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Review

Methods of Forecasting Electric Energy Consumption: A Literature Review

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Abstract: Balancing the production and consumption of electricity is an urgent task. Its implementation largely depends on the means and methods of planning electricity production. Forecasting is one of the planning tools since the availability of an accurate forecast is a mechanism for increasing the validity of management decisions. This study provides an overview of the methods used to predict electricity supply requirements to different objects. The methods have been reviewed analytically, taking into account the forecast classification according to the anticipation period. In this way, the methods used in operative, short-term, medium-term, and long-term forecasting have been considered. Both classical and modern forecasting methods have been identified when forecasting electric energy consumption. Classical forecasting methods are based on the theory of regression and statistical analysis (regression, autoregressive models); probabilistic forecasting methods and modern forecasting methods use classical and deep-machine-learning algorithms, rank analysis methodology, fuzzy set theory, singular spectral analysis, wavelet transformations, Gray models, etc. Due to the need to take into account the specifics of each subject area characterizing an energy facility to obtain reliable forecast results, power consumption modeling remains an urgent task despite a wide variety of other methods. The review was conducted with an assessment of the methods according to the following criteria: labor intensity, requirements for the initial data set, scope of application, accuracy of the forecasting method, the possibility of application for other forecasting horizons. The above classification of methods according to the anticipation period allows highlights the fact that when predicting power consumption for different time intervals, the same methods are often used. Therefore, it is worth emphasizing the importance of classifying the forecast over the forecasting horizon not to differentiate the methods used to predict electricity consumption for each period but to consider the specifics of each type of forecasting (operative, short-term, medium-term, long-term).

Keywords: forecasting; power consumption; modeling; energy saving; machine learning; deep learning; artificial neural network

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1. Introduction

The dynamics of the growth of electricity consumption have been maintained in the world for more than 30 years (Figure 1). There are no prerequisites for reducing electricity consumption in the future, since at the present stage of human development, electricity is a key resource—professional and household human activity are impossible without the use of electricity. According to statistics on the world energy and climate portal Enerdata for 2021, electricity consumption in that year amounted to 24,877 TWh, which is 5.5% and

4.8% more than in 2020 and 2019, respectively. The growth of electricity consumption is also confirmed by statistics in the field of global electrification of final consumption. The trend towards an increase in electrification in the world continues to be traced: in 2021, the indicator reached 20.4% (+1 point compared to 2019).

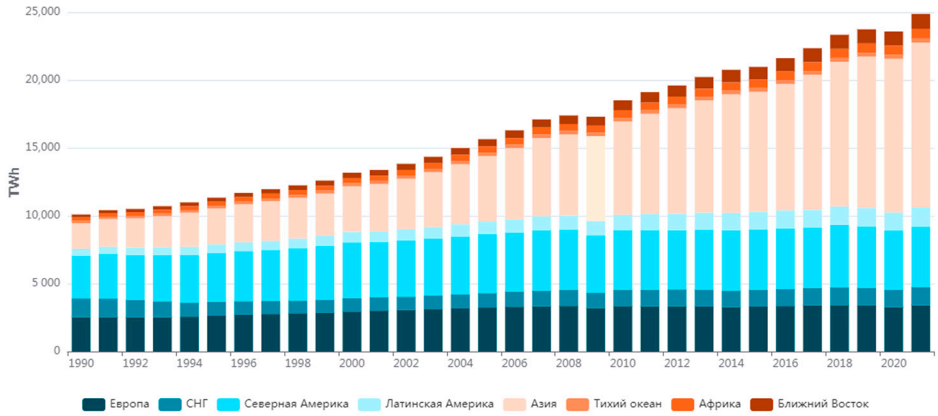

Figure 1. World Electricity Consumption for 1990–2021.

According to Enerdata's global energy and climate data, in 2021, Russia was among the top five countries in terms of electricity consumption. The highest electricity consumption was in China (7714 TWh), followed by the USA (3869 TWh), India (1355 TWh), Russia (963 TWh TWh), and Japan (916 TWh). According to the electricity consumption schedule for the period from 1990 to 2021, shown in Figure 1, there is a noticeable trend in the growth of electricity consumption in the world.

In Russia, from 2017 to 2021, electricity consumption increased by 58 TWh. The following dynamics of electricity consumption can be observed in a number of countries. For instance, in China, the consumption increased by 1834 TWh; in the USA, it decreased by 18 TWh; in India, there was an increase of 206 TWh; in Japan, consumption reduced by 64 TWh. The share of using electricity as an energy source is growing, and in 2021, it made up 10% of the world consumption of all types of energy sources (29% oil, 24% natural gas, 27% coal, 10% biomass).

The dynamic pattern of electricity consumption in the five countries with the highest electricity demand from 2000 to 2021 is shown in the Figure 2.

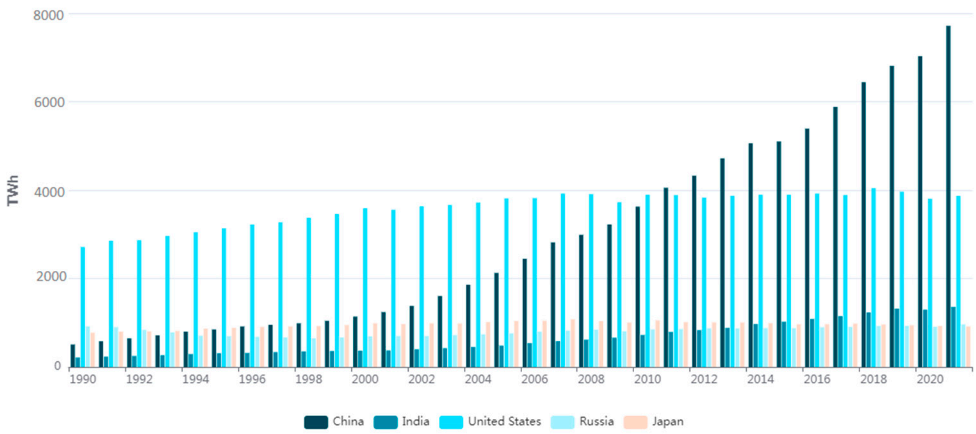

Figure 2. Dynamic pattern of electricity consumption in 2000–2021 in the five countries with the highest electricity demand.

