

Review

Advanced Optimisation and Forecasting Methods in Power Engineering—Introduction to the Special Issue

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Abstract: Modern power engineering is struggling with various problems that have not been observed before or have occurred very rarely. The main cause of these problems results from the increasing number of connected distributed electricity sources, mainly renewable energy sources (RESs). Therefore, energy generation is becoming more and more diverse, both in terms of technology and location. Grids that have so far worked as receiving networks change their original function and become generation networks. The directions of power flow have changed. In the case of distribution networks, this is manifested by power flows towards transformer stations and further to the network with a higher voltage level. As a result of a large number of RESs, their total share in the total generation increases. This has a significant impact on various aspects of the operation of the power system. Voltage profiles, branch loads, power flows and directions of power flows between areas change. As a result of the random nature of RES generation, there are problems with the quality of electricity, source stability issues, branch overloading, voltage exceedances and power balance. The occurrence of various types of problems requires the use of more and more advanced methods to solve them. This review paper, which is an introduction to the Special Issue *Advanced Optimisation and Forecasting Methods in Power Engineering*, describes and justifies the need to reach for effective and available mathematical and IT methods that are necessary to deal with the existing threats appearing in the operation of modern power systems. It indicates exemplary, current problems and advanced methods to solve them. This article is an introduction and justification for the use of advanced calculation methods and algorithms. Engineering intuition and experience are often not enough due to the size and complexity of power grid operation. Therefore, it becomes necessary to use methods based on artificial intelligence and other advanced solutions that will facilitate and support decision making in practice.

Keywords: power engineering; optimisation; metaheuristics; RES; machine learning; probability; statistics



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1. Introduction

The main subject of research in the Special Issue *Advanced Optimization and Forecasting Methods in Power Engineering* is the use of advanced optimisation and forecasting methods in the power industry. The main goal is to identify problems that can be subjected to optimisation or other methods based on artificial intelligence to formulate the objective function and to effectively solve optimisation tasks with as few simplifications as possible. Speaking of the power system as a whole, it boils down to taking into account, as far as possible, all the factors that determine a given issue. In the power industry, there are a number of problems that can be solved by the use of optimisation. It is well known that optimisation consists of finding the best solution from the point of view of the adopted criterion (objective function). There are many optimisation methods, such as classical, heuristic, hybrid, static and dynamic. In addition to optimisation, other ways to solve some problems are also possible, namely the use of artificial intelligence methods, such as machine learning, fuzzy logic or artificial neural networks.

The search for solutions to specific, practical problems can be based on experience, intuition and engineering knowledge. However, this does not always give the expected results and guarantee an optimal and reasonable result. If there is a need to eliminate line congestion, investment solutions related to their reconstruction and modernisation can be applied. However, the following question arises: will these treatments be economically justified and guarantee the achievement of the expected results at minimum costs? This is not always possible and not in all circumstances. Sometimes a better solution, from the economic point of view, is to change the network configuration, or change the generation distribution determined using specific mathematical tools [1]. This procedure can be much cheaper and, in some cases, more effective in relation to the modernisation of the existing state of the power system. The concept of optimisation in the power system has been known for a long time, just as solving the load flow problem. At the beginning, it mainly concerned the search for such a distribution of generated power between operating generating units that the total generation cost would be minimal. This problem has been defined as a Unit Commitment (UC) issue. Solving the UC task was possible provided that the characteristics of the generation costs of individual sources were known.

Currently, optimisation tasks in a power system are often called Optimal Power Flow (OPF) or (after taking into account the “N-1” criterion) Security Constrained Optimal Power Flow (SCOPF). Another class of problems concerns, for example, short-circuit calculations, power system stability, power quality or other issues, referred to as Special Optimal Power Flow (SOPF).

In order to realise the difficulty in creating an effective computer tool for solving the above issues, it should be emphasised that only some commercial programs used to analyse the operation of the power system contain the above-mentioned tools. There are programs such as DiGSiLENT PowerFactory [2], PowerWorld Simulator [3] or MatPower software [4], operating in the Matlab environment [5]. Moreover, many of these programs base their algorithms on linearisation of the problem. This is a significant simplification that can sometimes lead to erroneous conclusions, especially when analysing large networks. Computational difficulties that can be encountered while performing work related to the analysis of the power system prompt the search for new methods and alternative solutions.

According to the No-Free-Lunch theory [6], there is no algorithm that would solve all optimisation problems. This means that in a given class of problems some algorithms perform better, while in another set of tasks they are less efficient. Therefore, it is worth looking for new methods by means of which real problems occurring in the operation of power systems can be solved better than using commonly known algorithms.

The purpose of this Special Issue is to draw attention to new methods and opportunities to use the advantages of new methods, as well as their specific properties. Of course, these methods should not be understood as an antidote to all computational problems associated with the search for an optimal solution. Rather, they are a means to be used when other known and previously used methods have failed.

This review paper is organised in such a way that the subject under consideration is described in the first section. The second section contains a review of the literature. The third section presents and briefly describes the problems of modern power engineering, which are still waiting for an effective solution. The fourth point describes selected methods that allow to solve some of them. The last, the fifth point, contains a short summary of the whole article.

2. Literature Review

There are various papers in the literature related to the subject of the Special Issue *Advanced Optimization and Forecasting Methods in Power Engineering*. Generally, the problems encountered in the power industry can be divided thematically into problems related to the design of power system elements, planning its development and managing its operation.

As an example of a work representing the first mentioned group of problems, one can indicate the work [7], in which the authors dealt with the subject of multi-criteria,

effective and optimal transformer design. The main purpose of the analyses was to design an energy-saving transformer from the point of view of minimising losses and reducing the failure rate of the device. The topic of optimal design of insulators, from the point of view of minimising the probability of failures, was dealt with in [8]. Power grids and systems also require optimal design. Examples of such analyses include works [9,10]. They present the process of design and optimisation of an industrial network with the assumed different electrical loads of this network, as well as calculations related to planning the operation of the power system. In paper [11], the topic of optimal design of multimachine power system stabilisers was analysed. The topic of optimal design of wind farms, in terms of the location of wind turbines, can be found, among others, in works [12–14].

The next group of works are articles devoted to optimal planning of the development of the power system. In paper [15] a multi-level method of planning the optimal network expansion based on the binary dragonfly optimisation algorithm, taking into account distributed generation, was analysed. Similar considerations, also including aspects related to charging electric vehicles and probabilistics, were carried out in articles [16–21]. Selected issues related to the optimal development and planning of the power system are described in [22]. Interesting analyses were performed in the work [23], where the minimisation of investment and operating costs related to the expansion of the power grid by connecting island systems was considered. Optimal planning of the development of a distribution network with energy storage was, in turn, the subject of research presented, among others, in [20,24–28].

Many articles are devoted to analyses concerning conditions for the optimal operation of the power grid from the point of view of various aspects [29]. There are works describing the impact of renewable energy sources on the operation of the power system or, for example, electrolyzers and energy storage facilities on the medium- and low-voltage distribution network. Voltage, balance and power quality problems are often analysed. Different concepts of voltage control in medium voltage power grids, using the classic control of the HV/MV transformer under load and the active participation of distributed generation sources, can be found, for example, in works [30–35]. The active participation of energy storage and electrolyzers in improving the operating conditions of the distribution network was analysed, among others, in articles [36–43]. In other works, one can find topics related to the reduction in the switching angle of high-voltage power lines in order to eliminate current surges and to rebuild and restore the system to operation after system failures. Various optimisation methods are also used, most often aimed at minimising the negative phenomena caused by switching on the line with too large a difference in angles between the two poles of the circuit breaker. There are works in which this problem was treated as an optimisation problem with constraints [44–50]. Another topic that can be treated as an optimisation task is the optimal selection of parameter settings of power system stabilisers (PSS) [51–58]. Another optimisation problem is the selection of the location of synchronous compensators in order to obtain the appropriate short-circuit power in selected nodes of the power grid [59–62]. In some papers [63–66] there is also the subject of optimisation in the context of improving the stability of the power system. Ensuring optimal short-circuit conditions in the network was considered in articles [67,68]. It is also worth pointing out works dealing with optimisation issues in solving problems not directly related to the discussed subject, which were then used and adapted in the algorithms presented above. Examples of this type of work can be found in [69–71].

The next group of works are articles on solving various problems in the field of power engineering and forecasting based on artificial intelligence methods, such as machine learning and deep learning. In works [72–74], one can find an overview of solutions containing the use of these algorithms in analyses of the power system operation. Examples of topics considered as part of the use of selected machine learning methods concern the analysis of disturbances in the power system [75], operation, control, planning and diagnostics [76–78], as well as forecasting [79–83] and many others. These methods are used not only in power engineering but also in other fields of science and industry, e.g., in

aircraft (in aeronautics) [84–86]. This topic has been widely discussed in the last decade (European Clean Sky projects aiming at a “more electric aircraft”; for these projects there are scenarios for optimising the electric load, batteries and power flows). In these articles the control scheme is composed of a two-layer architecture, a low level based on a controller, i.e., an output is driven to a reference, and a high-level control used to guarantee the achievement of various objectives in a scenario where there are new loads and new sources.

Problems considered in practice are often random in nature. Sometimes the analysed quantities change randomly over time. Therefore, it is necessary to use probabilistics and statistical indicators to be able to analyse a given issue. Then, for example, Monte Carlo methods are used to identify a given issue and draw appropriate conclusions. An example can be the article [87], in which the authors dealt with energy management in isolated microgrids, taking into account failure and demand response. A novel stochastic IGDT formulation has been proposed. The paper [88] dealt with the energy management system in a system containing a photovoltaic installation, energy storage and an installation for hydrogen production by means of electrolysis. Optimal scheduling of the system operation was proposed in order to minimise the costs associated with the production of hydrogen. The work was therefore a combination of optimisation with randomly changing generation in photovoltaics. Statistics related to seasonal changes in electricity were also used. In the article [89], the authors used a new method for short-term probabilistic forecasting of global solar irradiance from complex-valued time series. The combination of probabilistics and forecasting turned out to be an effective method to solve the analysed problem.

