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Review

Application of Methods Based on Artificial Intelligence and Optimisation in Power Engineering—Introduction to the Special Issue

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Abstract: The challenges currently faced by network operators are difficult and complex. Presently, various types of energy sources with random generation, energy storage units operating in charging or discharging mode and consumers with different operating characteristics are connected to the power grid. The network is being expanded and modernised. This contributes to the occurrence of various types of network operating states in practice. The appearance of a significant number of objects with random generation in the power system complicates the process of planning and controlling the operation of the power system. It is therefore necessary to constantly search for new methods and algorithms that allow operators to adapt to the changing operating conditions of the power grid. There are many different types of method in the literature, with varying effectiveness, that have been or are used in practice. So far, however, no one ideal, universal method or methodology has been invented that would enable (with equal effectiveness) all problems faced by the power system to be solved. This article presents an overview and a short description of research works available in the literature in which the authors have used modern methods to solve various problems in the field of power engineering. The article is an introduction to the special issue entitled *Advances in the Application of Methods Based on Artificial Intelligence and Optimisation in Power Engineering*. It is an overview of various current problems and the various methods used to solve them, which are used to cope with difficult situations. The authors also pointed out potential research gaps that can be treated as areas for further research.

Keywords: power engineering; artificial intelligence; optimisation; neural networks; renewable energy; probabilistics

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1. Introduction

This article is an introduction to the special issue entitled *Advances in the Application of Methods Based on Artificial Intelligence and Optimisation in Power Engineering*, one of the authors of which is the guest editor. The purpose of this special issue is to consider and analyse various, real and, above all, current problems faced by contemporary power systems. Modern methods can be used to solve these problems. There are all kinds of problems in today's power systems. They occur both at the stage of power grid operation and in its planning. At virtually every level of network voltage, operators must deal with various states of its operation, contributing to, for example, current and voltage exceedances, problems with power balance, stability, faults, problems resulting from errors in forecasting, etc. Additionally, network operators impose their own requirements, which result from the specific nature of their network's operation. All this makes it necessary to use increasingly advanced methods to solve problems. Examples of such methods include methods based on artificial intelligence and optimisation methods. Figure 1 shows the general division of these methods.

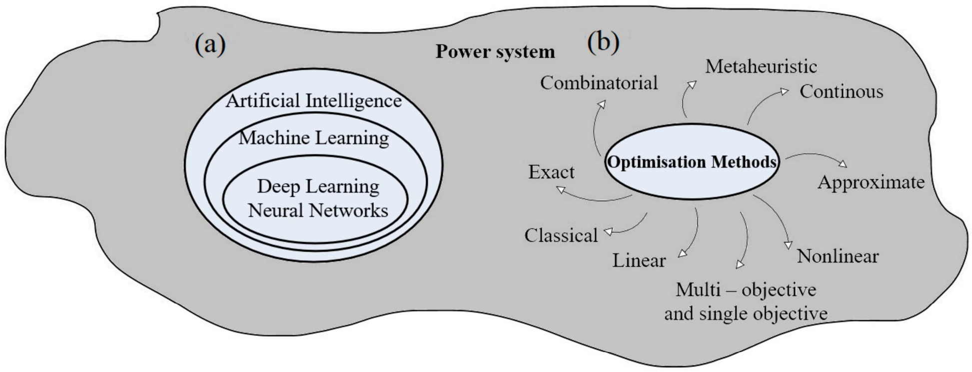

Figure 1. An example of a general division of methods that can be used to solve problems in power engineering: artificial intelligence (**a**) and optimisation (**b**) [1].

Actual network problems result, among others, from the connection of new facilities (loads, sources, energy storages) and changes in the network structure related to operator procedures, construction of new lines and installation of new transformers. Emergency situations are also very important. Due to dynamically changing operating conditions caused by variable loads and variable generation of renewable energy sources (RES), it is necessary to search for new methods and procedures to eliminate the negative impact of these facilities on the operation of the power system. The development of IT systems and the ever-increasing computing capabilities of computers enable the implementation of new, advanced algorithms and mathematical methods in power engineering, improving work, ensuring optimal solution of complex problems in real time and contributing to better planning of the development of power systems. However, there are real problems whose exact solution time, using previously known and used methods, is too long and unacceptable to operators in practice. Therefore, it is reasonable to look for methods/techniques based on artificial intelligence and optimisation that will significantly reduce the time to obtain results and can be used in real time or in planning the development of the power system. It is therefore necessary to perform an in-depth review of the literature on the topic under consideration, to thoroughly identify these methods and to determine the possibility of their application in solving current, real problems occurring in power engineering. Areas of possible application of modern methods include various analyses of power systems. The scope of analysis may cover areas such as the following:

- Transmission and distribution of electricity;
- Generation of electricity;
- Electricity storage;
- Reliability;
- Forecasting;
- Power quality;
- Faults;
- Planning and development;
- Operation;
- Economic issues;
- The impact of sources, energy storage, loads and other elements on the operation of the power grid.

The proposal of using advanced methods based on artificial intelligence and optimisation in power engineering results from the need to solve difficult problems that currently occur within the power system. Optimisation is the activity of searching for the optimal solution from the point of view of the considered objective function. Optimisation has been a key aim of electrical power engineering for a long time. Work on this topic initially addressed issues related to optimal power flow (OPF). The issues considered were aimed at the optimal selection of generating units (unit commitment—UC) and the optimal distribution of power generated in sources (economic dispatch—ED). If the issues also include ones related to the limitations and operational safety of the power system in, e.g., emergency conditions, then the analysed task can be defined as security-constrained optimal power flow (SCOPF). Currently, due to the presence in the power grid of a significant number of sources and loads with a random nature of operation and the requirements of network operators, the optimisation issues considered can be called SOPF (special optimal power flow).

Solving these types of problems requires the use of advanced software. In the past, classical optimisation methods were mostly used, the disadvantage of these is that they work only when the objective function has one optimum. If there are more optima, there is no certainty that the classical method will find the global optimum. The advantage of these methods is the short time it takes them to obtain a result with high accuracy. Currently, metaheuristic methods are increasingly being used; these allow the global optimum to be found with a certain probability. They can be used when a function has many optima and even when its form is unknown. Their advantages include their easy implementation, universality, flexibility and effectiveness. The main disadvantage of these methods is the long time needed for them to obtain a solution. To obtain relatively high accuracy and to significantly shorten the time taken to obtain the result, methods based on artificial intelligence can be used. For example, a previously trained machine allows a solution to a problem to be found with appropriate accuracy in an acceptable time. Computational difficulties that may be encountered when performing work related to the analysis of the power system prompt the search for new methods and alternative solutions.

This article is organised in the following way: Section 1 presents the issues of the special issue. Section 2 presents an in-depth review of the literature in the field of artificial intelligence-based methods. Section 3 presents a review of the literature in the field of optimisation methods. Section 4 presents a list of the methods described and used in the literature, along with the frequency of their use. Research gaps and possible areas of future application of methods based on artificial intelligence and optimisation were also indicated. Section 5 contains a summary.

2. Literature Review in the Field of Methods Based on Artificial Intelligence

In the chapter below, the authors will present examples of research from the literature covering issues related to the use of methods based on artificial intelligence and optimisation to solve various problems in the power system. This is a topic quite widely found in the literature; general problems related to power engineering can be divided into those related to the following: renewable energy and energy storage, identification of faults in the operation of the power system, ensuring the security of the power system, stability issues and optimisation of network operation.

Sections 2.1–2.7 contain a literature review on various problems in power engineering along with their solutions using various methods based on artificial intelligence. Particular emphasis has been placed on this type of algorithm due to its increasing popularity and effectiveness in solving problems, among others, in the field of power engineering. In general, the following methods based on artificial intelligence can be distinguished, which can be used to solve problems in the field of power engineering [1]:

- Machine learning (e.g., supervised learning, unsupervised learning);
- Deep learning, reinforcement learning, artificial neural network (e.g., deep networks for supervised or discriminative learning, deep networks for unsupervised or generative learning, deep networks for hybrid learning);
- Fuzzy logic-based approach (e.g., fuzzy logic systems);
- Expert system (algorithms for modelling expert systems);
- Hybrid approach, searching and metaheuristic optimisation (hybrid algorithms, combining different algorithms).

The main advantages of methods based on artificial intelligence include the following [1]:

- Process automation;
- Quick decision making;
- Easy handling of large data sets;
- Increase in productivity;
- No human errors.

The main disadvantages of methods based on artificial intelligence include the following [1]:

- Lack of creativity and unconventional thinking, work according to fixed schemes;
- Implementation cost;
- Unexpected behaviour of the machine when operated by inappropriate persons;
- No possibility of making corrections—artificial intelligence works on the basis of possessed data and algorithms.

2.1. Renewable Energy and Energy Storage

As examples in the literature relating to our first topic, we mention positions [2–25], in which the authors dealt with issues related to the uncertainty of the operation of power system arisings as a result of the increasing number of connected renewable sources. Solar and wind energy are the two most frequently used sources of renewable energy. Unfortunately, the high unpredictability of these sources significantly complicates the management of energy supply and demand in the national power system. This is a serious challenge for the system, as it is necessary to ensure reliable supplies while making optimal use of sources. An increasing number of energy storage facilities are installed in order to stabilise the operation of the power system; these are crucial to maintaining the power balance in the system and ensuring appropriate energy quality [2].

Liu et al. [3] proposed a method for ultra-short-term forecasting of wind power and speed based on the Takagi–Sugeno (T–S) fuzzy model, which is presented in Figure 2.

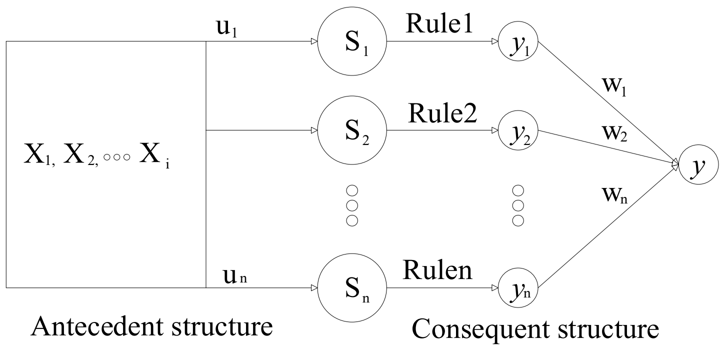

Figure 2. Structure of the T–S fuzzy model [3].

Meteorological data are used as input data for this model, and the parameters are identified using fuzzy clustering, the recursive least-squares method and the fuzzy C-means (FCM) method. The results obtained using this model were compared with those from other contemporary models based on machine learning using a support vector machine (SVM) and a back-propagation neural network (BPNN). The results obtained show that the model proposed by the authors can effectively improve the short-term forecast of wind power and speed, which can be used effectively in capacity planning in the power system from wind sources. Learning based on long short-term memory (LSTM) can also be used to forecast wind power and speed. This solution was used in the work of Almutari and Alrumayh [4]. The research has shown that the model proposed based on this architecture can effectively predict changes in the power generated in a wind farm, taking into account various random parameters, such as direction or speed. The main limitation observed in this method is the long computational time necessary for appropriate training. Wind speed is also predicted in articles [5,6] using the artificial neural network (ANN) method. The results obtained in this work confirm the thesis that this is a very effective forecasting method. Another commonly used method to predict wind speed is SVM [7]. In their work, Wu, Wang and Cheng [8] used the extreme machine learning (EML) algorithm to predict wind speed. They checked the effectiveness of the proposed method not only through simulations in the laboratory, but also on a real wind turbine.

In article [9], the authors use artificial intelligence (AI) and an artificial neural network to predict current demand in order to optimise the storage and distribution of electricity. The solution proposed by the authors can improve energy efficiency by making renewable energy sources more available and sustainable. ANN is one of the most frequently used machine learning techniques; a graphical representation of the frequency of its use was presented by Qadir and his team [10].

