

# Intelligent Forecasting and Optimization in Electrical Power Systems: Advances in Models and Applications

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## 1. Introduction

A modern power system is a complex network of interconnected components, such as generators, transmission lines, and distribution subsystems, that are designed to provide electricity to consumers in an efficient and reliable manner. These systems make use of advanced technologies and control systems to monitor and manage the flow of electricity, including integrating renewable energy sources (RESs), implementing smart grid systems, and using advanced forecasting and optimization techniques to ensure the stability and security of the grid. The aim of modern power systems is to provide a sustainable and reliable source of electricity that meets the needs of the growing population, while minimizing the environmental impact and reducing the costs.

A power system requires forecasts that predict the future electricity demand, the power generation from RESs, and meteorological data that are important regarding consumer demand and the level of generation from RESs. Accurate forecasting enables the effective operation of power systems of all sizes, including microgrids. It is necessary for energy mix optimization, energy storage management, hydro-thermal coordination, fuel reserve planning, electricity import and export planning, and security assessments. It is also crucial in competitive energy markets, as electricity prices are highly influenced by the demand for electricity and energy mixes. Thus, accurate forecasting is financially beneficial for all participants of the energy market.

The objective of optimization of power systems is to efficiently utilize available resources to meet a target outcome, such as reducing costs, increasing efficiency, or improving reliability. Optimization of power systems involves finding the optimal operating conditions for a system given constraints such as equipment capacity, energy prices, and system reliability requirements. This requires taking into account a wide range of factors, including energy generation and demand forecasts, load profiles, and the availability of energy storage and other resources. Typical optimization problems in power systems are unit commitment and optimal power flow. Unit commitment is the process of scheduling the available generating units to meet the expected load demand in the most economical way. This involves determining which generators to operate, their power outputs, and their start-up and shut-down schedules over a given time period. Optimal power flow is the process of finding the optimal settings for the controllable devices in the power system, such as generators, transformers, reactive power devices, and switches, to minimize the cost of generating and transmitting electricity in the system while satisfying system constraints, such as power balance, network stability limits, transmission limits, voltage limits, and device operational limits.

This Special Issue explores the latest developments and advancements in the application of artificial intelligence (AI) and machine learning (ML) for forecasting and optimization in the field of power engineering. In recent years, AI and ML have been gaining



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significant traction and are becoming one of the most important fields in computing. These methods have proven to be effective in solving forecasting and optimization problems in power engineering.

For this Special Issue, we invited researchers to submit original papers and review articles that showcase their latest research results in forecasting and optimization of electrical power systems. Topics of interest include, but are not limited to:

- AI/ML/deep learning for forecasting electricity generation from RESs;
- AI/ML/deep learning for forecasting power demand for electrical power systems;
- Optimization of electrical power systems;
- Forecasting of meteorological data (wind speed and solar radiation) that is important for forecasting electricity generation from RESs;
- Statistical analyses of data for forecasting models (including problems related to big, missing, distorted, and uncertain data);
- Reliability of electrical power systems.

Overall, this Special Issue aims to bring together the latest research and advancements in the application of AI and ML to forecasting and optimization in the field of power engineering and provide a platform for the exchange of ideas and the presentation of new findings.

## 2. Summary of the Contributions

There were 25 papers submitted to this Special Issue, and 18 papers were accepted. Although each paper covers a different topic, we can identify four categories into which the papers can be classified according to their main focus: electricity demand forecasting, wind power forecasting, photovoltaic power forecasting, and optimization.

### 2.1. Electricity Demand Forecasting

#### 2.1.1. Relevance of the Subject

Demand forecasting in power systems is the process of predicting the future electricity demand of a given area or region. It is an important aspect of power system planning, as it allows utility companies to estimate the amount of energy they will need to supply in the future and to make informed decisions about how to meet that demand. Accurate demand forecasting helps power system operators to avoid both shortages and excess generation, which can be costly and impact the stability of the electrical grid. Forecasting electricity demand can be challenging because it depends on a wide range of factors, including weather patterns, economic trends, and consumer behavior.