Some methods use a hybrid approach consisting of combining the advantages of different algorithms. An example is the work [90], which reviewed similar methods. Another article [91] proposed a novel hybrid model that combines denoising methods and optimisation algorithms with forecasting techniques. In [92], a neural network and a Kalman filter were used to improve the accuracy of wind speed forecasting. A similar problem was also considered in article [93], where a hybrid method was proposed to solve it, being a combination of Ensemble Empirical Mode Decomposition (EEMD) and the Support Vector Machine (SVM).

In general, it can be said that the use of advanced optimisation and forecasting methods is possible in virtually every area of power engineering, as evidenced by numerous publications available in the literature. It should be noted, however, that there is a constant need to create new methods, algorithms and methodologies, because modern power systems are constantly changing and transforming. There are more and more new, difficult problems that have to be solved online. The requirements of operators change, and unforeseen events or situations occur that in the past did not occur or occurred very rarely. Considering the above, constantly dealing with the subject of optimisation and forecasting is absolutely justified.

3. Problems of Modern Power Engineering

The subject of this Special Issue concerns aspects related to the operation of the power system and planning its development. Many years of experience of Guest Editors related to the performance of various works and research projects, expert opinions on the possibility of connecting new elements of power infrastructure to the power system, confirm the relevance of the problems arising from the connection of new sources, loads, lines and transformers in power networks. Calculation difficulties are sometimes caused by the specific nature of the power system operation, and sometimes by restrictions imposed by the operators. Simultaneous, continuous fulfilment of all requirements is connected with the need to organise the operation of the power system in such a way that its reliability and safety are maintained, taking into account economic aspects.

In their professional experience, Guest Editors have encountered many such problems. Some of them are presented in this section. The choice of such issues is dictated by the fact that some of them can be classified as nonlinear tasks, some (after linearisation of the power system model) as linear tasks and still others as combinatorial tasks. In general, they reflect the diversity of current problems in the power industry. The selected ones are listed below:

- Optimisation of reactive power flow:

The power system is characterised by a high demand for reactive power. From the point of view of rational use of the grid infrastructure, it is beneficial to generate reactive power near the place of its demand. Thanks to this, the load on the network with the flow of this power is reduced, and thus power and energy losses are reduced. A beneficial consequence is also the reduction in voltage drops, and thus the increase in voltage levels, especially where it is too low. Due to the fact that the capacity of the network is limited by the value of the apparent power, by reducing the flow of reactive power, the active power transmitted by the network elements can be increased without additional capital expenditure. Optimisation of reactive power flows is therefore an important issue, both as a technical and economic aspect [94].

- Minimisation of active power losses in the power system:

The topic of active power losses can be analysed from various points of view. As mentioned earlier, optimisation of reactive power flows can be used for this purpose, but also, e.g., appropriately shaping the structure of the distribution network or voltage profiles.

- Enhancement of power system connection possibilities (hosting capacity):

When planning the development of the power grid, its operator takes into account the plans for the development of the generation sector. To a large extent, these plans are determined by the expected development of wind or photovoltaic energy. The optimisation task will allow to indicate the maximum power that can be connected to the tested network area, while meeting the required constraints.

- Dynamic adjustment of the generation level to the transmission capacity of power lines and transformers:

At the stage of planning the connections of new customers and sources, operators very carefully examine the potential occurrence of overload threats, doing so with such extremely pessimistic assumptions that the system has a large margin of safety. As a result of random events (e.g., emergency shutdown of a line or a transformer), there may be situations in which other lines or power transformers are congested. Failure to respond or subsequent shutdown may lead to a system failure. The essence of optimisation is then to eliminate the congestions while minimising the costs of such operations.

- Optimal selection of partition points in the MV network:

The connection of more and more RESs to the distribution network at the medium-voltage level means that existing methods of determining the optimal location of split points in these networks may fail due to the dimension of the problem and the myriad of possible operating states. A good approach seems to be to treat this issue as an optimisation task, which will allow for the optimal selection of network split points. This issue has already been the subject of many publications [95–101], but it has often been marginalised and treated by distribution network operators as a purely scientific problem with no practical significance. In practice, network split points remain unchanged in distribution networks, although it is well known that, apart from their original role, their location may also affect the following: potential reduction in power and energy losses, improvement in network reliability, reduction in electricity distribution costs and improvement in operating parameters grid (voltage levels and energy quality indicators) [102–104].

Meanwhile, the changing nature of distribution network operation, the increasing number of RESs installed in the network, creates the need to dynamically optimise the location of network split points, depending on the current or forecast distribution generation (mainly RES generation) and loads in the network. The rationale for undertaking this type of work is the fact that more and more remotely controlled switchgear is being installed in MV distribution networks, which creates great potential for its use in the process of dynamic reconfiguration of the distribution network using optimisation and forecasting algorithms.

- Minimising the difference in voltage phasor angles when power lines are switched on:

Operational or emergency shutdown of a transmission line or a transformer entails the need to switch them on and restore the transmission capacity of the network. Closing the circuit breaker at a high value of the switching angle may cause a large current surge, which is dangerous for system components. Therefore, measures should be taken to limit the current surge in the conditions of switching on the elements of the transmission network. These operations are aimed at minimising the switching angle by changing the load or generation level in selected nodes. It is very difficult to clearly indicate the nodes (sources and loads connected to them) that have the greatest impact on the value of the switching angle. Often intuition or engineering practice can lead to wrong conclusions. It turns out that even a distant source may have a greater impact on the value of the standing phase angle in a given location than the closest source, hence the idea to use optimisation algorithms or algorithms using machine learning for this purpose.

The discussed issue can also be reversed, as it was presented in [46]. That is, optimisation algorithms can be used to find the highest, safe from the system's point of view, value of the standing phase angle and use this knowledge to find the optimal parameter settings of synchrocheck devices installed in transmission and distribution networks. Synchrocheck devices are more and more commonly installed in networks, and very often they are part of distance protection, so they are installed automatically. However, knowledge about the methods of their setting still needs to be supplemented, which can be achieved by conducting research in this area.

- Optimal management of inverters of photovoltaic installations:

Installing a large number of PV micro-installations in distribution networks can lead to an unfavourable increase in voltage above the permissible value, as well as power balance problems. Among the various methods of eliminating these problems, the appropriate selection of the $Q(U)$ and $P(U)$ characteristics of the inverters deserves attention. According to the information contained in the standards EN-50438 [105], EN-50549 [106], AS/NZS 4777.2:2015 [107] and AS/NZS 4777.2:2020 [108], the settings of the characteristics $Q(U)$ and $P(U)$ can be changed. Therefore, this problem can be treated as a problem of nonlinear optimisation with constraints and solved using, e.g., heuristic methods. It seems that the classical methods are not suitable here due to the iterative nature of the problem. The optimal selection of the settings of both curves is aimed at the smallest possible reduction in the energy that can be produced in micro-installations during the year.

- Optimal selection of energy storage and electrolyser parameters:

Distributed connection of RESs causes various problems, depending on the grid voltage level. In distribution networks, these are most often voltage and balance problems, while in high-voltage networks are also problems related to maintaining the power balance in the entire area and overloading lines and transformers. One of the ways to eliminate such threats may be to install energy magazines or electrolysers in optimally selected network nodes.

- Optimisation of the voltage quality indicator in the distribution network:

The random nature of generation in RESs connected to the medium- and low-voltage distribution grid affects the voltage values in individual nodes of the power grid. Using the possibilities of these sources as regards the consumption and generation of reactive power, as well as the range of changes in the transformer's tap changer, it is possible to optimally shape the voltage profiles in the network.

- Optimal redispatching of power with RES installations:

Problems with meeting the power balance as well as overloading of power system elements can be solved by the so-called redispatching, i.e., changing the distribution of power in the RES. The volume of power limitation should be as small as possible and the transmission capacity of the line should be used to the maximum extent, thus the way of implementing the limitation may be treated as an optimisation task.

- Cable pooling—optimal use of common network infrastructure by various types of renewable energy sources:

Power deriving from the RES is usually carried out by means of a power line dedicated to a given source. Often, however, the bandwidth of this link is not fully or optimally used. Therefore, it is possible to share a common grid infrastructure between different RESs, for example a wind and photovoltaic plant, in order to use it optimally.

The geographically close location of wind and photovoltaic power plants may also encourage investors to build a common grid infrastructure to transfer power from these sources. Taking advantage of the different specificity of generation in these power plants as well as different levels of generation at the same time, it is possible to optimally use the common network connecting these facilities with the power system.

- Optimal location of reactive power compensation devices:

The topic of the optimal location of devices for reactive power compensation affects the management of reactive power as well as the minimisation of power and energy losses in the power grid.

- Optimal selection of parameters of compensating device for a wind or photovoltaic farm connected to the power grid with a long cable line:

The issue of reactive power compensation in large wind and photovoltaic farms connected to the power grid by means of 110 kV cable lines with a length of several dozen kilometres is important from the point of view of meeting the requirements of the NC RfG regulation [109]. A wind or photovoltaic farm as an object connected to the power system, and in normal operating conditions supplies active power to the grid, while in terms of reactive power it can be its source or receiver. The regulatory effect of the farm is measured by the grid operator at its connection point. The NC RfG requirements relate to meeting the required power factor (and thus the $\text{tg}\varphi$ indicator) at the connection point, as well as the required voltage values. The purpose of the analyses is therefore the optimal selection of compensation devices for the farm, i.e., reactors or capacitor banks.

- Minimisation of the costs of balancing the demand for power:

The issues of optimising the costs of balancing the demanded power in the power system depend on many factors. The task of minimising the costs of balancing the power system should be classified as a nonlinear optimisation problem. The methods of determining them used so far are usually based on the linearisation of the power distribution problem. In practice, however, this approach may be too simplistic. Therefore, other, more accurate algorithms should be sought.