The authors of [11] propose an approach involving the use of deep learning (DL) to predict periods of energy production limitations, as well as the optimal use of energy storage systems and alkaline water electrolysers and their hybrid connection, which may minimise the effects of energy production limitations. According to the authors' research, it is possible, using the DL algorithm, to accurately predict periods in which there will be limitations in energy production in wind and photovoltaic power plants with minimal forecast error. As a result, with appropriate use of the battery energy storage system (BESS), it is possible to guarantee uninterrupted continuity of energy supplies. In modern power systems, hydrogen is becoming a key element and is used as an energy storage system, increasing the stability and reliability of the system. When there is a surplus of energy production, it is converted into hydrogen in electrolyser installations and is then stored. During times of increased energy demand, the reverse process occurs. These operations require the implementation of various systems that facilitate the connection of fuel cells and electrolysers to the power system. For this purpose, the authors of [12] present the use of machine learning in the form of the adaptive neuro-fuzzy inference system (ANFIS). It is also important to ensure the proper operation and efficiency of energy storage systems for their proper use within the power system. This issue was discussed in [13], where the authors used a machine learning technique in the form of the decision tree (DT) algorithm and support vectors to explain the impact of cooling air on temperature distribution and to predict the safety of battery modules. A decision tree algorithm is used to separate the relationship between cooling air and battery temperature distribution, while a support vector machine is used to predict the safety of the BESS. The conducted research shows that the air flow rate has a significant impact on both the maximum temperature and temperature differences of the batteries, while the air inlet temperature only affects the maximum temperature of the cells. The machine learning algorithm used by the authors enables an increase in the efficiency and, above all, the security of BESS warehouses, and therefore also contributes to ensuring greater stability in the power system. Flywheel energy storage systems (FEES), similarly to the use of BESS storage, improve the stability of network operation [14]. In [15], Yin and Liu propose the use of fuzzy vector reinforcement learning (FVRL) to control generation in a power system taking into account FEES. Hierarchical energy optimisation of the system to use flywheel storage to smooth the output power of wind farms based on the deep reinforcement learning (DRL) algorithm was proposed in [16]. Bearings are often damaged in warehouses of this type, therefore an attempt to solve this problem was proposed in [17,18]. In order to diagnose bearing damage, He and Liu [17] proposed a method based on the optimisation of energy parameters, while in [18] an original method was proposed where the prediction of bearing life is based on the Kriging model.

Microgrids are a solution that increases security and improves energy quality and operation in the power system. However, due to the large dispersion of these sources, optimal energy management is necessary. A machine learning approach was proposed in [19], where the authors used machine learning based on support vector regression (SVR). The connection of microgrid operation with battery energy storage systems using long short-term memory was also discussed in [20]. The use of energy storage in combination with machine learning based on an artificial neural network was also focused on in [21]. The authors of this work, based on supervised learning, created a selectively coherent model of converter system control for an LV grid (SCM_CSC), and then, using an ANN, trained the objective function, which consisted in maintaining the required voltage conditions for the LV grid and minimising the power flow to the MV line.

Near real-time small signal stability analysis (SSSA) is crucial to properly integrating large numbers of renewable energy sources. However, SSSA based on traditional computational methods is a time-consuming task, and therefore does not allow the assessment of the stability of the system in real time; this is why the authors of [22] propose an approach based on machine learning in the form of an artificial neural network. The speed and accuracy of the proposed solution were tested on a 9-node test network, and the results obtained prove that the calculation time can be drastically reduced without a significant loss of accuracy of the results. A solution to this problem using machine learning was also attempted in [23,24], using the K-means method. Jizhe Liu and his team also focused on the issue of stability of the power system operation as a result of connecting a large number of renewable sources. Their article [25] describes their original method based on graph neural networks (GNN). The proposed solution was tested by the authors on two network models, and from the obtained results it can be concluded that the proposed method can make emergency load shedding (ELS) decisions at the level of a few milliseconds, which makes it very useful for controlling system stability.

The authors of [26] propose a novel adaptive optimisation based on machine learning using K-mean clustering and density-based spatial clustering of applications with noise (DBSCAN). This optimisation aims to flexibly and accurately capture the uncertainty space of renewable wind energy forecast errors with decoupled structures. Compared to the classic "one size fits all" method, the authors' approach requires over 75% less computational time for the same problem. Table 1 provides a summary of the artificial intelligence techniques used in this section.

Table 1. Summary of the methods used in the literature under consideration in issues related to renewable energy and energy storage.

Artificial Intelligence		
	Machine learning	
Supervised learning	Deep learning	[4,11,16,18,20,24]
	Neural networks	[3,5,6,8–10,12,21,22]
	Regression	[19]
	Classification	[3,7,13]
Unsupervised learning	Clustering	[3,23,24,26]
Reinforcement learning	Q-learning	[15]

2.2. Forecasting Generation and Load in the Power System

Machine learning can be used to forecast both short-term and long-term generation. Short-term forecasting of PV output power is extremely important not only to ensure system stability, but first and foremost its safety.

The issue of short-term forecasting was described by Wang et al. [27] For this purpose, the authors proposed a novel hybrid model based on ensemble empirical mode decomposition (EEMD) as well as on the relevance vector machine (RVM). EEMD is used to divide a sequence of photovoltaic output power into several intrinsic mode functions (IMFs) and into several residual components. The sample entropy algorithm is used to reconstruct these components. The obtained results prove that the model proposed by the authors has a high forecasting accuracy.

Short-term forecasting of the power of photovoltaic power plants is also dealt with by Jakoplić et al. [28]. For this purpose, an innovative method is proposed, consisting in continuous photographing of the sky above the installation. Then, a hybrid convolutional neural network (CNN) and a long short-term memory model is used to analyse the photographs. Based on the analysis of the results, it can be concluded that the model is characterised by 74% prediction efficiency in relation to the actual future generation values. The long short-term memory model was also used by Elsaraiti and Merabet in [29]. Their proposed model was trained and tested using real electricity data from Halifax, Canada from 1 January 2017 to 31 December 2017. The obtained results were compared with the multi-layer perceptron (MLP) algorithm, which is a frequently used forecasting method. As can be seen in the tables below, the LSTM method presents better results in each of the tested performance parameters.

In order to forecast solar generation for seven locations in Spain, Gala Y. and her team [30] propose the use of hybrid machine learning based on several techniques: support vector regression, gradient-boosted regression (GBR), random forest regression (RFR) and a hybrid method combining them to further improve forecasting. An original model for forecasting generation from renewable sources is also proposed in [31], where an artificial neural network and a dynamic learning algorithm are used for this purpose. The proposed algorithm is compared, among others, with advanced particle swarm optimisation (APSO) and with the fine-tuning metaheuristic algorithm (FTMA); the results obtained are satisfactory. In [32], Fadare focused on predicting generation from photovoltaic sources in Nigeria using an ANN. Based on the results obtained, the author concluded that this model is promising and can be successfully used to forecast photovoltaic generation anywhere in the world. Also, in [33] an artificial neural network was used to predict photovoltaic generation. The main innovation in the proposed method in this case is the use of meteorological forecasts as input data. Meng and Song in [34] focus on the forecast of winter photovoltaic generation in North China using the random forest (RF) method. The research was conducted at the Zhonghe photovoltaic station from 1 November to 31 December 2018. The obtained results show that in the event of unfavourable weather conditions such as rain or snow, the forecast error increases from 2.83% to 3.89%. In [35] the authors analyse seven learning algorithms used in ANNs by using the nonlinear autoregressive models with exogenous inputs (NARX) architecture to estimate the generated active power from photovoltaic sources. The research shows that the best results were achieved using the Bayesian regulatory method. Another method for estimating generation from photovoltaic sources can be found in [36], where an algorithm based on the least absolute shrinkage and selection operator (LASSO) was used, which predicted energy generation based on a small amount of historical data. According to the authors' research, this method achieved much better accuracy compared to other analysed methods. The LASSO algorithm required the use of much less training data than the other tested algorithms. A solution to the problem of uncertainty in forecasting the power supplied from RESs may be the virtual power plant (VPP) concept, which can be implemented in modern smart grids. In order to efficiently use the capabilities of a virtual power plant, a system is need that can predict generation from renewable sources and their impact on the energy system. The authors of [37] attempted to solve this problem and proposed the use of artificial intelligence in the form of machine learning based on long short-term memory, which is a type of recurrent neural network (RNN). The method of combining these two methods (RNN-LSTM) was used in [38], where the accuracy of forecasting photovoltaic generation hourly in advance was tested and was then compared with, among others, the ANN and SVR methods. This method turned out to be the most accurate one in predicting energy production for each of the tested photovoltaic power plants.

In opposition to short-term memory learning, the authors of [39] propose an original algorithm for predicting the output power of PV systems called the powerful deep convolutional neural network model (PVPNet), which is based on a deep convolutional neural network (DCNN). The model can generate predicted 24 h output powers of PV sources based on meteorological information, such as temperature and solar radiation, as well as on historical data. According to the authors' research results, their algorithm is significantly superior to those created based on LSTM or MLP learning. According to the authors, the use of their algorithm can significantly reduce expenditure on monitoring and long-term maintenance costs of photovoltaic installations, and therefore can also reduce the operating costs of the power system.

The authors of [40] dealt with the issue of predicting wind energy generation, in which they propose an original forecasting system based on the learning ability of a deep neural network (DNN), as well as the transfer learning (TL) concept. In their deep neural network-based meta-regression and transfer learning (DNN-MRT) model, they use auto-encoders as the base regressors with the deep belief network (DBN) as the meta-regressor. According to the authors, the applied ensemble learning concept facilitates decisive decision making on the test data set, while the base regressors together with the meta-regressors enable a significant increase in the performance of their proposed model. The deep learning algorithm in wind energy was also used by Manshadi in [41]. He proposed using machine learning to predict generation from wind turbines in a specific location. The author's method proved effective, with an approximate accuracy of 0.96. In [42], Troncoso and his team performed a comparative analysis of eight different types of regression tree (RT) algorithms for short-term wind speed prediction. An approach using both SVM and decision tree (DT) was used in [43]. Wang et al. [44] proposed a deep learning approach to forecast wind energy production in the power system, while Wen et al. [45] proposed the use of a deep recurrent neural network (DRNN) combined with LSTM to forecast solar energy production in the system.

In [46], three different models based on artificial neural networks were used to forecast the generation of wind sources. These are the "Feed Forward Back-Propagation (BP)", "Radial Basis Function (RBF)" and "Adaptive Linear Element Networks (ADALINE)" models. Typical topologies of these networks are shown in Figures 3–5.

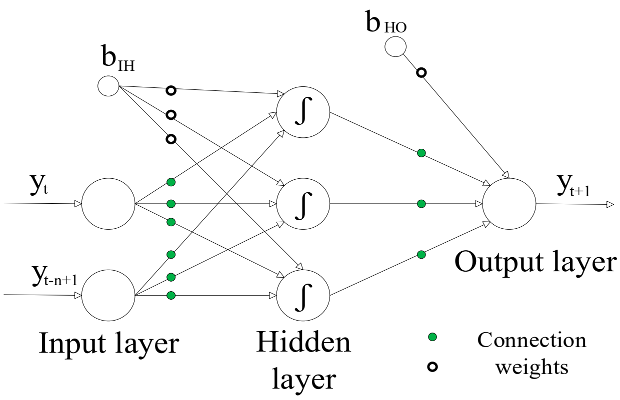

Figure 3. Typical topology of the BP network model [46].