In addition to its importance in day-to-day operations, demand forecasting is also critical for mid-term and long-term planning in the power sector. Accurate forecasting assists utility companies in making knowledgeable decisions about investments in new infrastructure, such as power plants and transmission lines, and can aid in optimizing the use of existing resources.

#### 2.1.2. Main Forecasting Problems

There are different types of forecasting problems that can arise in electricity demand forecasting, including:

- Very short-term forecasting, which refers to the prediction of electricity demand or production for a time horizon from seconds to a few hours ahead.
- Short-term forecasting, which refers to predicting electricity demand in the immediate future, usually up to several days ahead.
- Medium-term forecasting, which involves predicting electricity demand for a period of a few weeks to a few months ahead.
- Long-term forecasting, which involves predicting electricity demand for a period several years in advance.

- Peak electricity demand forecasting, which is forecasting of the highest level of electricity consumption within a particular period, typically daily or yearly.
- Seasonal forecasting, which involves predicting the electricity demand for different seasons of the year.
- Special event forecasting, which involves predicting the electricity demand for special events, such as holidays, sports events, or festivals.
- Probabilistic forecasting, which is forecasting of not only a single predicted value, but also a probability distribution or range of potential values with their associated probabilities.
- Uncertainty forecasting, which involves predicting electricity demand in the presence of uncertainty, such as changes in weather patterns, economic conditions, or energy policies.

Each type of forecasting problem requires different data, models, and techniques, and may have different levels of accuracy and uncertainty.

Electricity demand forecasting can be a challenging task due to various factors that can affect the consumption patterns of electricity users:

- Seasonality and trends. There can be significant seasonality and trends in electricity demand, such as increased usage during hot summer months or the growth in the electricity market over time.
- Volatility. Electricity demand can be volatile and subject to unexpected changes due to weather events, economic conditions, or other unforeseen factors.
- Data quality. Electricity demand data may be incomplete or contain errors, which can affect the accuracy of forecasting models.
- Non-linear relationships. There may be non-linear relationships between electricity demand and various factors such as temperature, time of day, and day of the week.
- Uncertainty. The accuracy of forecasting models can be affected by uncertainty around future events or conditions, such as changes in regulations or the introduction of new technologies.

To address these challenges, advanced forecasting techniques such as ML, time series analysis, and statistical modeling are often used to analyze historical data and identify patterns and trends that can help predict future electricity demand. There are many methods used for demand forecasting, including statistical models, AI and ML models, and hybrid models that combine the two. These models use historical data, weather forecasts, economic data, and other factors to make predictions about future electricity demand.

### 2.1.3. Overview of Article Content

The purpose of [1] is to predict the impact of electric vehicle developments on the Polish power system from 2022 to 2027. The study conducted multi-stage and multi-variant prognostic research by forecasting the number of electric vehicles using seven methods, and then forecasting the annual power demand arising from the operation of these vehicles, both with and without the impact of e-mobility growth, using six methods. The daily profiles of typical days were forecasted with and without e-mobility growth using three methods. To forecast the number of electric vehicles in Poland, a unique growth dynamics model was developed. The researchers also applied an artificial neural network (ANN), specifically the multilayer perceptron (MLP), in the extrapolation of non-linear functions for forecasting the number of electric vehicles and annual power demand without the impact of e-mobility growth. In another innovative proposal, they included two ANN models (MLP and long short-term memory (LSTM)) in an ensemble model for simultaneous extrapolation of 24 non-linear functions to forecast the daily profiles of typical days. The study revealed that e-mobility development in Poland for the next six years (2022–2027) may pose a challenge in terms of the additional demand for electricity. Electric vehicles' largest percentage share of the demand for electricity was in the peak evening time, while the smallest percentage share was during the night. Overall, this study provides important

insights for policymakers, energy planners, and stakeholders who need to make informed decisions on how to manage the expected increase in demand for electricity due to the growth of e-mobility in Poland.