In this regard, energy saving issues are extremely important to maintaining the uninterrupted operation of electric power systems and providing consumers with electricity of proper quality. Energy saving refers to a set of measures for the rational use of energy resources, increasing the share of renewable energy sources in total electricity production, and other measures aimed at reducing the use of energy resources and contributing to solving environmental problems. Without the availability of energy-saving measures, it is not possible to manage the growing demand for electricity every year. To ensure the uninterrupted operation of electric power systems (EES), it is necessary to maintain a balance of power and consumption in the EES. This implies the need to ensure the proper level of frequency and voltage in the EES. With sudden changes (increase or decrease) in electricity consumption, there is a violation of the balance of power and electricity consumption, which leads to failures and accidents in power plants. In addition, it is impossible to operate the wholesale electricity and capacity market without managing power consumption modes. Therefore, the management of operating modes in the EES is a complex task, and for its effective solution, detailed planning of electricity consumption is necessary.

One of the possible solutions to the problem of load planning of electric power systems is the forecasting of electricity consumption. The presence of a reliable forecast of electricity consumption contributes to the validity of decision making when managing the operating modes of power facilities.

Managing the process of electrical energy consumption is efficient due to the functioning of various incentive mechanisms that operate on the wholesale electricity and power market (WECM). This operates on the mechanism of economic management of consumer demand, known as the "Demand response", or DR. This mechanism includes a set of measures to reduce electrical energy consumption, including during peak hours, thereby contributing to a uniform and more efficient use of the capacities of generation facilities. DR can be referred to as the technology of price-dependent consumption, which implies the influence of consumers on the demand and electricity price in different periods of time (days). Therefore, for example, during peak hours on the WECM, consumers are offered lower-price electricity in return for reducing electricity consumption. The WECM uses such tools as a balancing market, a day-ahead market, bilateral agreements, competitive power take-off procedures, etc. The conditions created on the WECM encourage consumers to switch to economically advantageous conditions, assuming the existence of an accurate plan for electricity consumption. Therefore, forecasting is an urgent and important task whose solution will allow WECM participants (electricity buyers) to receive the opportunity to purchase electricity at favorable rates. The forecasting of electricity consumption by WECM participants in particular and the WECM's functioning as a whole contribute to the balance between supply and demand for the WECM and, as a result, improve the efficiency of managing the process of electricity production and consumption.

It is worth noting the key features of the electricity market, which are the difference between electricity and other types of goods and services. Firstly, the process of generating and transmitting electricity is a complex technological process, and the final consumer does not know electricity's cost as a commodity. Secondly, the transmission of electricity through the network occurs in accordance with the laws of electrical engineering; the logistics of electricity are different from those of other goods and services. Thus, electricity is a unique product, the rational use of which affects all spheres of society.

For many years, the efforts of researchers have been focused on finding the most effective methods of forecasting electricity consumption. The first publications on methods of forecasting electrical load appeared in the period from 1910–1920 [1,2]. In these publications, the results of experimental studies of power consumption in operating electrical installations were described and attempts were made to apply mathematical methods—in particular, elements of probability theory—to the calculation of the total power of electric receivers [1].

In the 1960s–1980s, one of the requirements for methods developed for use in design or operational practice was sufficient for their use without the need for powerful computers, saving machine time and memory resources. One example of this type is the method of ordered diagrams, in which simplifications led to a loss of accuracy [1]. Currently, these requirements are not decisive, and modern computing tools and systems allow us to bring to the fore the requirements of modeling accuracy and the quality of decisions made.

The 1980s–1990s were characterized by an expansion of the range of methods used for modeling power consumption as well as by a broader formulation of tasks and their solutions. During this period, there were studies on the application of game theory, decision theory, fuzzy set theory, technocenosis theory, pattern recognition theory, and cluster analysis in power consumption modeling [1]. During this period, there was a development of an integrated approach to solving power supply problems. The increase in the requirements of the economic indicators of the technical decisions influenced the further improvement of the methods of forecasting electricity consumption. During this period, the first review publications appeared, summarizing and systematizing the experience of using various forecasting methods. The Ref. [3] provides an overview of the application of expert systems in the electric power industry. The authors summarized the research results of more than 80 publications for the period from 1982 to 1988. The authors noted that the methods of expert assessments and the development of expert systems in general contribute to solving the problem of forecasting electricity consumption.

With the development of computer technology, the variety of methods began to be rapidly replenished by new methods. By the 1990s, the theoretical basis of power supply was formed. Probabilistic methods, methods of linear, nonlinear and dynamic programming, optimal control theory, tensor analysis, graph theory, group theory, etc., have become widely used. The use of computer technology in experimental and theoretical research, the design of power supply systems, and the introduction of automated energy management systems have opened wide opportunities for the practical use of theoretical developments in data processing and analysis and their modeling, aggregation, and forecasting. All this makes it possible to make wider use of the mathematical apparatus, which previously could only develop theoretically due to the difficulties of implementing computational procedures and the lag in the development of automated energy management systems and telemechanic systems.

In the 21st century, there has been a further development of methods of electricity consumption. As rightly noted in Ref. [1], on one hand, there has been an increase in the complexity of electric power systems, an increase in the degree of uncertainty when planning their operation, and the appearance of a wholesale electricity and capacity market; on the other hand, the availability of computer technology contributes to the development of forecasting methods, and there is an opportunity for a more detailed analysis of factors affecting the amount of electricity consumption—new, including hybrid, approaches to predicting electrical loads in Refs. [4–7], characterized by high speed and more flexible parameter settings.

Thus, the history of forecasting involves many studies Refs. [1–3,8–15], including review publications on forecasting methods. Such review studies allow us to provide a critical analysis of the existing methodological basis of the subject of research. Now, we will consider some of the previously conducted review publications in more detail.