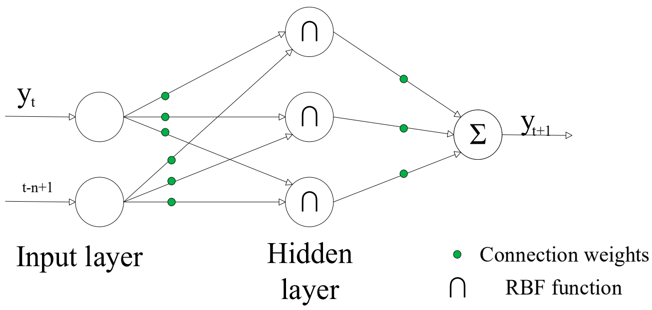

Figure 4. Typical topology of the RBF network model [46].

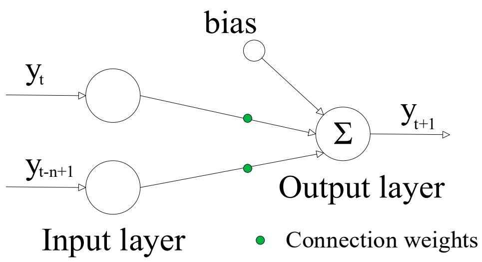

Figure 5. Typical topology of the ADALINE network model [46].

The effectiveness of individual models varied depending on the given input data, so a solid method of combining forecasts from different models is needed to obtain a complete picture of generation from wind sources. Wind generation forecasting based on the RBF neural network scheme was also proposed in [47]. In [48] the general regression (GR) method and back propagation were used. The authors compared the results obtained using both models, and it resulted that the BP method obtained better prediction results than the GR method. In [49], Saigustia and Pijarski used the eXtreme gradient boosting over decision trees (XGBoost) algorithm to forecast photovoltaic generation trends in Spain. The model proposed by the authors makes it easier to optimise the operation of the power system; by adapting generation to the periods of peak customer demand, the flexibility and reliability of the network increases.

Correct load forecasting is also very important for the proper operation of the power system. This load may be influenced by various external factors, which involves a high degree of uncertainty. This issue can be found in the literature, for example, in [50–59]. The authors of [50] discuss the three most frequently used machine learning methods for load forecasting: the support vector machine method, random forest and the long short-term memory method. The article analyses the features of the above-mentioned methods and proposes an original forecasting model that combines the advantages of SVM, RF and LSTM. This model, combining the advantages of the above-mentioned techniques, allows data pre-processing and a multi-stage forecasting strategy, significantly improving the accuracy of the results obtained. In order to improve the precision of short-term load forecasting, an artificial neural network was used in [51], in which the back-propagation algorithm is used to train samples. The proposed method does not require much computational time, and the patterns used in network training have a large impact on the forecasting accuracy. In [52] the possibility of building a medium-term load forecasting model for the power system was considered based on the following methods: support vector regression, decision tree regression, random forest, gradient boosting over decision trees and adaptive boosting over decision trees (AdaBoost). The model proposed by the authors allows for the forecast of the load in an isolated power system one week in advance. The best results were obtained using a model based on adaptive boosting over decision trees, which combined four linear regressions into one model. Via the increasing use of smart energy meters, it is becoming possible to accurately forecast the load even one day in advance [53]. Chen and his team used the deep neural network for this purpose. In [54], the artificial neural network method was used to forecast the load in the Greek power system. However, in [55] a hybrid model combining an artificial neural network and various combinations of Kalman filtering (KF) was used for short-term load forecasting. Zou et al. [56] proposed a combined MFF-SAM-GCN model in order to predict the short-term load in the system, which uses multi-feature fusion (MFF) and a self-attention mechanism (SAM) to form a multi-feature fusion structure. However, thanks to the use of a graph convolutional network (GCN), features such as wind strength and direction are extracted. In the summary, the authors emphasise that the simulation results show better prediction performance than the reference models. In [57], a hybrid method combining a deep neural network is proposed for weekly load forecasting. For the purposes of correct load prediction, expert systems are also used, as proven by references [58,59].

Article [60] proposed its own load modelling scheme via peak detection and then used this information for forecasting purposes. This was done by mapping time-series data; peaks were defined as load levels equal to or greater than 99 percentiles in the first case, 95 in the second and 90 in the third. These variants were modelled using classification algorithms and their results were used to improve forecasting models. The best results were obtained with SVM for peak classification and ANN for prediction. According to the authors, this approach is able to predict over 90% of energy demand with a margin of error between 2–3%. A support vector machine and Gaussian process regression (GPR) methods for forecasting photovoltaic generation were used in [61]. As a result of comparing the results obtained using these methods, it can be concluded that SVM is much less efficient compared to GPR, which provided an appropriate combination of accuracy and the required time for calculations.

Zong Woo Geem and William Roper [62] dealt with forecasting electricity demand in South Korea. For this purpose, they used an ANN model with the back-propagation error algorithm, the momentum process and data scaling. In [63], an innovative optimisation method based on an artificial neural network was proposed to forecast the energy demand in the system. However, in [64] Ekonomou used an artificial neural network to predict long-term energy consumption in Greece. The issue of energy use was also dealt with in [65]. The authors addressed the power system in Turkey and used the support vector machine and least-squares support vector machines (LS-SVM) for this purpose. In [66], the authors proposed a model combining long short-term memory with particle swarm optimisation (PSO) to forecast electricity demand. In [67] a DNN model was developed for this purpose, and in [68] the authors tested the performance of three regression-based prediction models: persistence-based auto-regressive (PAR), seasonal persistence-based regressive (SPR) and seasonal persistence-based neural network (SPNN). Guo Feng Fan and team [69] used a support vector machine for short-term forecasting of electricity demand. The SVM model is also used in [70,71]. In [71], a novel PSO and RVM approach was proposed for real-time load prediction. In order to improve the decision-making process in power systems, the current energy demand and the current production capabilities of photovoltaic and wind sources should be forecasted. Such an attempt was made by Maciejewska and her team [72]. Ahmad et al. [73] proposed the use of the nonlinear autoregressive model (NARM), which uses stepwise regression and the random forest method. Gou and team also used deep learning for short-term load forecasting, and compared their results with the random forest and gradient-boosting machine models [74]. In [75], Chena proposed the use of deep residual networks (DRNs) for short-term forecasting. Several works also note the use of hybrid methods to increase the accuracy of load forecasting in the power system. For example, Rafiei and team [76] proposed a method including, among others, extreme machine learning, and Ribeiro [77] proposed forecasting based on wavelet neural networks (WNN). In [78], the authors used fuzzy logic and an artificial neural network for short-term load demand forecasting. In [79], a hybrid model consisting of wavelet transform, neural networks and an evolutionary algorithm was proposed for short-term forecasting. The proposed method was tested on three power systems and compared with some of the forecasting algorithms used. A hybrid method using, among others, wavelet transform and long short-term memory for both short-term and long-term forecasting was proposed by Memarzadeh and Keynia [80]. A schematic of their hybrid model is shown in Figure 6.

In [81], both artificial neural networks and deep learning techniques were used to forecast electricity demand. The study was conducted for each of short-term, medium-term and long-term forecasting. The above work contains a comparison and evaluation of the above-mentioned techniques. In [82], Hassan, along with Khosravi and the rest, plotted a combination of fuzzy logic and extreme machine learning. The authors additionally conducted a comparative analysis of their proposed model with traditional models such as the adaptive neuro-fuzzy inference system (ANFIS), among others.

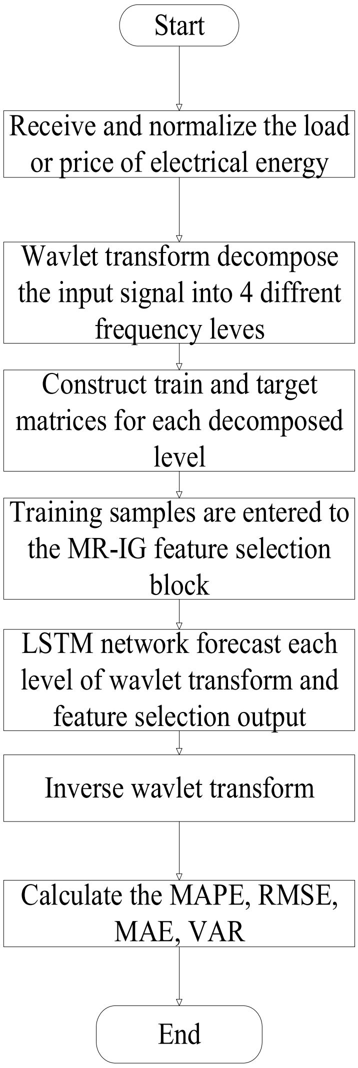

Figure 6. Block diagram of the hybrid model [80].

Table 2 presents a summary of the artificial intelligence techniques used in forecasting generation and load in the power system.

Table 2. Summary of the methods used in the literature under consideration in generation and load forecasting issues.

Artificial Intelligence		
Machine learning		
Supervised learning	Deep learning	[28,29,37–41,44,45,50,53,56,57,66,67,74,75,80,81]
	Neural networks	[29,31–33,46,47,51,54,55,60,62–64,68,76–79,81,82]
	Regression	[30,36,42,48,52,61]
	Classification	[43,50,52,60,61,65,69–71]
	Bayesian methods	[27,35,70]
Ensemble methods	Bagging	[34,50,52,73]
	Boosting	[30,49,52]
Expert system		[58,59]
Fuzzy logic		[78,82]

2.3. Power Quality

Monitoring energy quality is an important issue due to the increasing number of installed sensitive power electronic devices, energy storage facilities and the increasing number of distributed energy sources [83]. Unfortunately, connecting these devices to the system makes power quality issues increasingly difficult to maintain at an appropriate level [84–86]. Therefore, artificial intelligence and machine learning are increasingly used to maximise energy quality indicators in the power system.

Liu et al. [87] proposed an innovative approach to classifying power quality disturbances in the system using a deep convolutional neural network, multi-class support vector machine (MSVM) and segmented and modified S-transform (SMST). The test results showed that this method is characterised by high efficiency. A CNN-based quality event classification method was used in [88,89]. The classification of quality disturbances is also the main goal in [90]. For this purpose, the authors proposed a hybrid architecture combining CNN with LSTM. Additionally, they checked the performance of various deep learning architectures, such as reinforcement neutral network, identity-recurrent neural network (I-RNN) or gated recurrent units (GRU). A high accuracy rate for detecting and classifying disturbances was achieved in [91], where Shen et al. proposed an algorithm based on principal component analysis (PCA) and a convolutional neural network. This model achieved an accuracy of over 96%.

In [92], Le et al. achieved interference classification accuracy of over 99%. Accuracy of over 99% using RNN for noise classification was also obtained in [93–95]. In [93] an optimised RNN algorithm was proposed, in [94] a method for detecting and classifying voltage dips in real time was proposed, while in [95] the authors developed their own hybrid method based on a combination of wavelet transform, principal component analysis and RNN.

A frequently used type of machine learning is generative adversarial networks (GAN). The reader can see examples of its use to classify power quality disturbances in the system in [96–98]. In [96], an accurate and computationally efficient algorithm was developed based on GAN using phasor measurement units (PMU) data. This method achieved an accuracy of over 97%, making it accurate and suitable for real-time event detection. In [97], the GAN architecture was used to generate real data for training a classifier to detect power quality disturbances. Oliveira and colleagues [98] discussed the use of GAN-based machine learning for the classification of quality events and also highlighted its high accuracy.

Short fluctuations in photovoltaic power can lead to degradation of power quality because the use of regulatory reserves to compensate is usually very expensive. This issue was focused on by Golestaneh and his team in [99], who used extreme machine learning to establish quantile regression. In [100], Wan and his team developed an approach that combines quantile regression with extreme machine learning to determine prediction intervals for the quality of generated power.

