI in the electric power system has been successfully established in recent years. As shown in this paper, it can be used in various application areas for different tasks. The use of AI can give benefits for the planning and operation of electric power systems in several ways. So, in the sector of power generation, the AI algorithms can be used to supervise and optimize the operation of energy generation, reducing energy losses and emissions. The use of AI methods can also improve the safety and reliability of power generation plants via early detection and the diagnosis of plant failures. The use of AI can be used to predict energy demand and optimize the energy use from renewable sources such as wind and solar power. Predicting the load makes it possible to optimize the production of wind or solar power energy, by using it as input for planning and control systems. By predicting the load, one can better estimate how much energy is needed and control the feed-in of wind or solar energy accordingly. In this way, the load can be accurately predicted, allowing the production of wind energy or solar energy to be better planned in order to balance out the fluctuations in the load and reduce the need for conventional energy resources. In this way, load forecasting contributes to optimizing the use of wind energy and helps to improve the efficiency of the entire energy system.

Another important application area of AI methods in electric power systems is energy transmission and distribution. There, AI can optimize the management of energy transmission and distribution networks to reduce energy losses and improve the stability and reliability of the network. AI can be used to detect and diagnose faults in the network and optimize energy routing to minimize energy losses. AI can optimize energy consumption in buildings and industrial processes to reduce energy costs and emissions. AI can be used to predict energy consumption patterns and adjust energy consumption accordingly. AI can also be used to optimize the performance of HVDC systems, lighting protection systems and other energy-consuming devices.

It can also be used to create holistic benefits for the energy sector. It can improve energy efficiency. AI can also reduce energy waste, leading to improved energy efficiency. Another benefit is the optimization of energy production and consumption, which leads to a reduction in carbon emissions and helps to mitigate climate change. It can also improve reliability and safety by detecting and diagnosing faults in power generation and transmission equipment, reducing the risk of equipment failure and improving the safety and reliability of energy systems. The use of AI can also increase the integration of renewable energies. For example, AI can help integrate renewable energy sources into the energy grid through optimizing their production and consumption, leading to a more sustainable energy economy.

However, the use of AI in the energy sector also poses some challenges, which are briefly listed below.

- (1) **Data security and privacy:** By the operation of the electric power system, large amounts of sensitive data, including customer data, operational data and network data have been collected. The use of machine learning requires extensive data sharing and access, making data security and protection a key challenge. Stringent security measures must be taken to prevent data breaches and misuse.
- (2) **Lack of high-quality data:** AI methods require large amounts of high-quality data to develop accurate models. In some areas of the energy sector, especially new technologies or small utilities, data scarcity and quality can be a barrier to developing effective machine learning models.
- (3) **Complexity and interpretability:** Advanced machine learning algorithms such as deep learning models are often very complex and difficult to interpret. This can lead to trust issues, especially when decisions are made based on machine learning without fully understanding the underlying processes.
- (4) **Robustness and reliability:** In critical applications in the energy sector, such as grid control and monitoring, it is crucial that the applied machine learning models are robust and reliable. Disturbances, attacks or changes in environmental conditions could affect the performance of the models and lead to errors.
- (5) **Energy efficiency:** Machine learning often requires powerful hardware resources, especially when using deep learning. Energy efficiency can be a challenge, especially when machine learning is used in embedded or resource-constrained systems.
- (6) **Costs and resources:** The successful deployment of machine learning requires highly skilled personnel, adequate resources and financial investment. Small energy companies or start-ups may find it difficult to overcome these hurdles and benefit from the use of machine learning methods.
- (7) **Regulatory challenges:** In some regions, regulatory hurdles could hamper the deployment of machine learning in the energy sector. Policies and regulations may need to be updated or adapted to enable the use of new technologies while ensuring safety and reliability.

In the future, AI and machine learning ML will play an even more significant role for the optimal development and operation of electrical power grids. This includes the predictive maintenance of infrastructure elements, automatic detection and elimination of faults and dynamic adaptation to changing load profiles. ML-based models will help to improve the integration of renewable energy sources by enabling accurate forecasts for

their feed-in. In addition, AI-based systems will play a key role in strengthening the cyber security of electrical grids by detecting threats in real time and taking countermeasures. In the long term, autonomous grids could emerge that can self-optimize and respond to unforeseen events, ensuring a more robust and reliable power supply.

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