- Load forecasting:

Load forecasting is one of the main concerns of distribution system operators. In order to ensure the supply of electricity to consumers, it is therefore necessary to forecast future demand with high accuracy. This is possible thanks to advanced mathematical methods based on artificial intelligence.

- Generation forecasting in RESs:

Variable generation in RESs contributes to the fact that it is difficult to ensure the balance of power or the supply of electricity to consumers based on these sources. Optimal forecasting based on historical data and interfaces associated with the current weather forecast for the location of sources will allow the prediction of the operation of these sources with greater accuracy.

Most of the problems discussed above can be solved using optimisation algorithms, often single or multi-criteria optimisation with constraints. As constraints (in the power industry), the following are usually assumed:

- Equality constraints, e.g., balance equations that must be met for each grid node (power flowing into or generated in a node must be equal to the power flowing out).
- Inequality constraints, e.g., constraints on voltage values in grid nodes, constraints on active and reactive power sources and constraints resulting from transmission capacity of grid elements (lines and transformers).
- Limitations resulting from the need to ensure reliable operation of the power system, e.g., contingency analysis.
- Restrictions resulting from the specific requirements of network operators, e.g., the requirements of the NC RfG [109] or other network codes [110–114].

4. Optimisation and Forecasting Methods

Section 3 describes selected, contemporary problems encountered in the power industry. Therefore, the following question arises: how can they be solved? Optimisation, i.e., searching for the best solution from the point of view of the adopted criterion, seems to be an effective method. Optimisation is the activity of finding the point where the objective function reaches an optimum (minimum or maximum). This task is not easy, especially when there are numerous limitations. As mentioned earlier, the history of optimisation in the power industry dates back to problems related to solving the UC task. Solving the UC task was possible provided that the characteristics of the generation costs of individual sources were known. These characteristics are usually nonlinear. The task of minimising a nonlinear objective function with an equality constraint is solved by creating a Lagrangian function. The solution of the UC problem becomes much more complicated when taking into account constraints of the inequality type (technical minimums and maximum values of source power) and equality type (balancing equality constraints of power in the system, taking into account losses in the entire network). Contemporary, real problems in the field of power engineering are usually characterised by various types of constraints, both equality and inequality, and the requirements of network operators resulting from the specificity of the power system operation. The objective function can be linear or nonlinear. Often the form of the objective function is not explicit, and only its values are known. In connection with the above, various methods of solving optimisation problems are used, depending on the specificity and complexity of the considered problem. The above-mentioned issues include the previously mentioned OPF, SCOPF and SOPF tasks that require the use of advanced optimisation methods.

In general, the optimisation methods that can be used are presented below, according to the division taking into account their specificity. Figure 1 shows the main optimisation methods by type [115–119].

Table 1 shows the division of selected classical optimisation methods along with algorithms that can be used to solve problems used in power engineering.

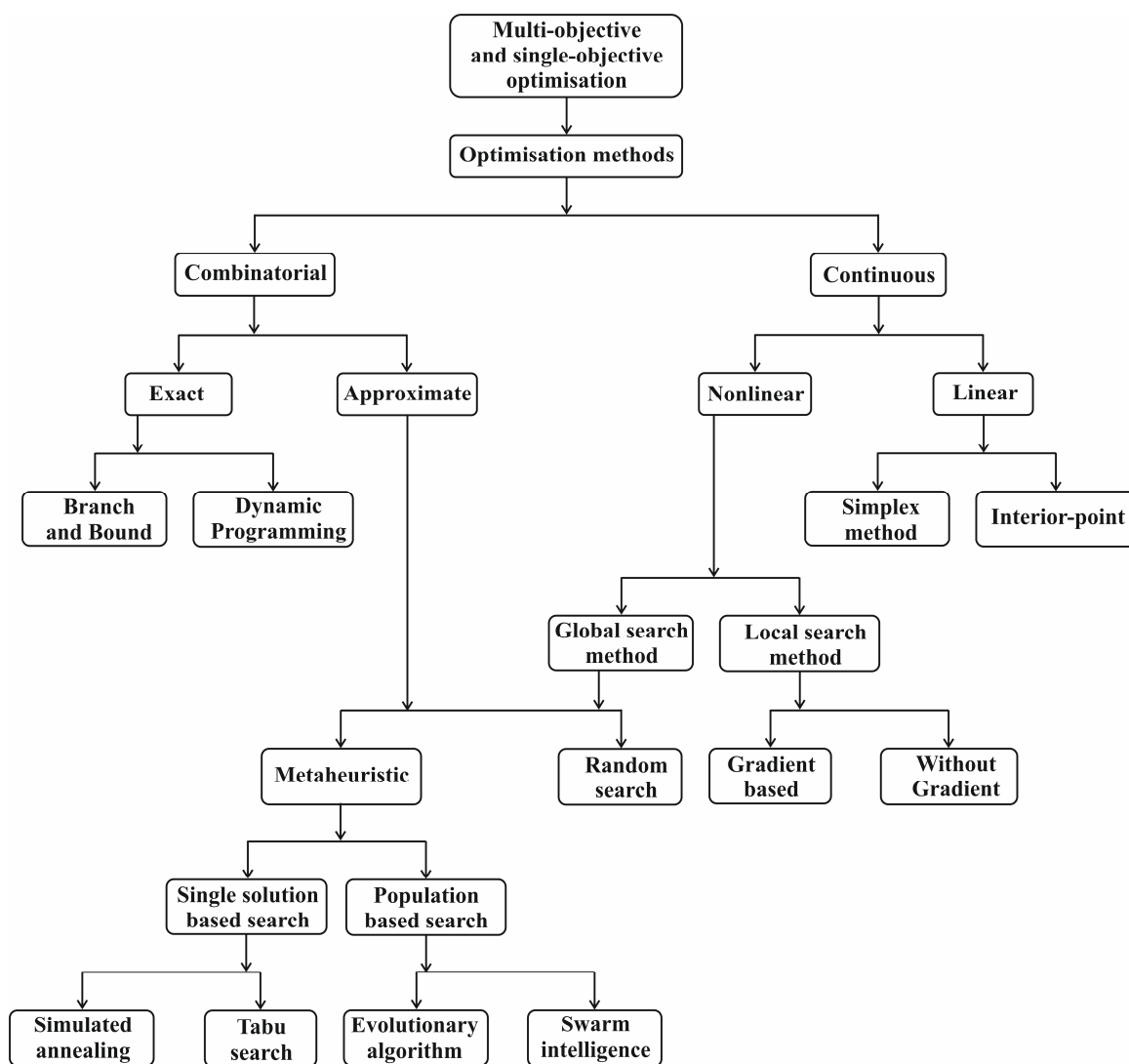


Figure 1. Division of optimisation methods that can be used to solve problems related to the power industry acc to [115–119].

Table 1. Selected classical optimisation methods with algorithms [116].

Optimisation Methods	Selected Algorithms
linear optimisation	simplex method, dual simplex method interior point method and
nonlinear optimisation	Newton_Raphson method unconstrained optimization methods, methods with a penalty function,
quadratic programming	trust region reflective algorithm and modified simplex method
mixed-integer programming	branch and bound method, cutting-plane method and Gomory’s mixed-integer programming

The advantage of classical optimisation methods is the high accuracy of calculations, short time to obtain a solution and a high probability of finding the optimal function. The disadvantage of classical optimisation methods [120–125] is that they can usually be

used when the form of the objective function is known and most often when there is only one optimum. However, the objective function is not always clearly defined. Moreover, sometimes the derivative of the objective function is not known, and furthermore, the objective function may be discontinuous at many points, that is, it is not differentiable. Some constraints may be implicit and, once incorporated into an objective function, it is impossible to predict what shape the resulting new function will take. Another obstacle to the use of classical methods is the occurrence of many optima, or the possibility of a divergent iterative process. Moreover, the problem may be the size of the task, in particular the multi-node power system, composed of a dozen or so to several tens of thousands of elements. Commercial programs containing optimisation options (e.g., DigSILENT PowerFactory [2] and PowerWorld Simulator [3]) have difficulty in obtaining a solution for such a large network. This is due to the fact that in normal states, for some reason some constraints are not met, and the program is not able to cope with it. If the above aspects are also accompanied by the need to meet “contingency analysis” or other specific conditions imposed by system operators, then the size and complexity of the problem increases, and it becomes so complicated that classical methods become less effective or even unsuitable for solving it. Taking into account the above-mentioned difficulties, it becomes reasonable to use metaheuristic methods [126–130]. Heuristic methods make it possible to solve various types of tasks that cannot be solved by classical methods, or the use of these methods is too time-consuming and laborious. Compared to classical methods, heuristic methods are characterised by the fact that they do not require knowledge of the form of the derivative of the objective function, and they are resistant to discontinuities of this function and the computational process is “stuck” in a local minimum. Heuristic methods can start from an unacceptable point (then a penalty for exceeding the constraints is added) to find themselves inside the domain of the function during calculations. These methods are used more and more often, not only in the power industry, because they are effective non-gradient methods for solving nonlinear optimisation problems with constraints, with a huge potential of possibilities. They are constantly developed, as evidenced by new publications presenting the advantages of new methods [126,129,131–133]. Table 2 presents the basic properties of heuristic methods.

Table 2. The most important properties of heuristic methods [116,134,135].

No.	Properties
1	Randomness that allows to search the entire solution space.
2	Applicable to problems of any dimension.
3	Applicability to “strongly nonlinearly dependent” problems.
4	Universality, which manifests itself in the fact that the algorithm is not related to the properties of a given problem.
5	Ability to remember the best solution found so far.
6	With some methods, it is possible to control the algorithm in a way that increases the probability of finding the global optimum.
7	With some methods (e.g., particle swarm), it is possible to use one set of parameters controlling the computational process to solve many problems.
8	With some methods (e.g., simulated annealing), it is possible to choose a worse solution during calculations, which increases the probability of finding a global solution.
9	Independence from the domain of the function—the algorithm can be used when the search space is discrete, continuous or when there are points of discontinuity of the function.
10	Applicable and adaptable to disordered and chaotic problems.