The issue of classifying power quality disruptions through machine learning based on LSTM, which is a type of RNN, is also described in [101–108]. In [108], an LSTM method combined with a CNN method was proposed, which achieved an accuracy of 97.3%. Models with similar accuracy were proposed in [101,102]. In [101], an algorithm based on a hybrid combination of convolutional neural network with bi-directional long short-term memory (Bi-LSTM) was used for correct classification. This model uses spectrogram images for its operation. However, in [102] the classification method is based on LSTM and achieves an accuracy of 97.7%. Even greater accuracy was achieved by the method proposed by Abdelsalam et al. [103]. They used LSTM to categorise quality events and a feature extraction method based on wavelet packet transform (WPT). Their proposed method achieved an accuracy of almost 99%. In [104], three different models based on architecture were analysed: CNN, LSTM and a CNN-LSTM hybrid. The results showed that the CNN-LSTM method had the highest accuracy, achieving an accuracy of 98.9%. Exactly the same accuracy was achieved by the LSTM method developed by Chiam et al. [105]. The method developed by Rajiv [106] demonstrated the highest accuracy among those discussed in this work. Their approach, which was based on a hybrid combination of LSTM and CNN, achieved an accuracy of over 99%. The least accurate of the presented works was the one by Rodriguez et al. [107], which was based on the Hilbert–Huang transform and the use of LSTM. Their proposed method achieved an accuracy of 95.4%.

Another quite commonly used machine learning method is the self-organising mapping (SOM) method, which is a type of ANN. In this review, we will focus only on a few articles selected by the authors, because this issue is described quite widely in the literature. The SOM method was used by Bentley et al. [109] to identify sources of PQ interference; the accuracy of their method was 95%. A much more accurate method was proposed in [110], where an accuracy of 97.2% was achieved. We can therefore notice that this method is characterised by much lower accuracy in classifying interference sources than the methods discussed earlier.

The issue of electricity quality was also described by Kwack and his team [111]. He used fast Fourier transform (FFT) and discrete wavelet transform (DWT) for these purposes.

Rajeshbabu and Manikandan [112] proposed the use of an expert system to classify various types of power quality disturbances occurring in the energy system due to integration with renewable sources. To verify the results, the authors used real-time sample data. The expert system can also be used for power system planning and analysis [113,114].

Table 3 lists all artificial intelligence techniques used in this section.

Table 3. Summary of the methods used in the literature under consideration in power quality issues.

Artificial Intelligence		
	Machine learning	
Supervised learning	Deep learning	[87–98,101–108]
	Neural networks	[99,100,109,110]
	Classification	[87,90]
Expert system	[112–114]	

2.4. Power System Security

The continuous economic development of the world and the people's comfortable lifestyles cause a constant increase in the demand for electricity [115]. In order to meet this demand, and due to the need to be low emission, an increasing number of renewable energy sources are being installed in the power system, in combination with the liquidation of conventional energy generating sources. This solution leads to a significant reduction in system inertia, which has a negative impact on safety and proper, i.e., stable operation of the system.

Quick detection and correct classification of electrical disturbances are extremely important for the proper operation of the system [116]. Due to the usually large scope and complexity of power systems, quick detection of disturbances is still a complicated issue and requires further work to speed it up. Machine learning was used for this purpose in [117,118]. Chen et al. in [117] use extreme machine learning to classify faults and locate them. As their research results show, this machine is computationally efficient and fully self-learning. In [118], Chothani and his team developed a fault identification method based on SVM enabling the identification of initial faults located inside and outside the busbar protection zone.

Stefenon et al. [119] focused on using machine learning to detect faulty insulators or those that may cause failure in the near future. Adaptive neuro-fuzzy inference system was used for time-series forecasting, and the Fourier transform was implemented to improve forecasting performance.

The authors of [120] focused on aspects related to the security of machine learning and the operation of the power system. The authors present a number of guidelines that, in their opinion, will ensure compliance with the stringent security requirements that must be met during machine learning related to the proper operation of the system. Security issues were also discussed in [121], in which the authors presented the increasingly common use of machine learning based on supervised and unsupervised learning to ensure the ability to dynamically detect the state of insecurity resulting from short circuits. The authors suggest that by using machine learning for dynamic safety forecasting, it is possible to eliminate the need to use complex dynamic models of synchronous generator-based DER (SGBDER) and inverter-based DER (IBDER), which may significantly facilitate the use of precise safety criteria. An example of supervised learning used in [122] is GAN and in [123,124], where the multi-class support vector machine (multi-SVM) method is used. The issue of dynamic assessment of the security of power systems in real time was also discussed in [125,126]. In [125], an ensemble model based on a hybrid learning machine was developed, and in order to increase the forecasting accuracy of their algorithm, the authors used the Levenberg–Marquardt backpropagation mechanism and applied a weighted averaging technique based on particle swarm optimisation. The proposed algorithm was tested on a 39-node and 68-node test network. The research shows that the algorithm proposed by the authors has 100% accuracy in classification and 97% accuracy in predicting TM values for a 39-node system and 100% accuracy in classification and 99.7% accuracy in predicting TM values for a 68-node system. However, in [126] the decision tree, artificial neural network and entropy network (EN) methods were used. These techniques were integrated with the actual driver of the security system module used for the island of Crete, helping to identify operating conditions that may lead to impaired system performance. Initially, interpretable rules were extracted from large sets of simulated examples using DT, and then they were used to determine the output variables for ANN, which ensured better performance. Finally, the EN network method was used, which was intended to combine the advantages of previously used methods, i.e., the transparency of the DT method and the accuracy of the ANN method. The research shows that each of these methods is able to provide the operator with better accuracy in classifying potential threats, giving an accurate estimate of the minimum frequency values in the event of certain disturbances.

Dynamic assessment of the operational security of the power system is a key aspect of the work of Petar Sarajcev [127,128]. The authors of [127] provide an introduction to the special issue and the author introduces the reader to the techniques currently selected to ensure the correct dynamic assessment of system security. In [128] Sarajcev et al. present a literature review of the most important machine learning methods used in this issue. Particularly noteworthy are [129–131], in which the authors focused on ensuring system security through reinforcement learning. The assessment of the transient stability of energy systems using ML techniques was also discussed in articles [132–136]. For this purpose, CNN was used in [132], RNN was used in [133] and LSTM was used in [134,135].

Stability is one of the basic requirements for power systems. Low-frequency oscillations that are commonly observed in systems can cause their instability; this is why it is so important to detect them quickly and suppress them. For this purpose, an original approach to tuning the parameters of the power system stabiliser was proposed in [136]. To perform it, the ensemble learning method was used, which combines many machine learning techniques, namely extreme machine learning, neurogenetic (NG) system and multi-gene genetic programming (MGGP). Various load conditions of the system were tested: light, medium and heavy to check the reliability of the method. The obtained results confirmed the effectiveness of the proposed solution and show that this method can fully stabilise the power system after an emergency. The key advantage of this solution is its ability to immediately predict the parameters of the power system stabiliser (PSS). The issue of predicting the transient stability of the power system was focused on in [137], which used a method based on extreme machine learning using synchrophasors. The correct operation of the algorithm was checked on a 39-node system, and the proposed method proved able to correctly and effectively predict the state of transient stability of the power system.

Sedghi and his team in [138] proposed and developed the DCNN method to estimate the transient stability index of the power system. According to the authors, the greatest advantage of their method is the reduction of the time needed for calculations to determine the critical clearing time (CCT) index, thanks to which transient stability can be determined in real time.

The issue of optimising the power system by eliminating unfavourable phenomena was dealt with in [139], where machine learning in the form of an artificial neural network was used to determine overvoltages in the system. In this method, voltage was used to classify the occurring overvoltages into two separate groups: switching overvoltages and fast overvoltages. It was shown that the peak value of the overvoltage, the duration of the overvoltage, and the total harmonic distortion (THD) are the most important factors for accurate classification. The extreme machine learning method with a modified genetic algorithm (GA) was used to optimise the operation of hydropower plants in [140]. When there are many hydroelectric power plants in a given area, they may be affected by similar weather conditions, so their tributaries cannot be independent. Therefore, according to the authors, for their proper operation it is necessary to accurately estimate their dependencies and joint distribution. The authors use a genetic algorithm for this purpose and handle the uncertainty of the power system using random constraints.

Due to the integration of renewable sources, as well as the need to respond to changing demand levels, for example due to the charging of electric vehicles when the system is more loaded, it is necessary to correctly estimate the state of the power system. In [141], three machine learning algorithms were used for this purpose: ANN, DT and XGboost. They were tested on networks of 14 and 30 nodes. Based on the results obtained, it can be concluded that all three algorithms demonstrate high accuracy, but the artificial neural network algorithm turned out to be the most effective method.

Liu and his team [142] used fuzzy logic combined with a weather model to predict the impact of hurricanes on the reliability of the power system, and the proposed method is effective, efficient and flexible. In [143], the use of fuzzy logic was proposed to classify emergency situations in the power system. The purpose of the authors' proposed study is to quickly and accurately propose potential failures from a large list of potential emergency events. In [144], this technique was used to optimize and improve the energy management system.

An expert system is a special type of computer software created by experts. This system contains extensive knowledge and experience in the operation of power systems [145,146]. The knowledge that the system has is usually stored separately from the procedural part of the program and is usually stored in the form of decision trees, models or frameworks. The issue of expert systems was dealt with several decades ago [147–154]. In the 1990s, the expert system was used, among others, to control the operation of power supply systems in individual power plant units [151], or even to control power flows in the system, as presented by Chowdhurry and his team in [150]. Expert systems have also been used to plan network maintenance [155–159]. Tanaka et al. [149] focused on the prospects for the development of expert systems on the example of Japan. This is a valuable article because it provides the opportunity to look at how the use of this technology in the future was imagined over 30 years ago. It should be remembered that in order to use the expert system, several conditions must be met. First of all, there must be specialist knowledge available about the field in which the expert systems are to be used. Secondly, the expert system must be able to explain the solution to a given topic. The final condition is that search and inference based on an expert system must be fast and reliable [160]. Therefore, expert systems are currently used slightly less frequently than before, but they are still used to support decision making regarding, for example, the control of reactive and active power [161]. The solution proposed by the authors was tested on a 30-node test network, and the results obtained are satisfactory. In order to increase the security of the power system, Hong [162] proposes the use of an expert system with fuzzy logic. He proposes its use to control the power flow in the line. The proposed solution was tested on a 30-node closed test network, as well as on a practical 265-node system in Taiwan. Sobajic and his team propose using an expert system to examine how a computer program is able to help the operator assess the system's security. For this purpose, the consequences of individual exclusions are examined [163]. The integration of an expert system to assess the safety of energy management system operation can also be found in [164]. An expert system can also be used to restore the energy system after a disaster [165,166].

A summary of all artificial intelligence techniques used in energy system security is summarised in Table 4.

Table 4. Summary of the methods used in the literature under consideration in issues related to security in the power system.