Paper [2] investigated the sources of uncertainty in short-term hourly electricity load forecasting and proposed a clustering-based bootstrapping method to increase the accuracy of multi-step ahead point forecasts. The proposed method, called SSA.KM.N, combines singular spectrum analysis and K-means clustering-based generation of Gaussian normal distribution to generate electricity load time series with lower variance and values around the original data. The study compares SSA.KM.N and KM.N using two Malaysian, one Polish, and one Indonesian electricity load time series using four benchmark models for electricity load forecasting: SARIMA, NNAR, TBATS, and DSHW. The results showed that the proposed method improves the accuracy of multi-step ahead forecast values, especially for the SARIMA and NNAR models. The study also noted that the number of bootstrapped series does not seem to affect the forecasting accuracy, and the model suitable for the original series is not necessarily appropriate for all bootstrapped series. The authors suggest combining several models and ensemble learning methods in future research. Overall, the study proposed a novel method for improving the short-term hourly electricity load forecasting accuracy by addressing uncertainty through bootstrap aggregation.

Paper [3] conducted a literature review of autoregressive methods applied to short-term forecasting of power demand, aiming to improve the forecasting efficiency while minimizing the financial costs and time taken. The review analyzed 47 articles and 264 forecasting models, focusing on autoregressive methods, but also including methods with explanatory variables. The analysis included 25 power systems on four continents that were published by 44 different research teams. The paper presents a new approach to developing literature reviews, ranking the forecasting models based on the mean average percentage error (MAPE), and also presenting a flowchart illustrating the process. The most effective models using the autoregressive approach include fuzzy logic, ANNs, wavelet ANNs, adaptive neuro-fuzzy inference systems, genetic algorithms, fuzzy regression, and data envelope analyses. The results of the review constitute an excellent starting point for further tests and pave the way for future research in this area. The paper also discusses the state of research in short-term power demand forecasting, including methods of AI, data mining, and big data.

ML ensemble models are the state-of-the-art in forecasting. Paper [4] explored the use of random forest, an ensemble model, for short-term load forecasting, and investigated various data representation and training modes. The study demonstrated that the proposed approach using random forest outperforms both standard statistical models and more sophisticated ML approaches in terms of accuracy for short-term load forecasting. The random forest model is easy to learn and optimize, with a small number of tuning hyperparameters. It has the ability to handle multiple exogenous predictors of different types. The study also shows that the performance of random forest depends significantly on data preprocessing and proper organization of the training process. The proposed approach extends pattern definition and introduces a global mode of training with additional predictors representing calendar data. The proposed model is suitable for forecasting problems with multiple seasonality, nonlinear trends, and varying variance in time series. In future work, the author plans to extend random forest with random data projection and use it for probabilistic forecasting.

A solution for predicting the monthly power demand using statistical methods such as ARIMA, ETS, and Prophet is proposed in [5]. These methods utilize pattern representation of seasonal cycles of the time series to unify the data, filter out a trend, and define longer seasonal cycles. The input and output variables in the pattern space are characterized by a less complex relationship, resulting in a simpler forecasting model. ARIMA and ETS construct global models, while comparative minimum distance methods, such as k-NN, construct local models individually for each query pattern. Outliers in the time series affect the selection of ARIMA and ETS parameters, leading to suboptimal models, while they

have a lesser impact on k-NN. Additionally, the statistical models generate forecasts one step ahead, while k-NN predicts the vector representing the entire predicted sequence in one step. A simulation study on monthly electricity load time series for 35 European countries confirmed the high accuracy of the proposed models.

Paper [6] proposed a smart home occupancy prediction technique using environmental variables such as CO<sub>2</sub>, noise, and relative temperature via an ML forecasting strategy. The LSTM neural network was used to process time series prediction, and two metaheuristic optimization algorithms (GA and PSO) were used to enhance the performance of the LSTM algorithm. The proposed methods were evaluated using real-world datasets. The results show that GA and PSO can adjust the LSTM model to perform significantly better than benchmark models, including other ML approaches such as basic LSTM. The predicted values were used to determine whether residents were present and control real electrical consumption. The authors suggest a potential field for future research in thermal parameter forecasting using recurrent neural networks for various places such as hospitals, hotels, and public establishments.

## 2.2. Wind Power Forecasting

### 2.2.1. Relevance of the Subject

The forecasting of power generation in wind farms is a much explored research topic. Five papers devoted to forecasting the energy generation of wind farms have been published in this Special Issue.