The disadvantage of heuristic methods is the relatively long time to obtain an acceptable solution and the fact that a global solution is always found with a certain probability, although there is evidence of global convergence of algorithms, e.g., simulated annealing.

Different methods can also be combined to increase the efficiency of the calculations. It is often the case that using one of the heuristic optimisation methods, we make a “rough” search of the solution space, while in the last phase of the algorithm, the classical method is used, which allows to accurately determine the solution. This procedure is appropriate, for example, when the objective function has many local optima, slightly different from each other. Then, the heuristic method ensures finding the area in which we can expect the global optimum, while the classical method allows to find it with high probability.

There are usually four main reasons why heuristics are becoming more and more common: simplicity, flexibility, freedom in creating new algorithms and avoidance of local optima. Sources of inspiration in the creation of new methods can be different. Solving optimisation tasks belonging to various fields of science does not require fundamental changes in algorithms. Virtually every objective function can be optimised without having to check its continuity or differentiability. Due to the random nature of heuristic methods, there is a high probability of finding a global optimum. The features presented above, and above all the advantages of heuristics, substantively justify its use in the power industry, as well as in any other field.

In recent years, the term metaheuristics (meta in Greek means “over”) has appeared in many studies. It can be said that metaheuristics are rules regarding the method of generating rules—the ones that can help the most in finding a good solution. Metaheuristics are therefore the framework and rules for generating rules for specific heuristic algorithms. Within one metaheuristic, it is always possible to propose at least several heuristic algorithms, which are variants of a certain general approach.

Table 3 presents a division into various, selected methods of meta-heuristic optimisation along with the algorithms used that can be used in the power industry.

Table 3. Selected methods of metaheuristic optimisation with algorithms [116,136–138].

Methods	Selected Algorithms
Single-based metaheuristic optimisation techniques	simulated algorithms, hill climbing, variable neighbourhood search and tabu search
Population-based metaheuristic optimisation techniques	evolutionary algorithm, particle swarm optimisation, cuckoo search, grey wolf optimiser, ant algorithms, bees’ algorithms, firefly algorithm, moth flame optimisation, mine blast algorithm, teaching–learning-based optimisation, gravitational search algorithm and efficient modified GWO with levy flight
Neural network	efficient hybrid GOA-MLP neural network, genetic algorithm–artificial neural network algorithm and genetic algorithm–adaptive neuro fuzzy interface system (GA-ANFIS)
Fuzzy systems	fuzzy adaptive partitioning algorithm, fuzzy memes in multimeme algorithms and fuzzy constructive heuristic algorithms

Each optimisation method has its advantages and disadvantages. Both classical and metaheuristic methods can be used to solve problems in the field of electrical power engineering. It should be noted here that some of them, being unusual, can be solved only with the use of metaheuristics due to the specificity of the problem. Of course, there is always the possibility of linearisation of the problem, but this usually leads to far-reaching simplifications, and even to obtaining erroneous results that are unacceptable in practice.

Another class of methods, also used to solve optimisation and forecasting problems [90,139–143], are methods based on artificial intelligence, e.g., artificial neural networks, fuzzy logic or selected machine learning methods [144–148].

Various forecasting methods are used, ranging from short-term, medium-term to long-term methods. There are also Holt–Winters methods [149,150], autoregressive integrated moving average, exponential smoothing, support vector regression, etc., as well as modern methods based on artificial intelligence. Artificial intelligence is a system based on the

concept of a machine that can influence real processes. It means the ability to solve real problems, the ability to adapt to changing conditions and the ability to make decisions. The term artificial intelligence itself refers to the intelligence of machines, systems, algorithms, programs and applications. It is one of the most important innovations in the energy sector and beyond. There are various techniques based on artificial intelligence that can be used in analyses in the field of power engineering. As mentioned earlier, these include the following methods and related helpful algorithms [151,152]:

- Machine learning:
 - a Deep learning;
 - b Reinforcement learning;
 - c Artificial neural networks.
- Fuzzy logic, which is used, among others, in the programming of artificial intelligence systems.
- Metaheuristic optimisation, which is used to solve artificial intelligence problems, such as constraint fulfilment.

Figure 2 shows the location of machine learning and deep learning in the field of artificial intelligence [153–155].

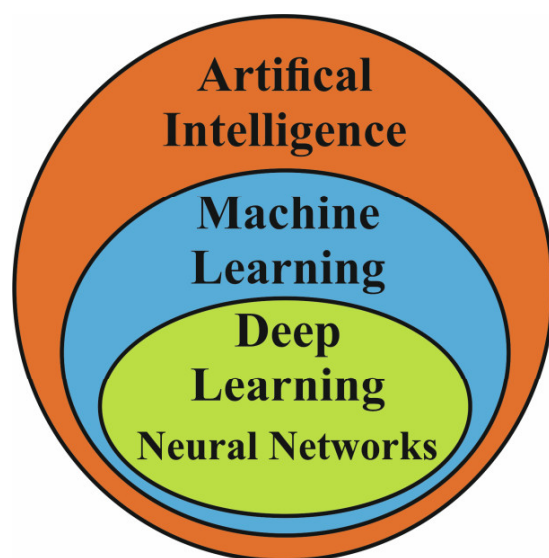


Figure 2. Relations between artificial intelligence and machine learning, deep learning and artificial neural networks [153–155].

Table 4 presents a division into various selected methods of artificial intelligence along with the algorithms used that can be used in the power engineering.

Table 4. Selected artificial intelligence methods with algorithms [154,156–158].

Artificial Methods	Selected Algorithms
Machine learning	supervised learning and unsupervised learning
Deep learning and neural network	deep networks for supervised or discriminative learning, deep networks for unsupervised or generative learning and deep networks for hybrid learning
Fuzz-logic-based approach	fuzzy logic systems and
Expert system	algorithms for modelling expert systems
Hybrid approach, searching and optimisation	hybrid algorithms combining different algorithms

The advantages of methods based on artificial intelligence include the following:

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

The disadvantages of methods based on artificial intelligence include the following:

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

Having large amounts of historical data on the operation of the analysed power grid, which enable tracking a very large number of its different states, it is possible to “teach the machine” (colloquial expression) so accurately that it is able to predict the behaviour of the network in various operating states and provide appropriate control in order to prevent emergencies or minimise the probability of their occurrence. These methods can be helpful in forecasting network operation and predicting emergency states. There are many works on this topic in the literature. Generally speaking, these methods can be used in areas such as modelling, predictive planning and process control.

The future application of methods based on optimisation and artificial intelligence in the power industry can be seen, among others, in the following:

- Forecasting the demand for electricity, both in the long term and short term, which is important for the production of energy and its sale in the future;
- Forecasting weather conditions such as wind speed and solar radiation intensity in order to predict generation in RESs;
- Reducing emissions of harmful compounds into the atmosphere by optimising the operation of coal-fired power plants;
- Creating virtual systems supporting the processes of accepting and registering notifications regarding power grid failures;
- Creating algorithms that enable fast processing of large amounts of data;
- Predicting and optimising electricity consumption in various facilities, private, industrial and public;
- Fighting the energy crisis;
- Improving and accelerating the energy transformation;
- Planning the development of the power system;
- Monitoring the operation of the power system;
- Minimising the probability of failure;
- Minimising the operating costs of the power system;
- Optimisation of the operation of the power grid;
- Increasing flexibility;
- Increasing energy efficiency;
- Increasing the security of the power system operation (avoiding digital threats, sabotage, cyberattacks, espionage and electricity theft);
- Improved assessment of underground, potential hydrocarbon deposits, appropriate design and management of microgrid operation

Forecasting can be helpful in making the best use of the power generated in power plants. The planning of future power plants can be closely related to the future expected power demand as well as weather conditions, as is the case with RESs. In addition, the development of power systems requires advanced methods of forecasting and optimisation in the era of increasingly complex and complex problems occurring in reality.

5. Conclusions

The research area under consideration in this Special Issue covers the problems currently encountered in analyses of the operation of power systems. Some of them can be eliminated based on experience and engineering logic (engineering reasoning). Some, however, require the use of advanced optimisation methods and algorithms based on artificial intelligence, due to the degree of complexity and dimension of the issue. It should also be emphasised that there has been huge progress in methods and programs for estimating the state of the system, which allow the use of on-line optimisation methods. Due to the constant changes taking place in the power system as well as the specific requirements of grid operators, new problems arise, such as unforeseen failures. Some of these problems result from the negative impact of new grid infrastructure elements. This entails the need to constantly search for and develop new advanced methods and algorithms to eliminate existing threats. This article addresses this topic. The authors presented the objectives of the research topic and drew attention to the growing need to deal with it in the era of energy transformation and dynamic changes taking place in the field of power engineering. The analysed field of research is extremely important due to the strategic role of the power system in the functioning of national and global economies as well as international cooperation and human security. Despite the wealth of literature devoted to this subject, there are still issues that require deeper research, a change of approach, resignation from simplification or extension and taking into account the new conditions of operation of power systems. Guest Editors therefore encourage potential Authors to take the trouble to prepare new articles on the indicated subject.