Artificial Intelligence		
Machine learning		
Supervised learning	Deep learning	[121,122,132–135,138]
	Neural networks	[117,119,126,137,139–141]
	Classification	[118,123,124,126,141]
Reinforcement learning	Q-learning	[120,129–131]
Ensemble methods	Bagging	[125,136]
Expert system		[145–166]
Fuzzy logic		[142–144]

2.5. Identification and Analysis Related to Power System Disturbances

Nowadays, the power system is undergoing constant modifications and expansions in order to adapt it to be as flexible and reliable as possible. For this purpose, it is also necessary to constantly improve diagnostic systems for detecting and eliminating undesirable operating conditions in the system as quickly as possible. For this purpose, machine learning techniques are increasingly used to help facilitate the operator's work. The literature is quite extensive on this issue, and below are selected articles that, according to the authors, best illustrate the rapid progress of machine learning in the field of disturbances in the power system. The authors of [167] discuss the deep learning neural network technique for fault diagnosis in power systems. The work presents a method of data processing and then, using machine learning, their appropriate division in order to classify damage. The issue of appropriate diagnosis of faults in the system was also dealt with in [168–173]. In [173], fault diagnosis was proposed based on noise-assisted multi-variate empirical mode decomposition (NA-MEMD) and multi-level iterative–LightGBM (MI–LightGBM). The obtained results proved that the proposed diagnostic method can achieve a satisfactory learning speed, but only when the classifier provides adequate performance. Appropriate diagnostics and quick action in the event of fault section diagnosis (FSD) are essential for the proper operation of the power system. The authors of [172] proposed a diagnostic model designed for extreme learning. In the authors' work, hierarchical extreme learning machines (HELM) are responsible not only for performing diagnostics of the internal sections of the subsystem themselves, but also for performing diagnostics of adjacent connections. According to the authors, the proposed method is characterised by higher accuracy and lower error than other module systems used for diagnostics. HELM was also used in [174], and its effectiveness in efficient fault finding was tested on the Siping power grid in China. A review of fault identification to protect the system from cascading faults when a fault occurs is dealt with in [171]. The authors first summarise the currently used machine learning algorithms, such as ANN and SVM, and then move on to the methods that, in their opinion, as a consequence of the need to process large amounts of data in the shortest possible time, will be used more and more often: DL, RL and TL. In [170], a hybrid artificial intelligence system was presented that combines neural networks with fuzzy logic to help the operator locate disturbances in power systems quickly and accurately. When the neural network detects a disturbance, fuzzy logic starts analysing it. According to the authors, the research results presented by them clearly prove that the hybrid model they used is an extremely efficient and reliable machine for finding and analysing existing problems in system diagnostics. The problem of interference identification is also extremely important in the case of microgrids. Such networks often experience a lot of faults during power distribution. In [169], a discrete wavelet transform-based probabilistic generative model is presented to explore accurate solutions for fault diagnosis. The model was trained using an unsupervised learning approach, in which the artificial neural network algorithm is designed to optimally tune the model to minimise the error between the real and predicted classes. The effectiveness of the model was tested by changing the input signal and sampling frequency. The obtained results prove that the proposed model is able to correctly detect and classify disturbances. An artificial neural network was also used in [168], where their potential use was discussed with an emphasis on showing how ANNs can support operators in quickly making error-free decisions.

Machine learning is also used to locate faults in photovoltaic farms and to detect interference in the photovoltaic cells themselves. In [175,176], a method for detecting photovoltaic cell damage using a multi-layer perceptron (MLP) neuron network was proposed.

The MLP architecture was also used by Cherifa [177]. In her work, she integrated MLP with neural network back propagation in order to identify short circuits in the photovoltaic system.

For the purpose of identifying faults in photovoltaic sources, the probabilistic neural network (PNN) architecture is also commonly used [178,179]. In [179], Akram proposes an original method for monitoring the condition of photovoltaic sources, which detects and classifies short circuits in real time. A similar solution was used in [178]. In this paper, a PNN-based method is used to diagnose faults on the DC side of a photovoltaic system and then compared with artificial neural network classifiers.

To ensure reliable operation and to avoid unannounced failures, proper management and maintenance of network assets is necessary. In [180], the authors use the deep learning method to detect anomalies in the operation of energy system devices.

Artificial intelligence in the form of fuzzy logic can also be used to determine the time needed to remove a failure, as well as to determine the shutdown rate [181]. Relationships to determine them are shown in Equations (1) and (2):

$$r_E = \frac{\lambda_N \cdot R \cdot r_N + \lambda_A \cdot (1 - R) \cdot r_A}{\lambda_N \cdot R + \lambda_A \cdot (1 - R)} \quad (1)$$

$$\lambda_E = \lambda_N \cdot R + \lambda_A \cdot (1 - R) \quad (2)$$

where r_E is the time needed to remove the failure and λ_E is the activation rate. The failure removal time indicator is given in hours, while the number of outages is given in relation to historical data.

The fuzzy logic form of artificial intelligence can also be used to diagnose and classify failures in transmission networks. This solution was proposed by Bouchiba et al. in [182]. In their work, they used 209 cases, of which 147 were used for training, 31 for validation and 31 for testing. The research was carried out on a test network of 14 nodes, and based on the results obtained, it can be concluded that the deep learning algorithm is more effective and more accurate than fuzzy logic. The general architecture of fuzzy logic systems is presented in [183].

In order to diagnose faults in systems, Ray and his team [184] proposed diagnostic methods based on SVM. This method is used to identify types of interference depending on its location. The SVM method was also used by Rudsari and his team [185]. He used this algorithm to locate faults for high-voltage circuit breakers. In [186], the authors used SVM to diagnose and classify system failures.

Lee et al. [187] propose the use of an expert system for power system diagnostics to detect disturbances. Abdelsalam et al. [188] used a fuzzy expert system in combination with discrete wavelet transform and the Kalman filter to identify and classify disturbances in the power system. Based on the research and analysis of the results, the authors concluded that this hybrid combination is able to effectively identify and classify disturbances with high accuracy and in a short computation time compared to other methods. Position [189] dealt with analyses of nuclear power plants and an appropriate expert system was designed for this purpose. Table 5 lists all artificial intelligence techniques used in this section.

Table 5. Summary of the methods used in the literature under consideration in power system disturbance issues.

Artificial Intelligence		
Machine learning		
Supervised learning	Deep learning	[167,180]
	Neural networks	[168–172,174–179]
	Classification	[173,184–186]
Expert system	[187–189]	
Fuzzy logic	[170,181–183]	

2.6. Stability Issues in the Power System

Stability testing is a significant and important issue from the point of view of the operation of the power system. It is estimated that the failure that occurred in 2003 in the USA and Canada led to a power outage in up to 50 million households [190]. Voltage stability was analysed, among others, in [191]. Voltage stability margin (VSM) on the receive bus can be calculated as follows [192]:

$$\mathrm{VSM} = \frac{P\mathrm{max} - P\mathrm{current}}{P\mathrm{max}} \tag{3}$$

where Pmax is the maximum supplied power and Pcurrent is the current demand for active power. Voltage stability margin is expressed in relative units.

The phenomenon of voltage instability is attributed to the operation of the power system at its maximum allowable power, reactive power deficiency and inadequacy of reactive power compensation tools [193,194]. In [194], the author proposes a technique based on the use of artificial immunity systems, which is used to predict the state of voltage stability of the power system. Moreover, a comparative study was performed between an artificial immune systems (AIS)-based system and an ANN-based system for voltage stability prediction. Based on the results obtained, it can be seen that the AIS method is characterised by a smaller mean square error and a better correlation coefficient. However, the AIS method needed 2 min more to perform the same calculations, so it is slower than the method based on an artificial neural network.

Voltage stability can be considered in terms of short-term stability or in terms of long-term stability [195]. The issue of short-term stability was addressed by Zhang and his team [196]. They proposed a hierarchical and self-adaptive data analysis method for short-term voltage stability in real time. The proposed method used a machine for extreme machine learning, and the results obtained are satisfactory. In practice, the proposed method can be used to detect a rapid voltage drop or to detect abnormal voltage behaviour after a disturbance.

The issue of short-term voltage stability (SVS) was also addressed in [197], where a model combining an incremental learning machine and a class-unbalanced learning machine was used for this purpose. The proposed solution was tested on the Nordic test system, and it was shown that the model is adaptive and resistant to new, unknown situations.

The issue of monitoring long-term stability in the power system using EML was addressed in [198]. The model proposed by the authors allows to predict the loss of voltage stability in the system caused by limitations in the transmission of reactive power, and provides a warning when there is a deficit of this power in one of the system areas.

Malbasa V. et al. [192] proposed an active machine learning technique for monitoring voltage stability in transmission systems. This approach makes it possible to improve existing machine learning algorithms, such as SVM, DT and ANN, through active interaction with online forecasts. The research presented by scientists proves a significant reduction in training time, prediction time and reduces the number of measurements necessary in order to obtain satisfactory prediction accuracy. In [199], machine learning based on artificial neural networks was proposed for this purpose, and then the performance of the model was tested on 14-, 30- and 118-node systems, as well as on a real 62-node section of the Indian power grid under various load variants. The artificial neural network approach was also used by Bahmanyar and Karami [200], Ashraf et al. [201] and is found in [202,203]. Further, in these cases, the effectiveness of the proposed solution was tested on a 39-node power system in the case of Bahmanyar and on 14- and 118-node systems in the case of Ashraf. The obtained results demonstrate that the proposed models are efficient and allow for effective and accurate estimation of VSM. The flowchart of the procedure proposed by Ashraf is shown in Figure 7.

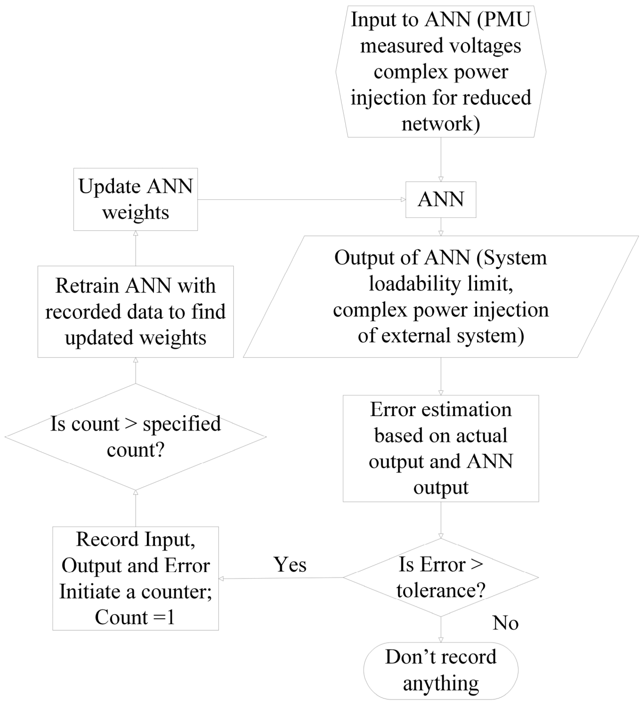

Figure 7. Flow chart for adaptive update of ANN weights [201].

In [204], in order to determine the voltage stability of the system, a hybrid model based on machine learning techniques such as RF and LSTM was proposed. Then, in order to verify the proposed method, a simulation analysis was performed on a 68-node system. The obtained results show that the proposed method provides better accuracy than two other methods that the authors chose for comparison.

Gomez et al. [205] proposed the use of the SVM method to accurately and, above all, quickly predict transient instability in the power system after a failure. The authors showed that data such as the bus voltage value or the generator rotor speed taken immediately after the failure was removed can be used as input data for SVM. The algorithm was tested on a 39-node network and showed over 97% prediction accuracy. In order to solve the voltage instability problem, Xu and his team in [206] proposed the use of multi-agent deep reinforcement learning (MA-DRL). The solution was tested on a 33-node closed test network.

The increased share of renewable energy sources in the system also increases its susceptibility to frequency instability, which in turn leads to increased challenges in maintaining its desired value [207,208]. In [207], the authors propose the use of logistic regression (LR) and the support vector machine to classify failures with unmaintained frequency values. Both proposed methods were tested on the energy system of the Spanish island of Las Palmas, and the results obtained by the authors indicate that their methods are characterised by accuracy and high flexibility. In [209] the authors propose the use of DL for this purpose, and in [210] a MA-DRL-based model is proposed. Xingyum et al. [211] proposed an algorithm based on XGBoost to predict frequency stability. The authors compared their proposed algorithm with others based on SVR, DL or CNN, and the results obtained prove that the XGBoost algorithm has better prediction performance.