Forecasting purposes vary by time horizon. The ability to precisely forecast power generation in the short-term for wind farms (especially large wind farms) is very topical, since such generation is highly unstable and creates problems for distribution and transmission system operators in appropriately preparing the power system for operation. Forecasts of the energy generation of wind farms, especially for the next day, play an important role in this process. They are also utilized in energy market transactions. Even a small improvement in the quality of these generation forecasts translates into an improved security of the system and savings for the economy. High quality forecasts of electrical energy generation are also very important for owners of small wind turbines due to the optimization of energy storage and optimization of the use of various energy carriers (especially in microgrid systems). Medium-term forecasts of wind farm power generation have other purposes: grid integration planning, determining the optimal use of backup power sources, and balancing the supply and demand of electricity. The applications of long-term forecasts of wind farm power generation are, e.g., maintenance scheduling, wind farm design, electricity market restructuring, and optimization of operating costs.

### 2.2.2. Main Forecasting Problems

For short-term forecasts (more than a few hours), it is not possible to accurately forecast electricity generation from wind farms without using wind speed forecasts. The accuracy of power generation forecasts depends strongly on the quality of wind speed forecasts. For extensive wind farms, an additional problem is the variety in atmospheric conditions (essentially wind speed) in different parts of the farm. The terrain in the vicinity of the wind farm (e.g., forests, hills, and lakes) is another factor that affects the amount of electricity generation. The amount of electricity generated is therefore to some extent dependent on the roughness of the terrain. On the macro scale, it is equally important to select a proper forecasting point from which meteorological variables can be derived. The location of numerical weather prediction (NWP) forecasting points has an impact on the quality of generation forecasts; NWP forecasts at locations far away from the wind farm can generate large forecasting errors.

The problem of the availability (amount of information) of data for the forecasting model is also very important; the more information related to power generation available to be used in the model, the more accurate the generation forecasts will be. Another problem is the use in forecasting models of wind speeds that were forecasted at a much different height

than the height of the wind turbines on the wind farm. The final important forecasting problem is that the quality of forecasts decreases as the forecast horizon grows (it is difficult to accurately forecast wind speed for a horizon greater than 6 h).

A fundamental problem for generating a forecast for a specific period of time, for example, for a 1-h period or a 15-min period, is that the instantaneous wind speed forecasts are unknown. Therefore, simplification of the model is necessary, which has an obvious impact on the accuracy of wind farm generation forecasts.

### 2.2.3. Overview of Article Content

Paper [7] concerns ensemble methods using ML and deep learning for one-day-ahead forecasts of electric energy production in two wind farms. It is worth noting that using two wind farms for forecasting considerably increases the credibility of newly created prediction methods and the conclusions made from them. The authors verified the accuracy of forecasts executed by single methods, hybrid methods, and ensemble methods (for a total of thirteen methods). However, the predictions made by the original ensemble forecasting method, called “Ensemble Averaging without Extremes”, had the lowest normalized mean absolute error (nMAE) among all tested methods. A new, original proposal, “Additional Expert Correction”, reduced the errors of energy generation forecasts for both wind farms. Using the original skill score (SS) metric proposed by the authors to compare the prediction accuracy proved to be very useful. This metric allows incorporation of both the nMAE and the normalized root mean square error (nRMSE) into the final quality assessment. The results of comparative tests (different sets of inputs to the predictive models) demonstrated that it is better to use NWP point forecasts for hourly lags (−3, −2, −1, 0, 1, 2, 3 (original contribution)) as input data than lags of 0 and −1 that are typically used in such situations. The authors demonstrated that it is better to use forecasts from two different NWP models as input data than from one NWP model. The conclusions drawn from this extensive work can be generalized, at least for Central Europe.

Paper [8] concerns offshore wind power short-term forecasting. ML models are accurate methods of wind power prediction; however, their accuracy depends on the selection of appropriate hyperparameters. The authors proposed a novel optimization algorithm to tune the LSTM model for short-term wind power forecasting. The new Optuna optimization framework was employed to optimize the hyperparameters of the LSTM model, including the number of lag observations, the exposure frequency, the number of nodes, the number of samples in an epoch, and the used difference order, to convert a nonstationary dataset into a stationary dataset. This proposed method improved the wind power prediction accuracy. The method’s effectiveness was validated using six distinct datasets, with noted accuracy improvements observed in all cases.