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References

1. Pruski, P.; Paszek, S. Location of generating units most affecting the angular stability of the power system based on the analysis of instantaneous power waveforms. *Arch. Control. Sci.* **2020**, *30 LXVI*, 273–293. [[CrossRef](#)]
2. DlgSILENT GmbH. *DIgSILENT, PowerFactory*; DlgSILENT GmbH: Gomaringen, Germany, 2023.
3. PowerWorld Corporation. *PowerWorld, Simulator 22*; PowerWorld Corporation: Champaign, IL, USA, 2023.
4. MATPOWER. *Free, Open-Source Tools for Electric Power System Simulation and Optimization*; Power Systems Engineering Research Center (PSerc), Cornell University: Ithaca, NY, USA, 2023.
5. MathWorks. *Matlab, Programming and Numeric Computing Platform*; MathWorks: Natick, MA, USA, 2022. Available online: <https://www.mathworks.com> (accessed on 1 March 2023).
6. Wolpert, D.H.; Macready, W.G. No free lunch theorems for optimization. *IEEE Trans. Evol. Computat.* **1997**, *1*, 67–82. [[CrossRef](#)]
7. Tamil Selvi, S.; Baskar, S.; Rajasekar, S. Application of Evolutionary Algorithm for Multiobjective Transformer Design Optimization. In *Classical and Recent Aspects of Power System Optimization*; Elsevier: Amsterdam, The Netherlands, 2018; pp. 463–504.
8. Stefenon, S.F.; Furtado Neto, C.S.; Coelho, T.S.; Nied, A.; Yamaguchi, C.K.; Yow, K.-C. Particle swarm optimization for design of insulators of distribution power system based on finite element method. *Arch. Elektrotechnik* **2022**, *104*, 615–622. [[CrossRef](#)]
9. Iderus, S.; Peter, G.; Praghsh, K.; Vadde, A.R. Optimization and Design of a Sustainable Industrial Grid System. *Math. Probl. Eng.* **2022**, *2022*, 4418329. [[CrossRef](#)]
10. Guerraiche, K.; Dekhici, L.; Chatelet, E.; Zebalah, A. Multi-Objective Electrical Power System Design Optimization Using a Modified Bat Algorithm. *Energies* **2021**, *14*, 3956. [[CrossRef](#)]
11. Abido, M.A. Optimal design of power-system stabilizers using particle swarm optimization. *IEEE Trans. Energy Convers.* **2002**, *17*, 406–413. [[CrossRef](#)]
12. Asaah, P.; Hao, L.; Ji, J. Optimal Placement of Wind Turbines in Wind Farm Layout Using Particle Swarm Optimization. *J. Mod. Power Syst. Clean Energy* **2021**, *9*, 367–375. [[CrossRef](#)]

13. Montusiewicz, J.; Gryniiewicz-Jaworska, M.; Pijarski, P. Looking for the Optimal Location for Wind Farms. *Adv. Sci. Technol. Res. J.* **2015**, *9*, 135–142. [[CrossRef](#)]
14. Pookpant, S.; Ongsakul, W. Optimal placement of wind turbines within wind farm using binary particle swarm optimization with time-varying acceleration coefficients. *Renew. Energy* **2013**, *55*, 266–276. [[CrossRef](#)]
15. Kakueinejad, M.H.; Heydari, A.; Askari, M.; Keynia, F. Optimal Planning for the Development of Power System in Respect to Distributed Generations Based on the Binary Dragonfly Algorithm. *Appl. Sci.* **2020**, *10*, 4795. [[CrossRef](#)]
16. Yang, Z.; Yang, F.; Min, H.; Tian, H.; Hu, W.; Liu, J. Review on optimal planning of new power systems with distributed generations and electric vehicles. *Energy Rep.* **2023**, *9*, 501–509. [[CrossRef](#)]
17. Chen, H.; Hu, Z.; Luo, H.; Qin, J.; Rajagopal, R.; Zhang, H. Design and Planning of a Multiple-Charger Multiple-Port Charging System for PEV Charging Station. *IEEE Trans. Smart Grid* **2019**, *10*, 173–183. [[CrossRef](#)]
18. Ding, Z.; Lu, Y.; Zhang, L.; Lee, W.-J.; Chen, D. A Stochastic Resource-Planning Scheme for PHEV Charging Station Considering Energy Portfolio Optimization and Price-Responsive Demand. *IEEE Trans. Ind. Appl.* **2018**, *54*, 5590–5598. [[CrossRef](#)]
19. Liu, Z.; Wen, F.; Ledwich, G. Optimal Planning of Electric-Vehicle Charging Stations in Distribution Systems. *IEEE Trans. Power Deliv.* **2013**, *28*, 102–110. [[CrossRef](#)]
20. Yao, W.; Zhao, J.; Wen, F.; Dong, Z.; Xue, Y.; Xu, Y.; Meng, K. A Multi-Objective Collaborative Planning Strategy for Integrated Power Distribution and Electric Vehicle Charging Systems. *IEEE Trans. Power Syst.* **2014**, *29*, 1811–1821. [[CrossRef](#)]
21. Mroczek, B.; Pijarski, P. DSO Strategies Proposal for the LV Grid of the Future. *Energies* **2021**, *14*, 6327. [[CrossRef](#)]
22. Abidin, A.F.; Zio, E. Optimal Planning of Electric Power Systems. In *Optimization in Large Scale Problems*; Fathi, M., Khakifirooz, M., Pardalos, P.M., Eds.; Springer International Publishing: Cham, Switzerland, 2019; pp. 53–65. ISBN 978-3-030-28564-7.
23. Silva, A.R.; Estanqueiro, A. Optimal Planning of Isolated Power Systems with near 100% of Renewable Energy. *IEEE Trans. Power Syst.* **2020**, *35*, 1274–1283. [[CrossRef](#)]
24. Jiang, M.; Wang, X.; Liu, Z.; Wang, J.; Li, G.; Zhou, M. Optimal Planning of Energy Storage in Power Systems with High Proportion of Renewable Energy. In Proceedings of the 2022 5th International Conference on Energy, Electrical and Power Engineering (CEEPE), Chongqing, China, 22–24 April 2022; pp. 1023–1028.
25. Mroczek, B.; Pijarski, P. Machine Learning in Operating of Low Voltage Future Grid. *Energies* **2022**, *15*, 5388. [[CrossRef](#)]
26. Valencia-Díaz, A.; Hincapié Isaza, R.A.; Gallego-Rendón, R.A. Optimal Planning of Secondary Power Distribution Systems Considering Renewable and Storage Sources: An Energy Management Approach. *Tecnológicas* **2022**, *25*, e2354. [[CrossRef](#)]
27. Huang, L.; Chen, Z.; Cui, Q.; Zhang, J.; Wang, H.; Shu, J. Optimal planning of renewable energy source and energy storage in a medium- and low-voltage distributed AC/DC system in China. *J. Eng.* **2019**, *2019*, 2354–2361. [[CrossRef](#)]
28. Saboori, H.; Hemmati, R. Optimal management and planning of storage systems based on particle swarm optimization technique. *J. Renew. Sustain. Energy* **2016**, *8*, 24105. [[CrossRef](#)]
29. Lezhniuk, P.D.; Pijarski, P.; Buslavets, O.A. Smart grid technologies in local electric grids. In *Photonics Applications in Astronomy, Communications, Industry, and High Energy Physics Experiments 2017*; Romaniuk, R.S., Linczuk, M., Eds.; SPIE: Warsaw, Poland, 2017; p. 1044566.
30. Dib, M.; Ramzi, M.; Nejmi, A. Voltage regulation in the medium voltage distribution grid in the presence of renewable energy sources. *Mater. Today Proc.* **2019**, *13*, 739–745. [[CrossRef](#)]
31. Kacejko, P.; Pijarski, P. Optimal Voltage Control in MV Network with Distributed Generation. *Energies* **2021**, *14*, 469. [[CrossRef](#)]
32. Małkowski, R.; Izdebski, M.; Miller, P. Adaptive Algorithm of a Tap-Changer Controller of the Power Transformer Supplying the Radial Network Reducing the Risk of Voltage Collapse. *Energies* **2020**, *13*, 5403. [[CrossRef](#)]
33. Ouali, S.; Cherkaoui, A. Elimination of the Impact Produced by DG Units on the Voltage Profile of Distribution Networks. *J. Appl. Math.* **2020**, *2020*, 1395943. [[CrossRef](#)]
34. Pijarski, P.; Kacejko, P.; Wancerz, M. Voltage Control in MV Network with Distributed Generation—Possibilities of Real Quality Enhancement. *Energies* **2022**, *15*, 2081. [[CrossRef](#)]
35. Zhang, D.; Li, J.; Hui, D. Coordinated control for voltage regulation of distribution network voltage regulation by distributed energy storage systems. *Prot. Control Mod. Power Syst.* **2018**, *3*, 3. [[CrossRef](#)]
36. Berkel, F.; Bleich, J.; Bell, M.; Liu, S. A Distributed Voltage Controller for Medium Voltage Grids with Storage-Containing Loads. In Proceedings of the IECON 2018-44th Annual Conference of the IEEE Industrial Electronics Society, Washington, DC, USA, 21–23 October 2018; pp. 3523–3528.
37. El-Taweel, N.A.; Khani, H.; Farag, H.E.Z. Voltage regulation in active power distribution systems integrated with natural gas grids using distributed electric and gas energy resources. *Int. J. Electr. Power Energy Syst.* **2019**, *106*, 561–571. [[CrossRef](#)]
38. Guo, Y.; Wu, Q.; Gao, H.; Chen, X.; Ostergaard, J.; Xin, H. MPC-Based Coordinated Voltage Regulation for Distribution Networks With Distributed Generation and Energy Storage System. *IEEE Trans. Sustain. Energy* **2019**, *10*, 1731–1739. [[CrossRef](#)]
39. Kryonidis, G.C.; Demoulias, C.S.; Papagiannis, G.K. A new voltage control scheme for active medium-voltage (MV) networks. *Electr. Power Syst. Res.* **2019**, *169*, 53–64. [[CrossRef](#)]
40. Li, Q.; Zhou, F.; Guo, F.; Fan, F.; Huang, Z. Optimized Energy Storage System Configuration for Voltage Regulation of Distribution Network with PV Access. *Front. Energy Res.* **2021**, *9*, 641518. [[CrossRef](#)]
41. Mazza, A.; Salomone, F.; Arrigo, F.; Bensaid, S.; Bompard, E.; Chicco, G. Impact of Power-to-Gas on distribution systems with large renewable energy penetration. *Energy Convers. Manag. X* **2020**, *7*, 100053. [[CrossRef](#)]