In [208], the authors focus on accurate estimation of the frequency nadir, which is important in order to prevent large fluctuations in the frequency itself. For this purpose, they propose using five different machine learning methods and comparing their results: linear regression, gradient boosting, support vector regression, artificial neural network and XGBoost. The best results were obtained using gradient boosting and XGBoost, the objective functions of which are presented in Equations (4)–(7):

- Gradient Boosting:

$$F_o(x) = argmin_{\gamma} \sum_{i=1}^{n} L(y_i, \gamma) \tag{4}$$

$$F_m(x) = F_{m-1}(x) + arg \min_{h_m \epsilon H} \sum_{i=1}^{n} L(y_i, F_{m-1}(x_i) + h_m(x_i)) \tag{5}$$

where, F and H are the learning functions and L is the loss function. The parameters x and y are the input variable and the output variable, respectively, and γ is the initialisation.

- XGBoost:

$$L^t = \sum_{i=1}^{n} l(\hat{y}_i, y_t) + \sum_{k} \Omega(f_k) \tag{6}$$

$$\Omega(f) = \gamma \mathrm{T} + \frac{1}{2} \lambda \parallel w \parallel^2 \tag{7}$$

where L is the loss function that measures the difference between the forecast $\hat{y}_i$ and the read value y_i. Function 7, on the other hand, is used to smooth the learned final weights to avoid overfitting.

Table 6 summarises the artificial intelligence techniques used in issues related to the stability of the energy system.

Table 6. Summary of the methods used in the literature under consideration in issues related to power system stability.

Artificial Intelligence		
	Machine learning	
Supervised learning	Deep learning	[204,206,209,210]
	Neural networks	[192,194–196,198–203,208,211]
	Classification	[192,197,205]
	Regression	[207,208]
Ensemble methods	Bagging	[204,208]

2.7. Aspects Related to Forecasting Energy Prices

Another important topic is forecasting energy prices in the power system [212–215]. As Fraunholz [216] presents in his work, increasing the accuracy of forecasting market prices by just 1% can bring multi-billion savings for operators.

An algorithm based on long short-term memory was used in [217] where stock market profits were forecasted one day in advance. Tschorna in [218] tested several machine learning methods for forecasting electricity prices. Their observations show that the best learning methods among the proposed ones are DNN and SVR. Kapoor and Witchitaxorn in [219] test the use of generalised autoregressive conditional heteroskedasticity volatility (GARCH) and stochastic volatility (SV) machine learning models combined with LASSO for daily electricity price forecasting in New Zealand. In [220] support vector regression was used to forecast energy prices in the eastern region of Saudi Arabia. The results obtained by the authors confirm that this method is also characterised by high forecasting accuracy. The SVM method is used by Singh and Mahapatra [221] and by Damaluri and his team [222]. In [221], the authors tested their model on the power systems of Great Britain, France and Germany, obtaining mean percentage absolute errors (MAPE) of 3.58, 3.96 and 5.37, respectively. Deep learning techniques were used in [223], where the authors carried out research on a 33-node IEEE network, and the results obtained were characterised by high efficiency. In [224], the DRNN algorithm was used for one-day-ahead forecasting. The authors used real English data for research purposes and compared the results obtained using their proposed model with an SVM and an improved hybrid machine based on SVM. The research confirmed that the model proposed by the authors achieved an accuracy that was 29.7% higher than a single SVM and 21.04% higher than a hybrid machine based on SVM.

Short-term forecasting of energy prices is a key issue for consumers. The authors of [225] used the LSTM algorithm for its correct prediction. For prediction purposes, the proposed model analyses input time series of different scales and processes each of them. The proposed method was tested on one of the real energy systems in the United States from April 2013 to December 2014. Ghimire and his team in [226] propose the integration of LSTM, CNN and the variational mode decomposition (VMD) algorithm to estimate half-hourly electricity prices. The solution they proposed was tested on a system in Australia, and the results obtained are satisfactory and exceed the reference values. Yang, Sun and the rest of the team in [227] propose the use of ELM, average values of mean absolute error (MAE), root-mean-square error (RMS), mean absolute percentage error, index of agreement and Theil's inequality coefficient give grounds to believe that this is a promising method and that its use can lead to accurate price forecasting.

In [228], transfer learning, a deep learning technique, was used to predict energy prices. The authors checked the correctness of their method on two real energy systems. Forecasting in the French energy system improved by 7% compared to other solutions used, and in the German energy system by 3%. Forecasting based on an artificial neural network was proposed in [229,230]. In reference [229], an approach based on a boosted neural network (BooNN) was proposed, where the following formula was used to calculate MAPE:

$$\mathrm{MAPE} = \frac{100}{T}\sum_{t=1}^{T} \frac{|y_t - \hat{y}_t|}{y_t} \tag{8}$$

where: y_t is the actual value of the occurring load, $\hat{y}_i$ is the predicted load value and T is the total number of samples used. MAPE error is expressed as a percentage.

The obtained results show that a low forecasting error can be achieved when the number of models for which calculations are performed is greater than or equal to 20. As the number of analysed models decreases, the forecasting accuracy decreases.

Table 7 summarizes the application of artificial intelligence techniques used in energy price forecasting issues.

Table 7. Summary of the methods used in the literature under consideration in energy price forecasting issues.

Artificial Intelligence		
	Machine learning	
Supervised learning	Deep learning	[217,218,223,225,226,228]
	Neural networks	[218,224,227,229,230]
	Classification	[218,222]
	Regression	[219–222]

3. Literature Review of the Application of Optimization Methods in Power Engineering

The second group of methods and algorithms taken into account in the special issue considered are optimisation methods that enable the search for optimal solutions from the point of view of various criteria (objective functions) [231–234].

This section presents a description of optimisation methods that can be used to solve problems in power engineering, along with examples of work in which they were used. These methods are presented separately to show their division and advantages and disadvantages. Due to the very wide application of these methods, they are presented collectively. They can be used in virtually all areas of research in the field of power engineering, for example:

- To improve the stability of the power system;
- To eliminating line overloads;
- To forecast the generation of solar and wind sources;
- Optimization of voltage profiles in nodes;
- Forecasting;
- Storage;
- Improving the power quality;
- Disturbance analysis.

Additionally, they can also be used for the optimal selection of hyperparameters in methods based on artificial intelligence. The previous chapter also contains works in which, in addition to methods based on artificial intelligence, optimisation methods were used, which often support and improve the computational process.

As previously mentioned, the appearance of an increasing number of random objects in the system, such as RESs, consumers and unpredictable disturbances, causing, e.g., changes in the network operation configuration, branch overloads, voltage exceedances or balance problems, causes the modern power engineering to grapple with problems it has never faced before. It is therefore necessary to use advanced methods, such as optimisation (classic and ever more often used heuristic and metaheuristic optimisation), thanks to which it is possible to eliminate them. There are many optimisation methods and algorithms. The general division of optimisation methods that can be used in power engineering is shown in Figure 8.

Classic optimisation methods include the following [1]:

- Linear programming (simplex method, dual simplex method, interior point method);
- Nonlinear programming (Newton–Raphson method, unconstrained optimisation methods, methods with a penalty function);
- Quadratic programming (trust region reflective algorithm, modified simplex method);
- Mixed-integer programming (branch and bound method, cutting-plane method, Gomory's mixed-integer programming).

The advantages of classical methods include high accuracy and the short time taken to obtain a solution. The disadvantage of these methods is that they can only be used in situations where the objective function has essentially one optimum. When the objective function has multiple optimums, there is a high probability of finding a local optimum.

Examples of works in the field of power engineering in which classical methods were used are presented below.

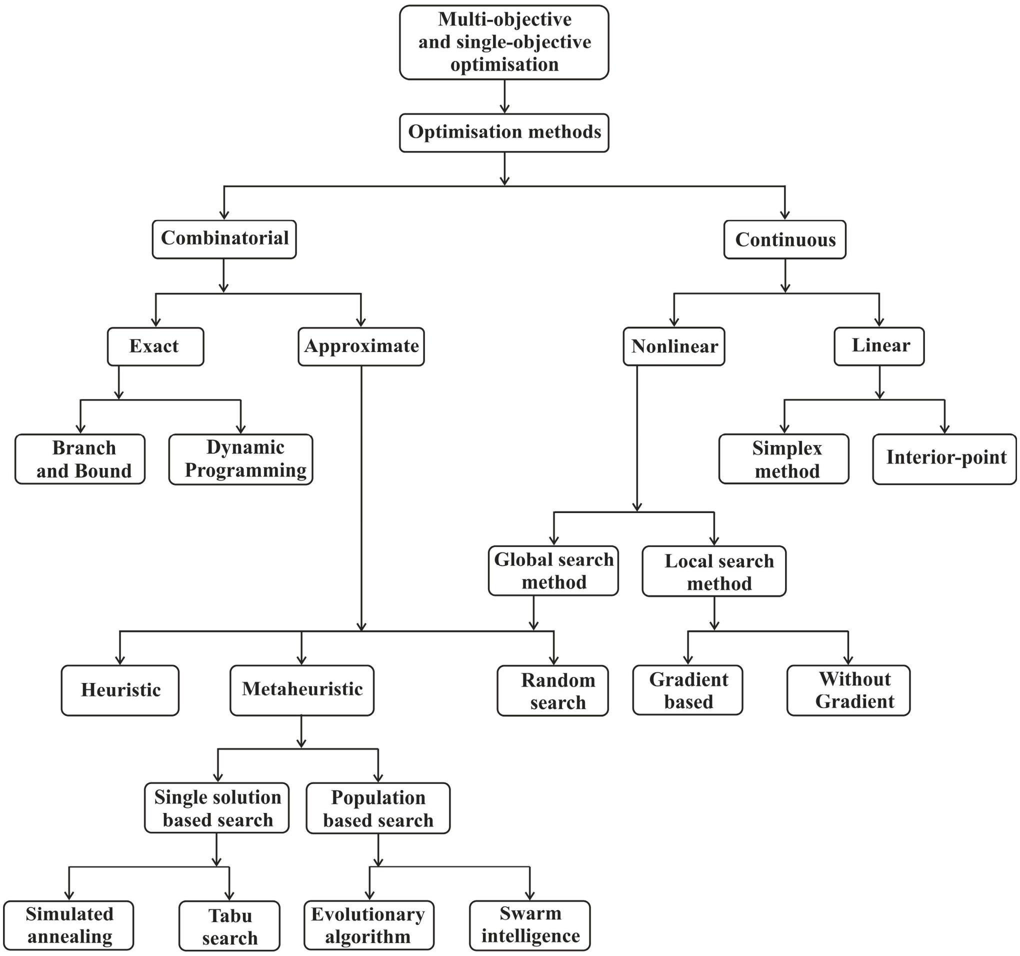

Figure 8. Division of optimisation methods that can be used to solve problems related to the power engineering [1].

Detailed information on theoretical issues related to classical optimisation methods that were used in the past and are currently used can be found in the books: Vasuki [235], Rao [236] and Jin et al. [237]. Examples of work in which classic optimisation methods were used are presented and briefly discussed below. Classical optimisation methods were also presented and described in the book [238] by Jin, Wang and Sun; a more detailed division can be found in [239]. As mentioned earlier, the significant advantages of classical optimisation methods include high efficiency and accuracy of the results obtained, as well as a relatively short time needed to obtain the results. The classical method also has disadvantages; namely, it requires, among other things, knowledge of the form of the objective function. Another disadvantage that may eliminate this method is the size of the problem under consideration (the need to meet constraints in multi-dimensional tasks). When solving a problem involving an extensive power system that has even several tens of thousands of elements, finding a solution is significantly difficult, and often even impossible [1]. More additional information about the classical method can be found in [240,241].