Previously, studies consisting of qualitative and quantitative analysis of methods for forecasting electricity consumption used in various conditions have been conducted. Similar reviews are described in Refs. [10–17]. However, it is worth noting that each analytical review of the literature on the chosen topic has its own goals and objectives. For example, in Ref. [10], the search for universal mechanisms of learning, optimization, and management using artificial intelligence was carried out. It is well known that intelligent methods, such as machine learning and the use of neural networks, are effective forecasting tools. However, this does not mean that intelligent methods show better accuracy for each specific case of electrical load forecasting.

In Ref. [10], a modification of the concept of a universal workflow is proposed. The basic concept of a universal workflow is described in detail in Ref. [18] and assumes that the researcher performs a sequence of steps to achieve the target result—building the most effective machine learning model. In Ref. [10], a modification of the concept of a universal workflow is proposed in relation to the problem of forecasting electricity consumption, and it is argued that its application contributes to energy conservation in six different industries (industry, heating and ventilation systems, lighting, etc.).

It is worth noting the importance of universal approaches to forecasting electrical loads. However, in Ref. [10], there is no detailed description of the approach to solving the forecasting problem in each subject area taking into account the initial data, the specifics of the organization of electricity consumption accounting, and the possibilities of electricity accumulation as well as other details. The concept developed in Ref. [10] allows us to form a certain basic algorithm for implementing an effective predictive model but does not allow us to take into account the specifics of each subject area (the structure of source data, equipment, technological/organizational process, user behavior, etc.). Thus, in moving from the general to the particular, additional research is needed to detail the concept of a universal workflow in solving the problem of forecasting power consumption to such a degree of detail that would take into account the characteristic features of each subject area and at the same time would not be overloaded with additional time-consuming data manipulation. In addition, the concept of a universal workflow does not allow taking into account the specifics of each type of forecasting according to the classification of forecasts by period of anticipation (given later in the text of the article).

The review in Ref. [14] contains the results of a qualitative and quantitative analysis of the methods used in the analysis of the electric power industry. The article analyzes the methods used in the following areas of the electric power sector: production, trade, transmission, distribution, and consumption of electricity. The authors distinguish the following analytics applications as: forecasting and prediction (controlled data analysis), clustering (uncontrolled data analysis), monitoring and management (both controlled and uncontrolled), and others. In addition, in Ref. [14], all approaches are differentiated by the methods used on time series models, regression models, neural networks, support vector machines, decision tree models, clustering models, hybrid models, and others. A distinctive feature of the review Ref. [14] is not only an extensive analysis of the existing methodological base but also an assessment of the level of availability of data necessary for case studies, an analysis of the number of innovative solutions by regions of the world, and a designation of promising research areas. One promising area of research identified by the authors is a comprehensive analysis of all stages of energy production and consumption (production, trade, transmission, distribution and consumption of electricity) and the identification of methods used in several of these areas at once.

In Ref. [15], an analysis of methods for forecasting power consumption for an industrial enterprise was carried out. The author notes that despite the wide variety of forecasting methods, it is necessary to take into account as many factors as possible that affect the amount of electricity consumption, especially emphasizing the complexity of forecasting electricity consumption for multi-nomenclature industries.

The review Ref. [8] compares statistical methods (multiple linear regression, semi-parametric additive models, autoregression and moving average (ARMA) models, and exponential smoothing models) and methods using artificial intelligence (artificial neural network, fuzzy regression models, support vector machines (SVM), and gradient boosting). The authors give the following rather general conclusions on the disadvantages of different types of models. Therefore, for the artificial neural network (ANN) model, the main disadvantage is the lack of interpretability of the results. That is, ANN models do not allow us to obtain a relationship between the electrical load and the factors affecting it. The use of statistical methods solves this shortcoming. However, to apply statistical methods, knowledge of statistical analysis is necessary to obtain a functional relationship between load and factors. On the other hand, the authors compare one-dimensional models (exponential smoothing and ARIMA), which are used in the absence of factor data, with multidimensional models (multidimensional regression model, support vectors and ANN), which require data on factors affecting power consumption (weather, etc.), and note that the prediction result is, as a rule, more accurate than when using one-dimensional models.

In addition to point-based forecasting of electrical load, the literature describes the use of probabilistic forecasting of electrical load in Refs. [8,9,19–24]. The process of probabilistic forecasting of load can be divided into three components: input scenario generation with simulated predictors, model-dependent construction of intervals and probabilistic forecasting models, and post-processing through residual modeling or a combination of forecasts. Probabilistic forecasting models include models with nonparametric estimation of probability density, Bayes models, sparse heteroscedastic models, and quantile regression. Thus, it is possible to obtain interval forecasts, including with the help of models used for point forecasts.

The review of probabilistic forecasting methods in Ref. [8] presents the main advantages of probabilistic methods for various forecasting horizons. Probabilistic forecasting is computationally more complicated, but it makes it possible to combine point forecasts to obtain an interval estimate and a confidence interval, which is an important indicator in the decision-making process in power management. The disadvantage of probabilistic forecasting is the greater complexity of implementation compared to point forecasting, the need for researchers to have competencies in the field of probabilistic forecasting, as well as the availability of historical data—scenarios for model factors. In addition, there are no uniform criteria for evaluating probabilistic forecasts. The authors in Ref. [8] recommend using the Winkler index (Winkler scale) to assess the accuracy of load prediction and the pinball loss function for quantile forecasts.