42. Pijarski, P.; Kacejko, P. Voltage Optimization in MV Network with Distributed Generation Using Power Consumption Control in Electrolysis Installations. *Energies* **2021**, *14*, 993. [[CrossRef](#)]
43. Robinius, M.; Raje, T.; Nykamp, S.; Rott, T.; Müller, M.; Grube, T.; Katzenbach, B.; Küppers, S.; Stolten, D. Power-to-Gas: Electrolyzers as an alternative to network expansion – An example from a distribution system operator. *Appl. Energy* **2018**, *210*, 182–197. [[CrossRef](#)]
44. Hazarika, D.; Sinha, A.K. An algorithm for standing phase angle reduction for power system restoration. *IEEE Trans. Power Syst.* **1999**, *14*, 1213–1218. [[CrossRef](#)]
45. Hazarika, D.; Sinha, A.K. Standing phase-angle reduction for power system restoration. *IEE Proc. Gener. Transm. Distr.* **1998**, *145*, 82–88. [[CrossRef](#)]
46. Kacejko, P.; Miller, P.; Pijarski, P. Determination of Maximum Acceptable Standing Phase Angle across Open Circuit Breaker as an Optimisation Task. *Energies* **2021**, *14*, 8105. [[CrossRef](#)]
47. Ketabi, K.; Ranjbar, A.M. New approach to standing phase angle reduction for power system restoration. In Proceedings of the 1999 PowerTech Conference, Budapest, Hungary, 29 August–2 September 1999; p. 78.
48. Shahidehpour, S.M.; YAMIN, H.Y. A Technique for the Standing Phase-Angle Reduction in Power System Restoration. *Electr. Power Compon. Syst.* **2004**, *33*, 277–286. [[CrossRef](#)]
49. Wunderlich, S.; Adibi, M.M.; Fischl, R.; Nwankpa, C.O.D. An approach to standing phase angle reduction. *IEEE Trans. Power Syst.* **1994**, *9*, 470–478. [[CrossRef](#)]
50. Ye, H.; Liu, Y. A new method for standing phase angle reduction in system restoration by incorporating load pickup as a control means. *Int. J. Electr. Power Energy Syst.* **2013**, *53*, 664–674. [[CrossRef](#)]
51. Izdebski, M.; Małkowski, R.; Miller, P. New Performance Indices for Power System Stabilizers. *Energies* **2022**, *15*, 9582. [[CrossRef](#)]
52. Lee, H.J.; Park, Y.M.; Kwon, T.W. Optimal Selection of the Parameters of Power System Stabilizer. *IFAC Proc. Vol.* **1989**, *22*, 307–312. [[CrossRef](#)]
53. Nocoń, A.; Paszek, S. Analysis of power system stabilizer Pareto optimisation when taking into account the uncertainty of power system mathematical model parameters. *Arch. Electr. Eng.* **2011**, *60*, 385–398. [[CrossRef](#)]
54. Peng, S.; Wang, Q. Power System Stabilizer Parameters Optimization Using Immune Genetic Algorithm. *IOP Conf. Ser. Mater. Sci. Eng.* **2018**, *394*, 42091. [[CrossRef](#)]
55. Paszek, S.; Nocoń, A. *Optimisation and Polyoptimisation of Power System Stabilizer Parameters*; 1. Aufl.; LAP LAMBERT Academic Publishing: Saarbrücken, Germany, 2014.
56. Paszek, S.; Nocoń, A. Parameter polyoptimization of PSS2A power system stabilizers operating in a multi-machine power system including the uncertainty of model parameters. *Appl. Math. Comput.* **2015**, *267*, 750–757. [[CrossRef](#)]
57. Nocoń, A.; Paszek, S.; Pruski, P. Multi-criteria optimization of the parameters of PSS3B system stabilizers operating Multi-criteria optimization of the parameters of PSS3B system stabilizers operating in an extended power system with the use of a genetic algorithm. *Arch. Control. Sci.* **2022**, *32 LXVIII*, 233–255. [[CrossRef](#)]
58. Paszek, S.; Boboń, A.; Berhausen, S.; Majka, Ł.; Nocoń, A.; Pruski, P. *Synchronous Generators and Excitation Systems Operating in a Power System: Measurement Methods and Modeling*, 1st ed.; Springer International Publishing: Cham, Switzerland, 2020.
59. Jia, J.; Yang, G.; Nielsen, A.H.; Muljadi, E.; Weinreich-Jensen, P.; Gevorgian, V. Synchronous Condenser Allocation for Improving System Short Circuit Ratio. In Proceedings of the 2018 5th International Conference on Electric Power and Energy Conversion Systems (EPECS), Kitakyushu, Japan, 23–25 April 2018; pp. 1–5.
60. Marrazi, E.; Yang, G.; Weinreich-Jensen, P. Allocation of synchronous condensers for restoration of system short-circuit power. *J. Mod. Power Syst. Clean Energy* **2018**, *6*, 17–26. [[CrossRef](#)]
61. Masood, N.-A.; Mahmud, S.U.; Ansary, M.N.; Deeba, S.R. Improvement of system strength under high wind penetration: A techno-economic assessment using synchronous condenser and SVC. *Energy* **2022**, *246*, 123426. [[CrossRef](#)]
62. Richard, L.; Nahid-Al-Masood; Saha, T.K.; Tushar, W.; Gu, H. Optimal Allocation of Synchronous Condensers in Wind Dominated Power Grids. *IEEE Access* **2020**, *8*, 45400–45410. [[CrossRef](#)]
63. Bhargavi, R.N.; Bhargavi, R.A. Optimal Location and Sizing of Reactive Power Compensation Devices for Voltage Stability Improvement of Radial Power Systems. *ECS Trans.* **2022**, *107*, 367–375. [[CrossRef](#)]
64. Ghasemi Marzbali, A.; Gheydi, M.; Samadyar, H.; Fashami, R.H.; Eslami, M.; Golkar, M.J. Optimal Reactive Power Control to Improve Stability of Voltage in Power Systems. In *Reactive Power Control in AC Power Systems*; Mahdavi Tabatabaei, N., Jafari Aghbolaghi, A., Bizon, N., Blaabjerg, F., Eds.; Springer International Publishing: Cham, Switzerland, 2017; pp. 251–273.
65. Sagara, M.; Sediqi, M.M.; Senjyu, T.; Danish, M.S.S.; Funabashi, T. Voltage stability improvement by optimal active power and reactive power output control of storage battery system. In Proceedings of the TENCON 2016–2016 IEEE Region 10 Conference, Singapore, 22–25 November 2016; pp. 2671–2674.
66. Machowski, J.; Kacejko, P.; Robak, S.; Miller, P.; Wancerz, M. Simplified angle and voltage stability criteria for power system planning based on the short-circuit power. *Int. Trans. Electr. Energ. Syst.* **2015**, *25*, 3096–3108. [[CrossRef](#)]
67. Alghamdi, H. Optimum Placement of Distribution Generation Units in Power System with Fault Current Limiters Using Improved Coyote Optimization Algorithm. *Entropy* **2021**, *23*, 655. [[CrossRef](#)] [[PubMed](#)]
68. Liu, C.; Cai, X.; Li, R.; Yang, R. Optimal short-circuit current control of the grid-forming converter during grid fault condition. *IET Renew. Power Gen* **2021**, *15*, 2185–2194. [[CrossRef](#)]