As a result of the problems associated with the use of classical methods mentioned earlier, the use of heuristic and metaheuristic optimisation algorithms is becoming more and more common, which are used, among others, in [242–246]. These methods owe their popularity, among others, to their universality, flexibility, simplicity and relatively high effectiveness [247,248]. The disadvantages include the fact that the obtained results with a certain probability allow us to claim that the found optimum is global and the relatively long computation time. Generally, these methods can be divided into the following [1]:

- Population-based methods (e.g., EA—evolutionary algorithm or SI—swarm intelligence);
- Methods based on a single solution (e.g., SA—simulated annealing or TS—tabu search).

When solving problems in the field of power engineering, it is also important that in the event of, for example, a divergent calculation process, the network model can be reloaded without losing the best solution found so far. Examples of works in the field of power engineering in which classical and metaheuristic methods were used are presented below.

In [249], Jiaqing and his team used the weak robust method for scheduling power systems with a large number of RES sources. Additionally, the authors used an improved bacterial colony chemotaxis (BCC) algorithm, which can make the final model even more efficient and environmentally friendly. This approach was aimed at minimizing operating costs and reducing pollutant emissions. In [250], Guo and his team proposed the use of the adaptive clustering-based hierarchical layout optimisation method of a large integrated power system in order to better take into account the energy balance, transmission losses, as well as the costs of its construction. Silveira, Tabares and the rest of the team [251] used classical optimisation methods to reconfigure the network. Based on their research, they concluded that the linear and conic methods are optimal for small and medium-sized systems. In [252], the authors used nonlinear optimisation to propose an optimal strategy for the distribution system operator (DSO) to provide flexibility services in areas with a large amount of distributed renewable sources. The authors of [253] used a single-step method for tracing power flows, which combines the accuracy of linear optimisation and the speed of heuristic methods for removing current overloads in power lines. For this purpose, they combined the optimisation method with the power flow tracking method.

Connecting several or more renewable sources in a given area may cause an overload of lines or transformers located in the immediate vicinity or at a certain distance from them. In order to reduce the occurrence of such overloads, it is possible to use simplex optimisation, as presented in [254–257].

Optimisation using linear programming was proposed by Kumar [258], who used it to determine the optimal location for the phasor measurement unit (PMU). These devices are essential to fully observe the energy system. Zhang, Woo and Choi [259] decided to use the same optimisation method. They used linear programming to analyse interval power flow (IPF), which is a promising approach to dealing with the issue of uncertainty associated with renewable energy sources in the system. In [260], linear programming was used to optimize the management of off-grid systems. The authors consider the development of a methodology for taking into account battery degradation processes in optimization models by defining costs as an important contribution. Munteanu and his team [261] used linear optimisation to optimise the control of wind energy systems. Munteanu also proposed the use of nonlinear optimisation to optimise the behaviour of the variable speed wind power system (WPS) [262]. Wen-Jing Niu et al. proposed the use of the classic quadratic programming optimisation method to optimise the operation of a hydroelectric power plant to reduce electricity shortages in the energy system [263].

In [246], the authors used a hybrid combination of metaheuristic optimisation in the form of the tree growth algorithm (TGA) and analytical optimisation to minimise power losses, as well as to improve voltage stability in the power system through the optimal location of distributed generators. The proposed method was thoroughly analysed on two test systems, i.e., IEEE 33 and IEEE 69-node networks, as well as on the actual 94-node Portuguese network. The obtained results showed that the proposed method works effectively, with very low power losses. Abdelinia et al. [245] used metaheuristic optimisation in the form of shark smell optimisation (SSO) combined with an artificial neural network to predict solar generation. This is necessary for the stable operation of the power system because unpredictable fluctuations in RES generation may lead to a loss of stability and reliability of the system. For verification purposes, the authors compared the entire proposed model to a real case, and also compared it with nine other forecasting methods. Additionally, the authors checked the effectiveness of the proposed metaheuristic algorithm by comparing it with six other optimisation methods for 24 test functions. In [264], a hybrid method combining the PSO metaheuristic optimization method with fuzzy logic was used to forecast solar and wind generation. The authors of [265], on the other hand, presented the use of the eagle arithmetic optimization algorithm (EAOA) metaheuristic combined with fuzzy logic to improve energy system management. Alasali et al. [244] proposed a new optimisation algorithm, manta ray foraging optimisation (MRFO), which aims to solve the problem of power flow from RESs. The authors defined four main objective functions related to optimal power distribution problems, which include, among others, transmission power losses and voltage deviations. Additionally, the algorithm was compared with six other modern metaheuristic optimisation techniques, and the results achieved by MRFO were the most precise. In [243], optimisation methods such as genetic algorithm, artificial bee colony (ABC) and grey wolf optimise (GWO) were used to tune wind turbine blade-pitch control to improve generation. The authors presented comparative studies of the proposed optimisation methods compared to conventional, commonly used methods such as the Zeigler–Nichols algorithm and the simplex algorithm. Based on the conducted research, the authors concluded that the method combining grey wolf optimise with proportional–integral–differential (GWO-PID) is more efficient than ABC, GA or conventional methods. In [266], the authors used intelligent genetic algorithms (IGA) to control the output power of wind turbines by optimising the pitch of the turbine blades. The authors tested the effectiveness of their method using the MATLAB program. Based on the results obtained, they concluded that the IGA method is a more efficient optimisation method than other genetic algorithms. The ABC algorithm was also used by Ravi with Duraiswarmy [267] to improve the stability of the power system. The artificial bee colony can also be successfully used to optimise the maintenance scheduling of generators in a power plant [268]. Effective maintenance planning is an extremely important issue for the operator to ensure stable and reliable operation of the entire system. The author's research has shown that the ABC algorithm is an extremely effective method for solving problems with generator maintenance scheduling (GMS). Heuristic methods are also often used in the case of PSS. For example, in [242] nondeterministic genetic sorting and the tabu search method were used to adjust the parameters of power system stabiliser controllers. Work on improving the operation of the PSS stabilizer was carried out in [269], where the orthogonal learning artificial bee colony was used. This approach has proven to be effective because it can improve the PSS system and fine tune its parameters. The authors of [270] focused on the development of the particle swarm optimisation method to estimate the optimal sizes as well as the most optimal location of energy storage systems. Compared to traditionally used models, much faster computational capabilities have been demonstrated. The proposed method was tested on a 24-node power system. In order to ensure reliable and sustainable operation of the power system with a large number of renewable sources, it is important to take into account the random nature of generation. The PSO method was also used by Kennedy Eberhart et al. [271]. They described, among others, the relationships between PSO, GA and AI. In [272], PSO was used to solve power system planning problems with a large number of plug-in electric vehicles (PEVs). In [273], the PSO method was used to optimize reactive power and active power to minimize the occurrence of active power losses. In turn, the proposed algorithm was tested on a 33-node IEEE test network. The ant colony optimisation (ACO) method is also successfully used to optimize active and reactive power losses, the use of which was proposed and tested on a 39-node test network in [274]. Ant colony optimization is also used for optimal scheduling of generating unit overhauls [275] and for improving the optimization of power system operations to reduce generated air pollution [276]. ACO is also used to optimize the routing of "overhead power transmitting lines" (OHPTL). This method makes it possible to reduce costs by selecting a more optimal route [277]. Some of the energy problems that metaheuristics in the form of the cuckoo search optimiser (CSO) also address include the optimisation of photovoltaic systems to better match the output power to the current cell shading [278]. The CSO method combined with the optimisation methods teaching–learning-based optimisation (TLBO) was used by Peddakapu in [279] in an automatic approach to automatic generation control (AGC). The cuckoo search optimiser was used to optimise the arrangement of wind turbines in [280]. Yet another issue in which metaheuristics are used is the optimisation of network topology in conditions of potential overload [281]. For this purpose, Antoniadis used variable neighbourhood search (VNS). Heuristic methods, unlike classical methods, do not need to know the derivative form of the goal, and in addition, they are even faster than classical methods. In their work, Pijarski and Kacejko [282] proposed the use of a new metaheuristic optimisation method, namely AIG. This method corrects the previous solution in each iteration process using specially selected multipliers. The advantage of the innovative shooter algorithm is its high accuracy and speed in solving various problems. Kareem et al. [283] examined and compared metaheuristic algorithms, including the GA, PSO, colony optimisation algorithm (ACO), simulated annealing (SA) and differential evolution (DE) algorithm. Yesilbudak [284] compared several optimisation methods, including the artificial hummingbird algorithm, artificial rabbits optimisation, enhanced Jaya algorithm, flow direction algorithm and artificial gorilla troops optimiser, to determine unknown parameters of photovoltaic cells. Based on the obtained research results, the author concluded that the studied metaheuristic techniques are able to estimate accurate and efficient design factors for photovoltaic systems. Pijarski and Kacejko [285,286] also used a metaheuristic method in the form of the algorithm of the innovative gunner (AIG) to optimise the voltage in the medium-voltage network. In [287], metaheuristic methods were used to determine the impact of electric vehicle load on the power system. The author attempted to minimise the harmful effects of vehicle charging stations on the system and used eight well-known optimisation methods: teaching–learner-based optimisation (MTLBO), JAYA, modified JAYA (MJAYA), ant-lion optimisation (ALO), whale optimisation technique (WOT), grasshopper optimisation technique (GOT), modified whale optimisation algorithm (MWOA) and hybrid whale particle swarm optimisation (HWPSOA). He verified his research on the 33-node IEEE 33-test network using Matlab software (https://www.mathworks.com/products/matlab.html, accessed on 16 January 2024). Other commonly used heuristic optimisation methods are the following: bacterial foraging optimisation (BFO) [288], glowworm swarm optimisation (GSO) [289] and bat algorithm (BA) [290]. In [291], Wang et al. used a combination of a bidirectional model for deep learning and hyperparameter optimisation using a new metaheuristic method called golden jackal optimisation (GJO). The authors of [292] focused on the issue of optimal reactive power distribution on the example of the CIGRE test network using two metaheuristic optimisation techniques. For this purpose, they used the simulated annealing and particle swarm optimisation method. In [293], the authors proposed a two-stage method to eliminate power line overloads on the example of a modified IEEE 118-bus test network. They used the algorithm of the innovative gunner to solve this problem. One can also distinguish works where the authors deal with optimal management of power system operation [294] and minimization of power losses [295].

More detailed information about metaheuristic optimisation methods can also be found in [296–298] and in books by Kumar [299] and by Yang [300].

4. A General Summary of Methods and Possible Areas of Their Future Application

Based on a review of the available literature, it can be concluded that network operators need advanced methods to solve difficult problems that currently appear in the power system. The authors' experience shows that operators expect new ways to improve the management of the power system. The use of modern methods based on artificial intelligence and optimization should take place both during the design, modernisation of the network and during its operation. With such tools, network operators will be able to make decisions more easily in conditions of high uncertainty.

Based on the extensive literature review presented in point 2, it can be concluded that some of the calculation methods are used frequently and some are used less frequently. Differences in the frequency of using them to solve real problems result, among others, from their effectiveness, efficiency, popularity and the time needed to obtain a solution. Based on the literature review, Figure 9 presents a general summary of the methods used in the literature, taking into account the frequency of their use.