At the present stage, in the process of forecasting electrical loads with a wide variety of forecasting methods, there are no universal methods for predicting electrical loads for all objects. This is mainly due to the changing requirements for the accuracy of the forecast, largely dependent on changes in the wholesale electricity and capacity market, the need to take into account the specifics of each energy facility, and other factors. In the field of modeling of electricity consumption and related processes, there are a number of unresolved problems that are of interest for the development of theory and practice of electricity supply. The historical excursion into the development of forecasting methods has shown the relevance and necessity of determining promising directions for their further development. Since there are a large number of forecasting methods and new ones have been appearing recently, it is extremely urgent to work on systematization and comparative analysis of data on these methods. In this study, we conducted a comparative analysis of existing methods. The purpose of this work was to analyze and systematize existing methods in accordance with the classification of these methods along the forecasting horizon in order to determine promising vectors for the development of methods for predicting electrical loads. To achieve this goal, we solved the following tasks in the article:

1. Conducted a comparative analysis of the methods by determining the main advantages and disadvantages, the scope, and specific features of the most popular methods used in forecasting electricity consumption.
2. Conducted a comparative analysis of the accuracy of existing forecasting methods using the magnitude of the average absolute error in percent (MAPE).
3. Conducted a comparative analysis of forecasting methods by the complexity of the implementation of the methods under consideration based on the level of requirements for computational capabilities and the complexity of reproducing the method.
4. Conducted a comparative analysis of the methods of the requirements for the initial data set required for the application of the method.
5. Identified the most promising and productive methods.

The solution of these problems allowed us to form recommendations on the optimal areas of application of each considered method of forecasting power consumption. We have determined the approximate accuracy of the forecast, which can be obtained as a result of the application of the considered methods in various conditions. As a result of the analysis of the experience of using the methods by various researchers, we tried to determine the necessary structure of the initial data sufficient to implement the appropriate method of predicting the electrical load.

2. Methods and Materials

In this paper, we have reviewed existing studies on the topic of forecasting electricity consumption. During the review, we considered research and review works for the period from 2014 and earlier. We focused on new works over the past 5 years. At the same time, however, we also paid attention to classical works reflecting the main directions of development on the topic of forecasting electricity consumption.

In accordance with the above, we conducted a comparative analysis of studies reflecting the methods used in forecasting electricity consumption according to a number of criteria. The results obtained are described in detail in Section 3. This section contains four subsections, each of which provides a comparative analysis of the methods used for the corresponding forecasting horizon. The Section 4 presents the main results of our review study and outlines prospects for further research.

Before proceeding to specific methods, we will classify forecasts used in this study by period of anticipation. There are different classifications of forecasts according to the lead period [8]. In the framework of this study, we will adhere to the following. We will consider long-term forecasts to be from a year to several years, medium-term from a month to a year, short-term from a day to several weeks, and operational for hours and minutes within one day (Figure 3).

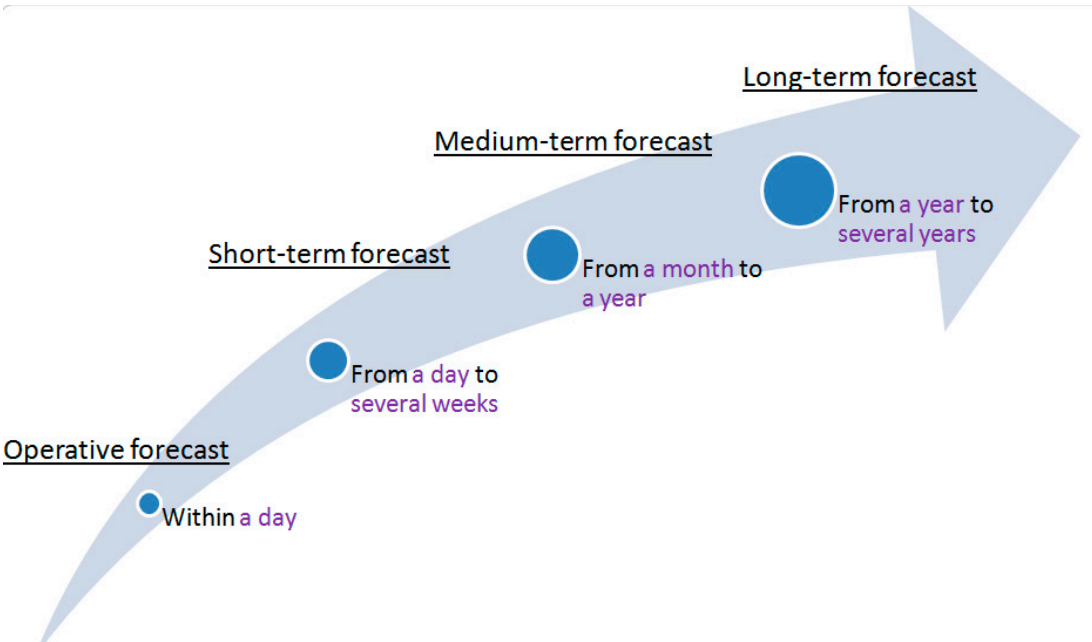

Figure 3. Classification of forecasts by lead time.

Differentiation of methods by forecast lead time allowed us to investigate in more detail the methods most effectively used for forecasting for the corresponding lead time. This separation of methods, in our opinion, allows us to better navigate the thematic literature and also allows us to identify the key features of the application conditions for each forecasting period.

It is also worth noting the problems encountered by the authors during this review. Firstly, it is worth noting the main drawback of most empirical studies, which consists of the difficulty of reproducing research results due to the difference in the conditions of their conduct, the unavailability of data, the insufficient level of detail of the solution, and other reasons that make it difficult to objectively evaluate each work. Therefore, the authors recommend that researchers, when choosing a forecasting method, pay attention not only to quantitative estimates of the results of using a particular method but also to the qualitative features of each method, the specifics of each subject area, and the assessment of the applicability of the method in specific conditions. This review presents the results of comparing the most popular and promising forecasting methods, analysis of the conditions of their application, and quantitative indicators of the applicability of these methods. The authors attempted to provide an objective qualitative and quantitative assessment of classical and modern approaches.

3. Comparative Analysis of Forecasting Methods

Forecasting electricity consumption is an effective tool in the process of making managerial decisions when planning electricity costs. An analysis of scientific research has been shown that firstly, there are no universal methods for predicting electricity consumption and that secondly, the constant increase in the requirements for forecast accuracy requires the development of new approaches. Therefore, it was decided that we would review the methodological basis for forecasting electricity consumption. Previously, similar reviews were carried out in Refs. [10–17]. A feature of this work is a comprehensive analysis of existing methods for predicting power consumption and an assessment of the prospects and risks of their application.