69. Khaleghi, M.; Farsangi, M.M.; Nezamabadi-pour, H.; Lee, K.Y. Pareto-Optimal Design of Damping Controllers Using Modified Artificial Immune Algorithm. *IEEE Trans. Syst. Man Cybern. C* **2011**, *41*, 240–250. [[CrossRef](#)]
70. Khanh, D.V.K.; Vasant, P.; Elamvazuthi, I.; Dieu, V.N. Optimization of Thermo-Electric Coolers Using Hybrid Genetic Algorithm And Simulated Annealing. *Arch. Control. Sci.* **2014**, *24*, 155–176. [[CrossRef](#)]
71. Orosz, T.; Rassólkin, A.; Kallaste, A.; Arsénio, P.; Pánek, D.; Kaska, J.; Karban, P. Robust Design Optimization and Emerging Technologies for Electrical Machines: Challenges and Open Problems. *Appl. Sci.* **2020**, *10*, 6653. [[CrossRef](#)]
72. Xie, J.; Alvarez-Fernandez, I.; Sun, W. A Review of Machine Learning Applications in Power System Resilience. In Proceedings of the 2020 IEEE Power & Energy Society General Meeting (PESGM), Montreal, QC, Canada, 2–6 August 2020; pp. 1–5.
73. Kumbhar, A.; Dhawale, P.G.; Kumbhar, S.; Patil, U.; Magdum, P. A comprehensive review: Machine learning and its application in integrated power system. *Energy Rep.* **2021**, *7*, 5467–5474. [[CrossRef](#)]
74. Ozcanli, A.K.; Yaprakdal, F.; Baysal, M. Deep learning methods and applications for electrical power systems: A comprehensive review. *Int. J. Energy Res.* **2020**, *44*, 7136–7157. [[CrossRef](#)]
75. Borges Hink, R.C.; Beaver, J.M.; Buckner, M.A.; Morris, T.; Adhikari, U.; Pan, S. Machine learning for power system disturbance and cyber-attack discrimination. In Proceedings of the 2014 7th International Symposium on Resilient Control Systems (ISRCs), Denver, CO, USA, 19–21 August 2014; pp. 1–8.
76. Bicer, Y.; Dincer, I.; Aydin, M. Maximizing performance of fuel cell using artificial neural network approach for smart grid applications. *Energy* **2016**, *116*, 1205–1217. [[CrossRef](#)]
77. Evangelopoulos, V.A.; Georgilakis, P.S.; Hatziargyriou, N.D. Optimal operation of smart distribution networks: A review of models, methods and future research. *Electr. Power Syst. Res.* **2016**, *140*, 95–106. [[CrossRef](#)]
78. Raza, M.Q.; Khosravi, A. A review on artificial intelligence based load demand forecasting techniques for smart grid and buildings. *Renew. Sustain. Energy Rev.* **2015**, *50*, 1352–1372. [[CrossRef](#)]
79. Abdul Majid, A. Forecasting Monthly Wind Energy Using an Alternative Machine Training Method with Curve Fitting and Temporal Error Extraction Algorithm. *Energies* **2022**, *15*, 8596. [[CrossRef](#)]
80. Al-qaness, M.A.A.; Ewees, A.A.; Abd Elaziz, M.A.; Samak, A.H. Wind Power Forecasting Using Optimized Dendritic Neural Model Based on Seagull Optimization Algorithm and Aquila Optimizer. *Energies* **2022**, *15*, 9261. [[CrossRef](#)]
81. Mukherjee, D.; Chakraborty, S.; Ghosh, S. Power system state forecasting using machine learning techniques. *Arch. Elektrotechnik* **2022**, *104*, 283–305. [[CrossRef](#)]
82. Niccolai, A.; Ogliari, E.; Nespoli, A.; Zich, R.; Vanetti, V. Very Short-Term Forecast: Different Classification Methods of the Whole Sky Camera Images for Sudden PV Power Variations Detection. *Energies* **2022**, *15*, 9433. [[CrossRef](#)]
83. Prusty, B.R.; Bingi, K.; Arunkumar, G.; Dhanamjayulu, C.; Gupta, N.; Tomar, A.; Sehgal, R. Machine learning application to power system forecasting. In *Smart Electrical and Mechanical Systems*; Elsevier: Amsterdam, The Netherlands, 2022; pp. 225–236.
84. Cavallo, A.; Canciello, G.; Guida, B. Energy Storage System Control for Energy Management in Advanced Aeronautic Applications. *Math. Probl. Eng.* **2017**, *2017*, 4083132. [[CrossRef](#)]
85. Cavallo, A.; Canciello, G.; Guida, B.; Kulsangcharoen, P.; Yeoh, S.; Rashed, M.; Bozhko, S. Multi-Objective Supervisory Control for DC/DC Converters in Advanced Aeronautic Applications. *Energies* **2018**, *11*, 3216. [[CrossRef](#)]
86. Sumsurooah, S.; He, Y.; Torchio, M.; Kouramas, K.; Guida, B.; Cuomo, F.; Atkin, J.; Bozhko, S.; Renzetti, A.; Russo, A.; et al. ENIGMA—A Centralised Supervisory Controller for Enhanced Onboard Electrical Energy Management with Model in the Loop Demonstration. *Energies* **2021**, *14*, 5518. [[CrossRef](#)]
87. Tostado-Véliz, M.; Kamel, S.; Aymen, F.; Rezaee Jordehi, A.; Jurado, F. A Stochastic-IGDT model for energy management in isolated microgrids considering failures and demand response. *Appl. Energy* **2022**, *317*, 119162. [[CrossRef](#)]
88. Abomazid, A.M.; El-Taweel, N.A.; Farag, H.E.Z. Optimal Energy Management of Hydrogen Energy Facility Using Integrated Battery Energy Storage and Solar Photovoltaic Systems. *IEEE Trans. Sustain. Energy* **2022**, *13*, 1457–1468. [[CrossRef](#)]
89. Voyant, C.; Lauret, P.; Notton, G.; Duchaud, J.-L.; Garcia-Gutierrez, L.; Faggianelli, G.A. Complex-valued time series based solar irradiance forecast. *J. Renew. Sustain. Energy* **2022**, *14*, 66502. [[CrossRef](#)]
90. Ahmad, N.; Ghadi, Y.; Adnan, M.; Ali, M. Load Forecasting Techniques for Power System: Research Challenges and Survey. *IEEE Access* **2022**, *10*, 71054–71090. [[CrossRef](#)]
91. Jiang, P.; Ma, X. A hybrid forecasting approach applied in the electrical power system based on data preprocessing, optimization and artificial intelligence algorithms. *Appl. Math. Model.* **2016**, *40*, 10631–10649. [[CrossRef](#)]
92. Shukur, O.B.; Lee, M.H. Daily wind speed forecasting through hybrid KF-ANN model based on ARIMA. *Renew. Energy* **2015**, *76*, 637–647. [[CrossRef](#)]
93. Hu, J.; Wang, J.; Zeng, G. A hybrid forecasting approach applied to wind speed time series. *Renew. Energy* **2013**, *60*, 185–194. [[CrossRef](#)]
94. Pijarski, P.; Kacejko, P. Methods of Simulated Annealing and Particle Swarm Applied to the Optimization of Reactive Power Flow in Electric Power Systems. *AECE Adv. Electr. Comput. Eng.* **2018**, *18*, 43–48. [[CrossRef](#)]
95. Abul’Wafa, A.R. A new heuristic approach for optimal reconfiguration in distribution systems. *Electr. Power Syst. Res.* **2011**, *81*, 282–289. [[CrossRef](#)]

96. Hasanpour, R.; Kalesar, B.M.; Noshahr, J.B.; Farhadi, P. Reconfiguration of smart distribution network considering variation of load and local renewable generation. In Proceedings of the 2017 IEEE International Conference on Environment and Electrical Engineering and 2017 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe), Milan, Italy, 6–9 June 2017; pp. 1–5.
97. Liu, L.; Yu, H.; Li, L. Distribution network reconfiguration based on harmony search/genetic hybrid algorithm. In Proceedings of the 2012 China International Conference on Electricity Distribution (CICED), Shanghai, China, 10–14 September 2012; pp. 1–4.
98. Naveen, S.; Sathish Kumar, K.; Rajalakshmi, K. Distribution system reconfiguration for loss minimization using modified bacterial foraging optimization algorithm. *Int. J. Electr. Power Energy Syst.* **2015**, *69*, 90–97. [[CrossRef](#)]
99. Nematshahi, S.; Mashhadi, H.R. Distribution network reconfiguration with the application of DLMP using genetic algorithm. In Proceedings of the 2017 IEEE Electrical Power and Energy Conference (EPEC), Saskatoon, SK, Canada, 22–25 October 2017; pp. 1–5.
100. Storti, G.L.; Possemato, F.; Paschero, M.; Rizzi, A.; Mascioli, F.M.F. Optimal distribution feeders configuration for active power losses minimization by genetic algorithms. In Proceedings of the 2013 Joint IFSA World Congress and NAFIPS Annual Meeting (IFSA/NAFIPS), Edmonton, AB, Canada, 24–28 June 2013; pp. 407–412.
101. Zhu, J.Z. Optimal reconfiguration of electrical distribution network using the refined genetic algorithm. *Electr. Power Syst. Res.* **2002**, *62*, 37–42. [[CrossRef](#)]
102. Pijarski, P.; Miller, P.; Sidor, K. Optimization of the selection of partition points in the MV network. In Proceedings of the Photonics Applications in Astronomy, Communications, Industry, and High-Energy Physics Experiments 2018, Wilga, Poland, 26 May–4 June 2018; p. 3.
103. Daniel, L.C.; Khan, I.H.; Ravichandran, S. Distribution Network Reconfiguration for Loss Reduction Using Ant Colony System Algorithm. In Proceedings of the 2005 Annual IEEE India Conference-Indicon, Chennai, India, 11–13 December 2005; pp. 619–622.
104. Raut, U.; Mishra, S. A Fast Heuristic Network Reconfiguration Algorithm to Minimize Loss and Improve Voltage Profile for a Smart Power Distribution System. In Proceedings of the 2017 8th International Conference on Information Technology (ICIT), Bhubaneswar, 21–23 December 2017; pp. 85–90.
105. European Standards. Requirements for Micro-Generating Plants to be Connected in Parallel with Public Low-Voltage Distribution Networks (EN 50438). Available online: <https://standards.iteh.ai/catalog/standards/clc/ec27ccfe-33fa-4434-bc21-72a2182fcbf3/en-50438-2013> (accessed on 25 January 2023).
106. European Standards. Requirements for Generating Plants to be Connected in Parallel with Distribution Networks-Part 1: Connection to a LV Distribution Network-Generating Plants Up to and Including Type B, 2019 (CSN EN 50549-1). Available online: <https://www.en-standard.eu/csn-en-50549-1-requirements-for-generating-plants-to-be-connected-in-parallel-with-distribution-networks-part-1-connection-to-a-lv-distribution-network-generating-plants-up-to-and-including-type-b/> (accessed on 25 January 2023).
107. Australian/New Zealand Standard. Grid Connection of Energy Systems via Inverters, Part 2–Inverter Requirements, 2015 (AS/NZS 4777.2:2015). Available online: <https://www.standards.govt.nz/shop/asnzs-4777-22015/> (accessed on 25 January 2023).
108. Australian/New Zealand Standard. Grid Connection of Energy Systems via Inverters, Part 2: Inverter Requirements, 2020 (AS/NZS 4777.2:2020). Available online: <https://www.standards.govt.nz/shop/asnzs-4777-22020/> (accessed on 25 January 2023).
109. European Commission. *Commission Regulation (EU) 2016/631 of 14 April 2016 Establishing a Network Code on Requirements for Grid Connection of generators: (EU) 2016/631*; European Commission: Brussels, Belgium, 2016.
110. European Commission. *Regulation (EU) 2019/943 of the European Parliament and of the Council of 5 June 2019 on the Internal Market for Electricity: Regulation (EU) 2019/943*; European Commission: Brussels, Belgium, 2019.
111. European Commission. *Commission Regulation (EU) 2015/1222 of 24 July 2015 Establishing a Guideline on Capacity Allocation and Congestion Management: (EU) 2015/1222*; European Commission: Brussels, Belgium, 2021.
112. European Commission. *Commission Regulation (EU) 2017/1485 of 2 August 2017 Establishing a Guideline on Electricity Transmission System Operation: (EU) 2017/1485*; European Commission: Brussels, Belgium, 2017.
113. European Commission. *Commission Regulation (EU) 2017/2195 of 23 November 2017 Establishing a Guideline on Electricity Balancing: (EU) 2017/2195*; European Commission: Brussels, Belgium, 2017.
114. European Commission. *Commission Regulation (EU) 2017/2196 of 24 November 2017 Establishing a Network Code on Electricity Emergency and Restoration: (EU) 2017/2196*; European Commission: Brussels, Belgium, 2017.
115. Zgurovsky, M.; Sineglazov, V.; Chumachenko, E. Classification and Analysis of Multicriteria Optimization Methods. In *Artificial Intelligence Systems Based on Hybrid Neural Networks*; Zgurovsky, M., Sineglazov, V., Chumachenko, E., Eds.; Springer International Publishing: Cham, Switzerland, 2021; pp. 59–174.
116. Pijarski, P.D. *Heuristic Optimization in the Assessment of Operating Conditions and Development Planning of the Power System*; Lublin University of Technology Publishers: Lublin, Poland, 2019.
117. Janga Reddy, M.; Nagesh Kumar, D. Evolutionary algorithms, swarm intelligence methods, and their applications in water resources engineering: A state-of-the-art review. *H2Open J.* **2020**, *3*, 135–188. [[CrossRef](#)]
118. Alonso, G.; Del Valle, E.; Ramirez, J.R. Optimization methods. In *Desalination in Nuclear Power Plants*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 67–76.
119. Martins, J.R.R.A.; Ning, A. *Engineering Design Optimization*; Cambridge University Press: Cambridge, UK, 2022.