Paper [9] concerns NN-based wind power forecasting models for neuromorphic devices. The authors proposed the use of biologically inspired algorithms adapted to the architecture of neuromorphic devices, such as spiking artificial NNs. They proposed a short-term wind power forecasting model based on spiking artificial NNs adapted to the computational abilities of Loihi (a neuromorphic device developed by Intel). One-step-ahead wind power forecasts were executed using wind power generation data from Ireland. The authors demonstrated that neuromorphic computing offers a new paradigm to create energy efficient, low latency algorithms in contrast to the present state-of-the-art ML/DL strategies, thus potentially reducing the computational cost of training and deploying AI-based forecasting models.

Paper [10] presented a selective review on the recent advancements in long-, short-, and ultra-short-term wind power predictions. A detailed review of recent research achievements and performance and the possible future scope of research are presented. Each category of forecasting methods is divided into four subclasses and a comparative analysis is presented. This review paper also provides future recommendations and discussions on recent development trends in forecasting methods. An analysis of papers showed that hybrid methods are probably the best choice for all three prediction horizons.

Paper [11] concerns an evaluation of the metrics for wind power forecasts. The “Introduction” section provides a valuable and extensive description of the major factors that affect the quality of wind power forecasts. In the “Performance of Forecasting Model” section, a comprehensive inventory of error metrics is presented, which includes both popular and occasionally used metrics, totaling 19 error metrics. This paper conducted a comprehensive review (quantitative analysis) based on more than one hundred papers concerning forecasts of energy generation from wind farms (offshore and onshore). Moreover, the paper includes an extensive statistical analysis of errors (qualitative analysis). In the “Comprehensive Error Analysis” section, the quotients of the nRMSE and nMAE were calculated and a new, unique error dispersion factor (EDF) metric was thus introduced (a combination of two frequently used error metrics). This research presents a unique and novel approach to studying errors in power generation forecasts for wind farms. The EDF shows the average variability of the moduli of error, regardless of the magnitude of the error. The decrease in the EDF with a rise in the forecasting horizon indicates that the variability in the errors decreases with an increasing forecasting horizon. An analysis of the errors and the EDF depending on the class of forecasting methods demonstrated that the variability in the moduli of errors of the best methods (smallest forecasting errors) was usually larger than for the “single method” class (much larger forecasting errors). The moduli of errors in the “single method” class are much larger and much closer in value than in the best (ensemble or hybrid) methods.

### 2.3. Photovoltaic Power Forecasting

#### 2.3.1. Relevance of the Subject

Photovoltaic sources (PV) are perceived by the public as an opportunity for emission-free electricity generation on various scales. Of course, sources of this type are intermittent and often difficult to manage. Depending on the size of the power system and the size of the connected PV system, there is a growing need for increasingly more precise forecasts of energy production. Therefore, the topic of forecasting energy production from PV sources is quite popular, leading to the next three papers in this Special Issue. As it was mentioned above, PV system sizes may vary. For household use, they can be few hundred Watts, for small microgrids, they may be dozens of kW, and for PV farms, they can reach dozens of MW. Electricity produced from a PV source can be utilized in many ways in power systems of different sizes and purposes. Depending on these factors, different prediction horizons and prediction quantization may be chosen. The typical applications of PV forecasts are summarized in the following:

- Control of microgrid elements (sources, receivers, and storage), especially important and difficult in islanded operation mode;
- Energy market participation of PV source operators;
- Control and operation planning of conventional electricity sources (transmission system operator level);
- Control and operation planning of power grids (distribution system operator level).

Control applications usually require ultra-short-term forecasts, with horizons from a number of seconds up to few hours ahead and with quantization from seconds to dozens of minutes. For planning applications, short-term forecasts are used. In this context, short-term refers to horizons from a few hours up to one week. It is obvious that without forecasts, most of the businesses and technical processes mentioned above are not plausible. Furthermore, using PV energy forecasts results in substantial economical savings.