Now, we will more closely review the goals of each type of forecasting.

Short-term and operational forecasting is necessary for effective management of the electricity demand, its accumulation possibility. Having an accurate forecast for a day or several days ahead helps to reduce peak loads. The analysis of literary sources confirms the idea that operational and short-term forecasting is relevant for planning electricity demand both for regional energy systems (regional dispatch offices, megacities, etc.) and for so-called microgrids, which are individual large consumers of electricity: buildings (office, educational, administrative, households, hotels, etc.), various infrastructure facilities (treatment facilities, etc.), industrial enterprises, etc.

Medium-term forecasting of electricity consumption is necessary for planning the production and maintenance of the electrical network. Monthly forecasting plays a particularly important role in the operation of thermal power plants, which are among the most important bases for dispatching coal and electricity trade Ref. [25].

Long-term forecasting is used in elaborating the strategies for the development of energy systems at the state level, separately within a particular field (industry, etc.), and for planning capital construction or repair of major production and infrastructure facilities. To obtain electricity consumption forecast values, several different development scenarios are usually used (GDP volume, production growth rates, etc.). In addition, an accurate long-term forecast is necessary to develop effective environmental strategies (decarbonization of industry, etc.).

Different methods are used depending on the forecasting horizon. The most popular method at present is the use of classical and deep-machine-learning algorithms, genetic algorithms, wavelet analysis, singular spectral analysis, etc. However, the choice of methods depends on the problem being solved and the structure of the initial data, and—as many researchers note—classical methods used in forecasting electricity consumption often make it possible to obtain a forecast whose accuracy is comparable to that obtained as a result of forecasting by more complex and computationally intensive intellectual methods.

Let us consider in turn the methods most frequently used and recommended in the literature in accordance with the classification according to the forecast anticipation period.

3.1. Operative Forecasting

Operational forecasting is the research subject of many scientists; it touches upon the issues of operational management of the operating modes of power facilities. The day-ahead market provides for hourly differentiation of the electricity tariff within a day, so intraday forecasting is especially important when the WECM operates. The papers in Refs. [26–44] present approaches to solving the forecasting problem through various methods.

In Ref. [26], hourly forecasting is presented using an artificial neural network of direct propagation (perceptron) with reference to the regional power system. As a result of a series of experiments, the authors chose a three-layer perceptron with a sigmoidal activation function as a network configuration. In total, 24 variables were fed to the network input as retrospective data of the electric power load. The hidden layer contains five neurons; the output layer contains one predicted value Ref. [26]. A detailed description of the network configuration and learning algorithm is given in Ref. [26]. The authors Ref. [26] developed adaptive feedback integrated into an artificial neural network model, which made it possible to reduce the root mean square prediction error by about 1.5%.

In Ref. [27], an approach was proposed that uses a long short-term memory (LSTM) network using the "Butterfly" optimization algorithm and preliminary feature normalization. The algorithm developed in Ref. [27] was tested by the authors on two sets of data from the electrical energy consumption by households. Using the metaheuristic approach, a more accurate forecast was built compared to using the linear regression algorithm, support vector regression (SVR), and neural networks of various architectures—bi-directional long short-term memory (Bi-LSTM), LSTM, and convolutional neural network (CNN)—for both datasets. The average absolute forecast errors were 9% and 5%, respectively, which allows us to consider this method to be effective. It should be noted that the method proposed in Ref. [27] is also productive from the point of view of the forecast execution time since it allows the creation of a forecast faster than any of the algorithms considered by researchers.

The use of artificial neural networks made it possible to predict the peak load of the building of justice in the United States Ref. [28]. The researchers developed an artificial neural network, the use of which made it possible to obtain a fairly accurate forecast of peak electricity consumption (the average absolute percentage error was 3.9%). The developed model was compared to classical approaches to modeling intraday load curves: moving average, linear regression, and a multidimensional adaptive regression splines (MARSplines) model.

The study Ref. [29] presents the results of implementing the system project for monitoring and predicting peak loads of mining industry electricity. During the implementation of this project, the following results were achieved. The electricity consumption at the selected site (the Ben Guerir quarry, Morocco) was studied using machine learning tools. Several power-demand-forecasting models based on historical data were created (artificial neural network model, neuro-fuzzy inference time series model, SVM support vector regression model, and fast forest quantile regression), among which the best forecast results were obtained using the forest fast quantile regression model (FFQR). In the considered project, a new infrastructure for the energy management system for a mining facility (quarry) is proposed, from which data on the quality of electricity and the state of the electrical network are obtained in real time. The authors note that such infrastructure will make it possible to apply methods for optimizing and planning loads on the energy system, promote decentralized electricity production using renewable sources and energy storage systems, and simplify energy audit procedures. The implementation of the project will allow the mining enterprise to increase productivity through accurate planning of electricity consumption and improve the efficiency of production management as a whole. The authors note the need for additional research, including the study of various neural network architectures for predicting peak loads and comparing them with the fast forest quantile regression model already developed in Ref. [29].

Of particular interest are the works in which the study of flexible approaches necessary for real-time forecasting models was carried out Refs. [40–43]. We decided to attribute them also to operational methods in accordance with the classification by lead period described earlier. Thus, the paper Ref. [40] describes an approach that makes it possible to improve the process of managing electricity demand by introducing optimization procedures for the aggregator of small prosumers with participation in the energy market. Two optimization procedures are proposed in Ref. [40]: a two-stage stochastic optimization model for determining supply and demand and optimization of the predictive control model (MPC) for managing aggregated flexible loads in real time. Under conditions of uncertainty, the proposed strategies (called smart) surpass other theoretical guidelines, such as deterministic, flexible, and inflexible approaches. The two-stage stochastic optimization model increases the reliability of energy applications by taking into account uncertainty and flexibility in the optimization process. This reduces the costs to the aggregator, particularly the cost of regulation.

Table 1 summarizes the analysis of the methods used by researchers to solve the problem of operational forecasting of power consumption.