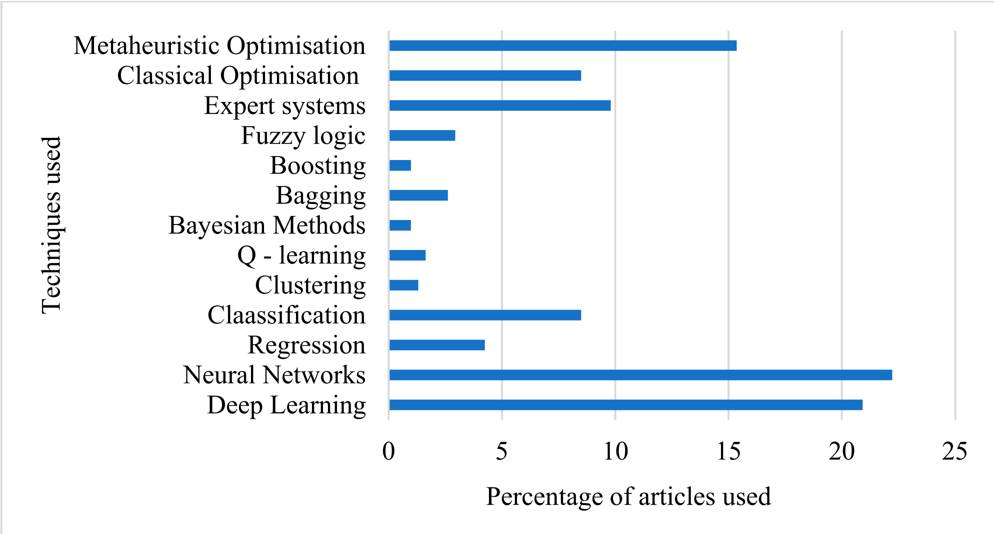

Figure 9. A summary of various methods based on artificial intelligence and optimisation along with the frequency of their use.

The graph presented in Figure 9 illustrates the general trend in the use of these methods to solve problems in the power industry. Looking at Figure 9, it is also possible to determine which methods are the most effective and efficient by analysing the frequency of their use. By analysing the data contained in Tables 1–7, it is also possible to determine which problems are most often considered in the literature. Additionally, methods can be identified that are most often used for specific problems.

Based on the figure, it can be said that deep learning and neural networks are the most frequently used methods. They have been used almost 70 times in the literature discussed. Bayesian methods, Q-learning, boosting and clustering methods are used least often in the literature considered. It is also worth paying attention to the optimisation techniques used. It can also be noticed that classical methods prevailed in the past. Currently, metaheuristic methods are being used increasingly, as can be seen in Figure 9. It should be noted that this article provides only a general presentation of the problems considered and the methods and algorithms to solve them. Also important are various types of computing platforms that facilitate and improve computation, such as the "Edge Computing platform in Feeder terminal unit (FTU) for distributed networks", presented in [301]. Solving computational problems in power engineering also requires the use of appropriate software or the development of custom computer applications using various programming languages or programming tools such as Python or Matlab, for example.

Of course, the articles presented in this review, which is an introduction to the special issue, do not completely exhaust the topic, but they show a certain trend which methods are most popular among authors and which are not appreciated often enough in the literature.

This extensive literature review also indicates certain areas that constitute the so-called research gaps. They constitute potential topics for scientific development. These include, among others:

- Technical and economic analyses allowing to determine the probability of annual loss of electricity generation from renewable energy sources;
- Eliminating overloads of power lines in a high-voltage network saturated with renewable energy sources and energy storage;
- Analyses aimed at examining the possibility of participation of RESs and energy storage in the processes of rebuilding the generating capacity of power plants after a catastrophic failure;
- Analyses for determining the connection possibilities of the power system;
- Minimising the difference in voltage phasor angles when power lines are switched on;
- Optimal redispatching of power with RES installations;
- Optimal selection of a compensation device for a wind or photovoltaic farm connected to the power grid by cable;
- Cable pooling—optimal use of common network infrastructure by various types of renewable energy sources;
- Optimal location of energy storage and electrolysis installations in the power grid;
- Optimal management of inverters of photovoltaic installations,
- Forecasting RES generated power or power demand using modern hybrid algorithms.

The research problems mentioned are examples of issues that can be solved using modern methods based on artificial intelligence and optimisation. Other research areas are certainly possible. This article, which is an introduction to the special issue, is intended as an encouragement and inspiration for potential authors to prepare their future publications that could concern the discussed topic.

5. Summary

As mentioned earlier, this article is an introduction to the special issue entitled *Advances in the Application of Methods Based on Artificial Intelligence and Optimisation in Power Engineering*. The authors defined the goals and scope of the research topics. They also drew attention to the constant need to deal with this topic due to the ongoing energy transformation and dynamic changes taking place in the field of electricity. It presents an extensive literature review on the topic under consideration. Examples of research areas and modern computational methods have been indicated that allow solving real, current problems faced by current power systems. Some of them can be eliminated based on acquired experience and engineering logic (engineering reasoning). Others, however, require the use of advanced methods and algorithms due to the degree of complexity, complexity and size of the issue. It is therefore necessary to search for new methods and improve the existing ones in view of the fact that no method has been found so far able to solve all the problems faced by the power system. It is also worth mentioning the enormous progress in methods and programs that allow their use online. Both problems and methods have been divided into suitable groups. It is shown how often certain computational methods are used in the literature. Some research gaps were also identified, which may constitute further areas of application of methods based on artificial intelligence and optimisation. The subject matter under consideration is extremely important from the point of view of the role of the power system in the functioning of national and global economies, as well as from the point of view of international cooperation and human security. Despite the relatively large number of items devoted to this topic in the literature, it is still possible to identify issues that require deeper research, a change in approach, the removal of simplifications or a greater extension and consideration of the current requirements and conditions of the operation of the power system.

Collaboration should be sought between experts from various scientific fields, e.g., artificial intelligence, optimisation, mathematics, computer science and power engineering. Interdisciplinarity is therefore recommended. Cooperation between experts in the field under consideration should take place through the exchange of experiences, joint problem solving, meetings, participation in projects and conferences. Therefore, when planning work related to solving problems related to the operation of the power system, the possibility of involving various experts should be considered. Their role would be to recognise the problem, propose appropriate methods and implement them, create a computational model of the network, perform analyses and develop the most important conclusions. In order for the proposed solutions to be used in practice, cooperation with operators is also necessary. Network operators know best what problems occur in the power system. They have up-to-date data and statistics and constantly monitor and manage the operation of the power system. They know what the possibilities are of using advanced methods in practice. Also, the cooperation of experts with network operators makes it possible to achieve even greater effects and to learn about the possibilities of using the proposed methods/algorithms in real-world situations.

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Nomenclature

T–S	Takagi–Sugeno	RBF	Radial basis function
SVM	Support vector machine	BP	Back propagation
BPNN	Back-propagation neural network methods	ADALINE	Adaptive linear element networks
LSTM	Long short-term memory	GR	General regression
ANN	Artificial neural network	RT	Regression tree
ELM	Extreme machine learning	DT	Decision tree
DL	Deep learning	XGBoost	eXtreme gradient boosting
BESS	Battery energy storage system	AdaBoost	Adaptive boosting over decision trees
AWE	Alkaline water electrolysers	GPR	Gaussian process regression
ESS	Energy storage system	LS-SVM	Least-squares support vector machines
ANFIS	Adaptive neuro-fuzzy inference system	PSO	Particle swarm optimization
FESS	Flywheel energy storage systems	NARM	Nonlinear autoregressive model
DT	Decision tree	MFF	Multi-feature fusion
FVRL	Fuzzy vector reinforcement learning	SAM	Self-attention mechanism
RNN	Reinforcement neutral network	GCN	Graph convolutional network
SVR	Support vector regression	Bi-LSTM	Bi-directional long short-term memory
VMD	Variational mode decomposition	1D-CNN	One-dimensional convolutional neural networks
SSSA	Small signal stability analysis	WT	Wavelet transform
GNN	Graph neural networks	NN	Neural network
ELS	Emergency load shedding	EA	Evolutionary algorithm
DBSCAN	Density-based spatial clustering of applications with noise	AI	Artificial intelligence
EEMD	Ensemble empirical mode decomposition	ML	Machine learning
RVM	Relevance vector machine	DCNN	Deep convolutional neural network
IMF	Intrinsic mode functions	MSVM	Multi-class support vector machine
CNN	Convolutional neural network	SMST	Segmented and modified S-transform
SE	Sample entropy	I-RNN	Identity-recurrent neural network
MLP	Multi-layer perceptron	GRU	Gated recurrent units
GBR	Gradient-boosted regression	PCA	Principal component analysis
RFR	Random forest regression	GAN	Generative adversarial network
APSO	Advanced particle swarm optimization	PMU	Phasor measurement units
FTMA	Fine-tuning metaheuristic algorithm	WPT	Wavelet packet transform
RF	Random forest	SOM	Self-organizing mapping

NARX	Nonlinear autoregressive models with exogenous inputs	FFT	Fast Fourier transform
VPP	Virtual power plant	DWT	Discrete wavelet transform
LASSO	Least absolute shrinkage and selection operator	SGBDER	Synchronous generator-based DER
EN	Entropy network	LR	Logistic regression
PVPNet	Powerful deep convolutional neural network model	IBDER	Inverter-based DER
DNN-MRT	Deep neural network-based meta regression and transfer learning	DSA	Dynamic security assessment
DBN	Deep belief network	TM	Time margin
CCT	Critical clearing time	RL	Reinforcement learning
THD	Total harmonic distortion	LFO	Low-frequency oscillations
DLNN	Deep learning neural network	PSS	Power system stabilizer
NA-MED	Noise-assisted multi-variate empirical mode decomposition	NG	Neurogenetic
MI–LightGBM	Multi-level iterative–LightGBM	MGGP	Multi-gene genetic programming
FSD	Fault section diagnosis	OLABC	Orthogonal learning artificial bee colony
HELM	Hierarchical extreme learning machines	GA	Genetic algorithm
PNN	Probabilistic neural network	CNN-LSTM	Convolutional neural network-long short-term memory
VSM	Voltage stability margin	AIS	Artificial immune systems
SVS	Short-term voltage stability	ILM	Imbalance learning machine
MA-DRL	Multi-agent deep reinforcement learning	DDN	Deep neural network
GARCH	Generalized autoregressive conditional heteroskedasticity volatility	SV	Stochastic volatility
MAPE	Mean percentage absolute error	DRNN	Deep recurrent neural network
STPF	Short-term price forecasting	VMD	Variational mode decomposition
BooNN	Boosted neural network	RES	Renewable energy sources
MRFO	Manta ray foraging optimization	ABC	Artificial bee colony
GWO	Grey wolf optimizer	IGA	Intelligent genetic algorithms
FCM	Fuzzy c-means	DRN	Deep residual networks
MAE	Mean absolute error	RMS	Root-mean-square error
AIG	Algorithm of the innovative gunner	ACO	Colony optimization algorithm
BCC	Bacterial colony chemotaxis	SCM_CSC	Selectively coherent model of converter system control
DRL	Deep reinforcement learning	DNN	Deep neural network
SPR	Seasonal persistence-based regressive	PAR	Persistence-based auto-regressive
WNN	Wavelet neural networks	SPNN	Seasonal persistence-based neural network
Multi-SVM	Multi-class support vector machine	GWO-PID	Grey wolf optimise with proportional–integral–differential
OHPTL	Overhead power transmitting lines	DSO	Distribution system operator
TGA	Tree growth algorithm	WPS	Wind power system
GMS	Generator maintenance scheduling	SSO	Shark smell optimisation
PEV	Plug-in electric vehicles	BA	Bat algorithm
CSO	Cuckoo search optimiser	TLBO	Teaching–learning-based optimisation
AGC	Automatic generation control	SA	Simulated annealing
VNS	Variable neighbourhood search	DE	Differential evolution
MTLBO	Modified teaching–learner-based optimisation	ALO	Ant-lion optimisation
MJAYA	Modified JAYA	WOT	Whale optimisation technique
GOT	Grasshopper optimisation technique	GJO	Golden jackal optimisation
HWPSOA	Hybrid whale particle swarm optimisation	BFO	Bacterial foraging optimisation
MWOA	Modified whale optimisation algorithm	EAOA	Eagle arithmetic optimization algorithm
SOMA	Self-organizing migrating algorithm	IPF	Interval power flow

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