120. Bairagi, D. Proximal Support Vector Machine Classifier based on LMS Algorithm. In Proceedings of the 2019 International Conference on Innovative Trends and Advances in Engineering and Technology (ICITAET), Shegoan, India, 27–28 December 2019; ISBN 978-1-7281-1901-4.
121. Vasuki, A. *Nature-Inspired Optimization Algorithms*; Chapman and Hall: London, UK; CRC: Boca Raton, FL, USA, 2020.
122. Jin, Y.; Wang, H.; Sun, C. (Eds.) *Data-Driven Evolutionary Optimization*; Springer International Publishing: Cham, Switzerland, 2021.
123. Rao, S.S. (Ed.) *Engineering Optimization Theory and Practice*; Wiley: Hoboken, NJ, USA, 2019.
124. Silveira, C.L.B.; Tabares, A.; Faria, L.T.; Franco, J.F. Mathematical optimization versus Metaheuristic techniques: A performance comparison for reconfiguration of distribution systems. *Electr. Power Syst. Res.* **2021**, *196*, 107272. [[CrossRef](#)]
125. Keller, A.A. *Multi-Objective Optimization in Theory and Practice I: Classical Methods*; Bentham Science Publishers: Sharjah, United Arab Emirates, 2017.
126. Radosavljević, J. *Metaheuristic Optimization in Power Engineering*; The Institution of Engineering and Technology: London, UK, 2018.
127. Zhu, J. (Ed.) *Optimization of Power System Operation*; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2015; ISBN 9781118887004.
128. Kothari, D.P. Power system optimization. In Proceedings of the 2012 2nd National Conference on Computational Intelligence and Signal Processing (CISP), Guwahati, India, 2–3 March 2012; pp. 18–21.
129. Zobaa, A.F.; Aleem, S.H.E.A.; Abdelaziz, A.J. *Classical and Recent Aspects of Power System Optimization*; Elsevier: Amsterdam, The Netherlands, 2018.
130. Bansal, R.C. Optimization Methods for Electric Power Systems: An Overview. *Int. J. Emerg. Electr. Power Syst.* **2005**, *2*, 1021. [[CrossRef](#)]
131. Montoya, F.G.; Baños, R.; Alcayde, A.; Manzano-Agugliaro, F. Optimization Methods Applied to Power Systems. *Energies* **2019**, *12*, 2302. [[CrossRef](#)]
132. Hajiabbas, M.P.; Mohammadi-Ivatloo, B. *Optimization of Power System Problems: Methods, Algorithms and MATLAB Codes*; Springer Nature: Cham, Switzerland, 2020.
133. Mirsaedi, S.; Devkota, S.; Wang, X.; Tzelepis, D.; Abbas, G.; Alshahir, A.; He, J. A Review on Optimization Objectives for Power System Operation Improvement Using FACTS Devices. *Energies* **2023**, *16*, 161. [[CrossRef](#)]
134. Yang, X.-S. *Nature-Inspired Metaheuristic Algorithms*, 2nd ed.; Luniver: Frome, UK, 2010.
135. Michalewicz, Z.; Schoenauer, M. Evolutionary Algorithms for Constrained Parameter Optimization Problems. *Evol. Comput.* **1996**, *4*, 1–32. [[CrossRef](#)]
136. Mohamed, A.W.; Hadi, A.A.; Mohamed, A.K. Gaining-sharing knowledge based algorithm for solving optimization problems: A novel nature-inspired algorithm. *Int. J. Mach. Learn. Cyber.* **2020**, *11*, 1501–1529. [[CrossRef](#)]
137. Kareem, S.W.; Hama Ali, K.W.; Askar, S.; Xoshaba, F.S.; Hawezi, R. Metaheuristic algorithms in optimization and its application: A review. *JAREE J. Adv. Res. Electr. Eng.* **2022**, *6*. [[CrossRef](#)]
138. Pijarski, P.; Kacejko, P. A new metaheuristic optimization method: The algorithm of the innovative gunner (AIG). *Eng. Optim.* **2019**, *51*, 2049–2068. [[CrossRef](#)]
139. Fuller, J.; Obiomon, P.; Abood, S.I. *Power System Operation, Utilization, and Control*; CRC Press: Boca Raton, FL, USA, 2022; ISBN 9781003293965.
140. Catalão, J.P.S. *Electric Power Systems*, 1st ed.; CRC Press: Boca Raton, FL, USA, 2016; ISBN 978-1439893944.
141. Hammad, M.A.; Jereb, B.; Rosi, B.; Dragan, D. Methods and Models for Electric Load Forecasting: A Comprehensive Review. *Logist. Sustain. Transp.* **2020**, *11*, 51–76. [[CrossRef](#)]
142. Jahan, I.S.; Snaes, V.; Misak, S. Intelligent Systems for Power Load Forecasting: A Study Review. *Energies* **2020**, *13*, 6105. [[CrossRef](#)]
143. Catalão, J.P.S. (Ed.) *Electric Power Systems: Advanced Forecasting Techniques and Optimal Generation Scheduling*; CRC Press: Boca Raton, FL, USA, 2017; ISBN 9781138073982.
144. Khodayar, M.; Liu, G.; Wang, J.; Khodayar, M.E. Deep learning in power systems research: A review. *CSEE J. Power Energy Syst.* **2021**, *7*. [[CrossRef](#)]
145. Chatzivasileiadis, S.; Venzke, A.; Stiasny, J.; Misyris, G. Machine Learning in Power Systems: Is It Time to Trust It? *IEEE Power Energy Mag.* **2022**, *20*, 32–41. [[CrossRef](#)]
146. Donnot, B.; Guyon, I.; Schoenauer, M.; Panciatici, P.; Marot, A. Introducing machine learning for power system operation support. *arXiv* **2017**, arXiv:1709.09527.
147. Nazari-Heris, M.; Asadi, S.; Mohammadi-Ivatloo, B.; Abdar, M.; Jebelli, H.; Sadat-Mohammadi, M. (Eds.) *Application of Machine Learning and Deep Learning Methods to Power System Problems*. Springer International Publishing: Cham, Switzerland, 2021; ISBN 978-3-030-77695-4.
148. Chen, Y. *Bridging Machine Learning to Power System Operation and Control*; University of Washington: Seattle, WA, USA, 2020.
149. Rossi, M.; Brunelli, D. Forecasting data centers power consumption with the Holt-Winters method. In Proceedings of the 2015 IEEE Workshop on Environmental, Energy and Structural Monitoring Systems (EESMS), Trento, Italy, 9–10 July 2015; pp. 210–214, ISBN 978-1-4799-8215-8.
150. Tulang, A.; Bello, A. Forecasting Power Load Demand Using Holt-Winters Model. *Int. J. Educ. Res. High. Learn.* **2018**, *24*, 6. [[CrossRef](#)]
151. Mediavilla, M.A.; Dietrich, F.; Palm, D. Review and analysis of artificial intelligence methods for demand forecasting in supply chain management. *Procedia CIRP* **2022**, *107*, 1126–1131. [[CrossRef](#)]

152. Sarajcev, P.; Kunac, A.; Petrovic, G.; Despalatovic, M. Artificial Intelligence Techniques for Power System Transient Stability Assessment. *Energies* **2022**, *15*, 507. [[CrossRef](#)]
153. Likas, A.; Blekas, K.; Kalles, D. Artificial Intelligence: Methods and Applications. In Proceedings of the 8th Hellenic Conference on AI, SETN 2014, Ioannina, Greece, 15–17 May 2014.
154. Sarker, I.H. AI-Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems. *SN Comput. Sci.* **2022**, *3*, 158. [[CrossRef](#)]
155. Segato, A.; Marzullo, A.; Calimeri, F.; de Momi, E. Artificial intelligence for brain diseases: A systematic review. *APL Bioeng.* **2020**, *4*, 41503. [[CrossRef](#)]
156. Yang, C.-H.; Chen, B.-H.; Wu, C.-H.; Chen, K.-C.; Chuang, L.-Y. Deep Learning for Forecasting Electricity Demand in Taiwan. *Mathematics* **2022**, *10*, 2547. [[CrossRef](#)]
157. Tratar, L.F.; Strmčnik, E. Forecasting methods in engineering. *IOP Conf. Ser. Mater. Sci. Eng.* **2019**, *657*, 12027. [[CrossRef](#)]
158. Bourbakis, N.G. *Artificial Intelligence Methods and Applications*; Springer International Publishing: New York, NY, USA, 2014.

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