#### 2.3.2. Main Forecasting Problems

Electricity production of photovoltaic sources depends strictly on meteorological conditions. This makes these sources similar to wind sources. However, in the case of photovoltaic sources, the geographic location of the source and the season of the year are also important, as these factors affect the maximum insolation during the day. In order to obtain forecasts of electricity production from PV sources of the highest possible quality,

it is necessary to use weather forecasts and to take into account seasonal dependencies in predictive models. Most solutions use NWP forecasts. They are indispensable in the case of short-term forecasts and some (longer horizons) ultra-short-term forecasts. In the case of the latter (for shorter horizons), different measurements are utilized to create so-called “nowcasting” meteo forecasts. These measurements may include insolation, energy production of neighboring PV sources, and also images of the sky taken with a camera. Seasonal dependencies are in some way taken into account in NWP forecasts. For example, insolation and temperature are given for the exact time and date. However, there can be some factors, which can grow to considerable depending on the class of prediction models. For physical models, the main problem is the exact determination of PV panel orientation and inclination angle. Machine learning methods generally do not require such data. It is more important to collect and prepare proper datasets for model learning and testing. These datasets should reflect phenomena that can be described by the included parameters. As an example, the influence of various types of precipitation on energy generation (e.g., snow and rain) should be modeled. Another problem is that the soiling of PV panels and their periodic cleaning must be taken into account. Both the problems of precipitation and soiling may influence the energy generation from a few tenths of a percent to several tens of percent.

### 2.3.3. Overview of Article Content

Paper [12] concerns ultra-short-term forecasting of photovoltaic source power generation. In this case, the forecasting horizon was next step forecasting and the forecast quantization was 5 min. The paper starts with a literature overview and a description of photovoltaic system performance. The data gathered for the presented research are derived from a 3.2 kW PV system. A very detailed statistical analysis of power generation data is presented. On the basis of this analysis, sets of explanatory variables are proposed. There are eight different sets with different numbers of inputs (explanatory variables), varying from one up to fifteen. The authors proposed ten different forecasting models: single (naive, LR, KNNR, MLP, SVR, and IT2FLS), ensemble, and hybrid. Almost every model was tested for more than one set of explanatory variables, giving a total of almost 40 configurations. All the results were evaluated using four quality criteria, i.e., RMSE, nMAPE, nAPEmax, and MBE. The best results were obtained by the hybrid and MLP models when using sets of explanatory variables with higher numbers of variables. The authors presented a detailed analysis of the results.

Paper [13] concerns short-term forecasting with a 1 to 144 h horizon and hourly quantization. The authors presented in detail the dataset used, which includes lagged power production, global horizontal irradiance, NWP forecasts, and regional aggregated solar power predictions. Then, a one-step-ahead model configuration was presented. The authors proposed the use of separate models for (a) the 1st hour ahead, (b) the 2nd to 56th hour ahead, and (c) the 57th to 144th ahead. XGBoost (XGB) and CatBoost (CTB) methods were used to build the prediction models. As evaluation criteria, the RMSE and RMSE scores were selected. The RMSE skill score utilizes the complete history persistence ensemble (CH-PeEn) as a benchmark method. Such a criterion can be used as a comparison for the proposed model with simple forecasting based on historical data. The authors also investigated the model’s performance with respect to the development of separate models for each month, for 3 months, or for a universal model. The results of the tests were presented and discussed in detail. The best results were obtained for separate models built for each month of the year.

Paper [14] concerns day-ahead forecasting (24–47 h horizon) with hourly quantization of PV and wind sources. The main idea of this article is the use of multi-task learning (MTL) autoencoders. The authors determined whether MTL autoencoders can be utilized to predict day ahead electricity generation for different sources in non single-task learning. This led to other investigations, such as determining the quality of such predictions and determining whether additional encoder fine-tuning will be necessary. To answer to these

questions, the authors used the following datasets: PVOPEN, PVSYN, PVREAL, WIN-DOPEN, WINDSYN, and WINDREAL. These datasets include over 600 renewable power stations with additional NWP data. The authors tested different autoencoder architectures varying the parameter number by three orders of magnitude. During experiments, the RMSE and nRMSE were used as quality criteria. When considering a multi-task approach, the authors reduced the trainable parameters by up to 203 times. The authors also concluded that the amount of layers requiring fine-tuning depends on the architecture and the model.