Based on the analyzed works, it can be concluded that neural networks are used for operational forecasting. Machine learning algorithms, including deep learning, are used to train these networks. The following neural network architectures were used in the analyzed works: multilayer perceptron in Refs. [26,28] and recurrent LSTM networks with the Butterfly hyperparameter optimization algorithm in Ref. [27]. According to the researchers, the developed models of forecasting electricity consumption based on neural networks allow us to build a more accurate forecast compared to traditional approaches to forecasting electricity consumption—linear regression, moving average models, and others. If we compare them to each other, then recurrent LSTM networks are a more optimal option since they cope much better with a large amount of data (require fewer computing resources), have a memory mechanism, and effectively cope with the problem of gradient attenuation. Using this architecture, a forecast can be obtained faster than by using a perceptron.

However, it should be emphasized that for each specific task, the process of choosing the optimal architecture and selecting hyperparameters of the neural network model is individual. Therefore, the adaptation of the models recommended in the literature takes into account the composition and structure of the source data. Thus, the use of a fully connected neural network is recommended for intraday forecasting of power consumption in the regional dispatching department Ref. [26]. To predict the power consumption of individual objects (including several administrative buildings Ref. [28] or households Ref. [27]), the use of both perceptron and recurrent LSTM networks is recommended. It is worth noting that these recommendations do not exclude the possibility of using other regression algorithms in forecasting. For example, the researchers in Ref. [29] suggest using the fast forest quantile regression algorithm, which allows one to obtain a reliable forecast of electricity consumption for the mining industry with a developed infrastructure for monitoring electricity consumption. At the same time, the authors of Ref. [29] consider the construction of neural network models and the comparison of their prediction accuracy with the developed FFQR model to be a promising study.

It can be argued that the studies reviewed confirm the effectiveness and prospects of using neural network algorithms since they often allow us to better solve the problem of operative predicting power consumption.

Thus, all the methods used for operational forecasting can be conditionally divided into time series forecasting methods and probabilistic forecasting methods. As a result of the analysis of the use of various methods for operational forecasting, it was revealed that in most cases, the use of artificial neural networks is an effective solution to the problem of operational forecasting of power consumption. Moreover, of the large diversity of different neural network architectures, perceptron and recurrent neural networks (including LSTM) are usually used. The nonlinearity of the time series of power consumption is approximated fairly accurately in neural network models, and this distinguishes them as a powerful and most accurate method of operational forecasting of power consumption. However, it is worth considering the fact that neural network models are poorly interpreted. That is, with a sufficiently accurate forecast, it is difficult to explain exactly how the model builds it. The construction of surrogate models based on classical well-interpreted algorithms for neural networks is one of the significant prospects for further research in this area.

Table 1. Analysis of methods used in operational forecasting of power consumption.

Method	Scope of Application	Forecasting Error		Identified Problems	Advantages of the Method	The Possibility of Using the Model to Solve Short-Term Forecasting Problems (i.e., How it Will Behave for Long Intervals)	Main Publications	Initial Dataset	Performance (Forecast Execution Time, s)
		%	Estimation (+/−)						
Perceptron	Forecasting of power consumption in regional control rooms, the building of justice in the USA	1.25 (standard error per day) 3.9	+	Overfitting; problems of obtaining detailed data; complexity of interpretation of results.	The random component is taken into account due to the presence of an adaptation contour, with the help of which deviations in the model are taken into account.	The model is applicable to the problem of short-term forecasting provided that previous temperature observations are taken into account.	[26,28]	1. The actual load of the system at time t. 2. Previous load observations (t-n). 5760 fifteen-second data values of all input data for each type of day during a 90-day data period: heating, ventilation and air conditioning kW, type of day (weekend/working), time of day, external temperature, humidity.	No information available
LSTM network using the "Butterfly" optimization algorithm	Private households	9.5 (tested on two datasets)	+	The complexity of implementation, the need to take into account a large number of factors.	Productive (in terms of forecast execution time) compared to other models (ensemble-based deep-learning model, CNN with GRU model, multilayer bidirectional GRU with CNN) due to the use of the algorithm for selecting optimal hyperparameters of the Butterfly network. Tested on publicly available datasets. LSTM networks have a memory mechanism and effectively cope with the problem of gradient attenuation.	More research is needed	[27]	Detailed data on power consumption: for the first data set, 29 parameters related to the energy consumption of appliances, lighting and weather information (pressure, temperature, dew point, humidity, wind speed, etc.); for the second data set, the original data set contains nine attributes, such as voltage, minutes, global intensity, month, global active power, year, global reactive power, day, and hour. Three more variables are obtained from sensors.	12 and 13 for two datasets

Table 1. *Cont.*

Method	Scope of Application	Forecasting Error		Identified Problems	Advantages of the Method	The Possibility of Using the Model to Solve Short-Term Forecasting Problems (i.e., How it Will Behave for Long Intervals)	Main Publications	Initial Dataset	Performance (Forecast Execution Time, s)
		%	Estimation (+/−)						
Quantile Regression Fast Forest	Mining industry: Ben Guerir Quarry, Morocco	1%	+	Additional research of the model is needed for the possibility of real-time application.	Good performance of the method	The model is applicable for operational and short-term forecasting.	[29]	The model is designed to function in SCADA systems as an intelligent module. It is possible to connect alternative energy sources.	10
Autoregressions of the integrated moving average ARIMA	The building of justice in the USA	6.9	+	The need to re-evaluate the model when adding new data to the model, the low generalizing ability of the algorithm, the complexity of parameter selection.	A well-developed mathematical apparatus, a formalized method of checking the model for adequacy to experimental data	More research is needed. High probability of applicability of the method for the problem of short-term forecasting	[28]	5760 15-second data values of all input data for each type of day during a 90-day data period: heating, ventilation and air conditioning kW, type of day (output/working), time of day, external temperature, humidity.	No information available
Linear regression	The building of justice in the USA	15.2	−	Inefficient in the case of complex dependencies in the source data, unstable to outliers and omissions in the data	Ease of implementation and interpretation of results	More research is needed	[28]		No information available

On the other hand, probabilistic forecasting is sometimes a more reliable solution than neural networks, since it allows you to make a forecast taking into account the estimate of the probability of the value of electricity consumption for the previous period.