## 2.4. Optimization

### 2.4.1. Relevance of the Subject

The competitiveness of the economy depends on the ability to save energy and the ability to propose innovative solutions in optimization of power systems. Furthermore, in electrical power engineering, optimization often uses the results of forecasting, creating a synergistic effect. Solving an optimization problem requires several steps, usually problem description, criteria definition, mathematical model construction, objective function definition, optimization method application, and testing. For many problems, these are relatively time-consuming tasks because most of them do not have ready-made toolkits. In this Special Issue, there are four papers concerning different aspects of optimization of power systems.

### 2.4.2. Overview of Article Content

Paper [15] concerns the optimization of the configuration and operation of a hybrid AC/DC low voltage microgrid. For optimization purposes, the CLONALG algorithm was chosen. The CLONALG algorithm belongs to the family of artificial immune system (AIS) computational intelligence methods. In the presented application, it was equipped with a modified hypermutation operator. The author stated three different optimization tasks: minimization of total active power losses, minimization of costs associated with the operation of the hybrid AC/DC microgrid, and maximization of the level of power generated by the RES. For each task, there is an appropriate mathematical definition of the problem. The test hybrid microgrid consists of AC and DC networks coupled with an electronic power converter. The microgrid supplied a single family housing estate and connects PV, wind, and distributed generation sources. It also included energy storage. The optimization results of the proposed version of the CLONAG algorithm are presented in detail and compared to the evolutionary algorithm. The proposed algorithm achieved better results in most cases.

Paper [16] concerns voltage control in MV networks with distributed generation. Widespread incorporation of distributed generation (DG) (especially renewable) to medium voltage (MV) and low voltage (LV) networks causes many operation problems. One of these problems is the rise in voltage during high energy generation in DG and vice versa. This results, for example, in limitations of PV source generation on sunny days. The main idea of this article is to overcome the voltage problems by appropriately setting the transformer's on-load tap changers and using additional measures such as capacitor banks, reactive power generation in the RES, and energy storage. As an optimization method, the authors used the algorithm of the innovative gunner (AIG). This algorithm, as a computational intelligence method, is generally similar to other methods, especially swarm methods. One feature that distinguishes it from other swarm methods is its method of decision vector modification. Usually, algorithms use additive formulae. However, the AIG uses multiplicative modifications, which makes optimization more dynamic (especially at the beginning). The authors presented the test network and AIG optimization results compared to cuckoo search (CS) and moth-flame optimization (MFO) algorithms.

Paper [17] concerns the reliability of MV distribution networks with distributed generation and ICT infrastructure. Distribution power networks (both MV and LV) were originally designed as hierarchical for unidirectional power flow from generating units connected to higher voltage levels to receivers connected to lower voltage levels. Incon-

poration of distributed generation (DG) and RESs has changed this operation model. To obtain a better performance of the networks, their structures and operation model must change. Obviously, information and communication technology should be a part of this transition. This article presents a reliability analysis to answer the questions of what the future network structure should be and what additional elements need to be incorporated to obtain the optimal reliability. The authors used several indices (SAIFI, CAIFI, ASAI, ASUI, and EENS) to answer to this question, analyzing five network structures.

Paper [18] concerns the optimization of industrial refrigeration system operation. The authors decided to define this problem as a multi-objective problem with two conflicting objectives: maximization of the effectiveness of the cooling towers and minimization of the overall power requirements of the refrigeration system. The objectives are contradictory because the efficiency of the system increases with the required system power. The structure of the test refrigeration system and objective functions were presented. To solve the optimization problem, the authors proposed and described three different evolutionary algorithms: the non-dominated sorting genetic algorithm (NSGAI), the micro-genetic algorithm (Micro-GA), and the strength Pareto evolutionary algorithm (SPEA2). As determining the optimal solution (in the case of multi-objective optimization) is difficult, the authors introduced a third criterion: the energy efficiency ratio. After many analyses of the obtained results by using this third criterion, the authors proved that the best solution was achieved using the SPEA2 algorithm.

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