It is also worth noting that in operational forecasting, it is important to take into account external factors affecting the amount of electricity consumption. Therefore, in most cases, data from weather sensors and data on power consumption for previous points in time are used. For intraday forecasting, it is important to obtain operational information about these factors in real time, which requires additional technical solutions when implementing predictive analytics systems.

3.2. Short-Term Forecasting

Researchers often combine short-term and operational forecasting into one class according to forecast anticipation period since the results of forecasting for a day and within a day can be represented as a subclass of short-term forecasting. Since the main purpose of this work is a comprehensive analysis of the main methods used in forecasting electricity consumption, the methods of intraday and daily forecasting were assigned to different classes. Short-term forecasting of electricity consumption is the most popular type based on the constantly growing number of publications Refs. [26,45–94]. The relevance of short-term forecasting is due to the need to have an accurate forecast of electricity consumption for a day or several days to productively anticipate most WECM procedures. The increasingly complex requirements of the WECM for the forecast quality (for a day ahead, for several days or weeks) and the emergence of new data mining algorithms (new neural network optimization algorithms, new neural network architectures, hybrid models, etc.) contribute to the growth of ongoing research in this area. In addition, the results of short-term forecasting are required for making managerial decisions when planning the operation modes of the electric power system.

In Ref. [26], two models of short-term forecasting were proposed: one that is based on an artificial neural network (ANN) and one using fuzzy logic in the work of an ANN (fuzzy neural networks—FNN). The network configuration was described in detail in Ref. [26]. The authors submitted 48 neurons to the ANN input, corresponding to hourly loads for the day preceding the predicted and week-old days. In addition, the ANN model developed in Ref. [26] takes into account working days, weekends, and holidays.

The fuzzy neural network contains three layers, the network inputs are similar to ANN, and the hidden layer contains the "IF-THEN" block of rules. The FNN learning algorithm is described in detail in Ref. [26]. The authors note that compared to the forecast obtained using ANN, the FNN forecast is more accurate.

Hybrid models are widely used in solving the problem of short-term forecasting. They include a combination of several data-mining methods, thereby increasing the forecast accuracy obtained using the model.

As the analysis of thematic works has shown, fuzzy neural networks are often used as part of hybrid forecasting models, which are a combination of various methods of data analysis and processing. In Ref. [47], short-term forecasting models for a megapolis were presented, taking into account meteorological factors (air temperature and natural light). The author developed a fuzzy neural network model and a hybrid model that includes multidimensional singular spectral analysis and a fuzzy neural network. The results of experimental studies presented in [47] testify to the effectiveness of the applied hybrid model in predicting daily load schedules in comparison with models of a neural network, a fuzzy neural network, etc.

In Ref. [48], the effect of temperature on the time series of electricity demand in the cities of Nepal for short-term load forecasting were investigated. The emphasis in the work was on the study of temperature as a factor influencing the electric power load.

In Ref. [49], the results of forecasting the power consumption of treatment facilities using a recursive multi-stage approach were presented. According to the authors, the processes performed at treatment facilities require significant electrical energy resources, while, as noted in Ref. [49], energy-saving measures are practically not provided. The empirical data of the study Ref. [49] were daily data on energy consumption, data characterizing the water flow volume at the inlet of the treatment plant, and meteorological factors (25 factors, including temperature, humidity, wind speed, etc.) for the period from January 2016 to May 2020. The authors in Ref. [49] described the technological process occurring at the facility under consideration and the prediction was made taking into account its features. At the initial stage, the researchers preprocessed data, filling in the missing values. Then, a correlation analysis was carried out: the undertaken study consisted of checking the data set for compliance with the normal distribution law using the Kolmogorov–Smirnov test. It was revealed that the distribution of features is non-Gaussian, so Spearman's non-parametric rank correlation coefficient was used. According to the results of the correlation analysis, insignificant features were removed. Thus, the researchers retained the following features in the data set: year, month, temperature, flow volume, and energy consumption value. The applied normalization algorithm and the study stages are described in more detail in Ref. [49]. Three deep-learning models were built and compared with each other: LSTM, GRU, and one-dimensional convolutional neural networks (CNN). Hyperparameters were selected using the grid search method, various scenarios were tested. The best prediction result was obtained using the CNN model. Moreover, during training, a transfer approach was applied, which consisted of preliminary training of a one-dimensional CNN model. The authors noted that if there were more factors characterizing the technological process of treatment facilities—such as, for example, a concentration indicator of the pollutants in water—the forecast accuracy would increase. However, this will affect the forecast time, since the water pollution data must be obtained in the laboratory; therefore, the time of obtaining these data (one day) makes it impossible to obtain a forecast for the day ahead.

The effectiveness of a hybrid model for short-term forecasting of power consumption is presented in Ref. [50]. The authors have developed a model for short-term forecasting of power consumption in which the daily schedule is approximated by two sinusoidal functions: the first is for approximating daytime power consumption, and the second is for nighttime. The model coefficients were selected using an artificial neural network. The approach proposed by the researchers makes it possible to obtain a forecast with an average absolute percentage error of 1.49%.

The work Ref. [51] proposes a model for predicting the power consumption of large federal districts of the Russian Federation based on a recurrent neural network. The empirical data were on power consumption of the federal districts for 13 years, meteorological data, information on the day of the week according to the production calendar, and features of industrial production in the corresponding federal district (statistical information). The authors obtained the following configuration of the LSTM recurrent neural network: the first layer of the LSTM with the hyperbolic tangent activation function includes 62 neurons; the second layer is dropout, with a threshold of 0.15; and the third layer is linear. The researchers argue that in order to obtain a reliable forecast using the model developed in Ref. [51], it is sufficient to have data on electricity consumption for three days preceding the forecast date. The forecast based on the developed model was compared to the forecast values obtained using linear regression models. It showed the smallest average absolute percentage forecast error (2.1%).

Forecasting load curves for determining the optimal operating modes of distribution systems were given in Ref. [52]. The authors studied microgrid load graphs. The researchers noted that load curves for aggregated environments (regions, countries, etc.) differed significantly from disaggregated environments (Smart Grid technology, smart home, microgrids, etc.). The authors compared the load curves in different conditions of countryside, small towns, industrial zones. In Ref. [52], the proposed concepts were experimentally studied using two sets of data. In this way, the work Ref. [52] covered the issues of improving the forecasting of load curves for small electrical networks, for which renewable sources acted as energy sources. The results of the study allowed prediction of the required amount of electricity which should be generated using alternative energy sources (solar, wind, etc.) a day in advance.

Using a deep-learning model, an accurate forecast of electricity demand was obtained in Ref. [53], in which the main focus was shifted from predicting the total power consumption of large facilities (megacities, industrial associations, etc.) to predicting the individual load, taking demand into account. The researchers noted that there was a tendency to shift the boundaries between the process of generation and consumption of electrical energy. This is due to the fact that now, the end user of electricity can also generate electricity. One can also use electric energy storage devices and other methods of generating electricity. This complicates the problem of forecasting the electricity demand. The authors Ref. [53] proposed a deep neural network model, with the help of which more accurate forecasts were obtained than those based on traditional methods, such as the Holt–Winters exponential smoothing model, integrated moving average autoregression, and others.

The study Ref. [54] predicted the daily load schedules of educational buildings using a multiple regression model. The authors studied six factors that affected daily power consumption: ambient temperature, solar radiation, relative air humidity, wind speed, index of the day of the week (working or weekend), and building type (administrative or academic building). Only three of these turned out to be significant for the model: temperature, index of the day of the week, and building type. The authors noted that in order to obtain a more accurate forecast, it was necessary to take into account additional factors that affect electricity consumption—for example, employment data.

The electric power industry is also actively developing in Saudi Arabia in Ref. [55]. In view of this, the Saudi Arabian government, together with scientists, is currently implementing the ambitious Vision 2030 concept, which plans to make Saudi Arabia a global center for smart energy technologies by 2030. Using real power grid datasets of Jeddah and Medina for 2021 with a time resolution of one hour, the researchers successfully tested hybrid deep-learning approaches with recurrent neural networks in combination with the long short-term memory (LSTM) algorithm. The study result was a significant decrease in the value of the normalized root mean square error (NRMSE) quality metric, which indicates an improvement in forecasting accuracy.

Japanese scientists Ref. [56] developed another hybrid algorithm, which consisted of metoeuristics and a deep-learning algorithm. The goal of this algorithm was short term prediction for the cooling tower. In addition to deep learning, multiple regression analysis and random forest algorithms were applied. The best forecasting results were achieved using the deep-machine-learning algorithm. In conclusion, the researchers concluded that this approach to forecasting electricity consumption was quite universal, and could be adapted both for other similar facilities and district power facilities.

In Ref. [57] the researchers solved the problem of short-term forecasting of the power consumption of buildings, taking into account the behavior of the owners. Decision trees, ensemble packetization trees (EBT), and deep-learning algorithms were applied. It was proven that people's behavior had a significant impact on the level of electrical energy consumption. The most accurate predictions were obtained using a deep-learning model.

In Ref. [58], the power consumption of the Melbourne wastewater treatment plant was predicted. Hydraulic, climatic, and temporal factors were considered, and those with the greatest influence on the target variable were selected using the feature selection algorithm. Among the methods under consideration were the recurrent neural network (RNN), random forest (RF), perceptron (ANN) and gradient-boosting machine (GBM) models. The best result on the test data set was obtained using the GBM model.

The authors Ref. [59] predicted a daily standard network load profile for an enterprise. It was determined using a one-dimensional cluster approach. In addition, to improve the accuracy of the power consumption forecast, an algorithm of artificial neural networks was implemented based on the real state of the enterprise in question and external weather conditions.

The traditional methods of short-term forecasting of electricity consumption include the integrated moving average autoregression model (ARIMA), the Holt–Winters model, and others. As noted in Ref. [54], the ARIMA model did not take into account the recent trend in electricity consumption. The Holt–Winters (DSHW) model considered daily and weekly seasonality, but sometimes the patterns generated by the model were unusual, indicating abnormal consumption in the past.

The analysis of methods for short-term forecasting of power consumption showed that the use of data mining methods in modeling time series of power consumption became widespread. As a rule, researchers use the apparatus of artificial neural networks (recurrent networks, including LSTM, multilayer perceptron, convolutional neural networks, etc.) and machine learning algorithms, such as various boosting models (XGBoost, LightGBM, GBM, CatBoost, etc.) and decision trees (Random Forest, etc.). The generalized conclusions based on the results of the analysis are given in Table 2.

Compared to neural network models, the difference between the actual and predicted values for the ARIMA and DSHW models is larger; therefore, these models are more susceptible to outliers, which reduces prediction accuracy. Neural network models are more stable; they take into account the influence of seasonal fluctuations and make it possible to obtain a reliable forecast of power consumption Ref. [54].

Special attention should be paid to the use of autoregressive models, which can be used to quickly obtain an accurate forecast for stationary time series. However, in statistical autoregressive models, when new data are added, the prediction accuracy deteriorates, which entails the need to reconfigure the model parameters. Therefore, if the time series of electricity consumption is stationary, it is possible to obtain an accurate forecast using an autoregressive model. However, as the researchers note, the time series of power consumption are most often non-stationary, so more complex algorithms are used to model them. The most effective methods for predicting non-stationary time series are neural network models that allow finding and considering non-linear dependencies in data. Therefore, when solving the problem of forecasting power consumption, a promising direction is the development of artificial neural network models that allow processing large amounts of data and obtaining accurate forecasting results.

Thus, all methods used in short-term forecasting can be divided into classical (linear regression, autoregressive model of integrated moving average, exponential smoothing, etc.) and intelligent (artificial neural networks, fuzzy neural networks, etc.). In addition, for short-term forecasting, an effective method is the construction of hybrid forecasting models that combine advantages of several methods. A reliable forecast can be obtained by applying preprocessing of a number of power consumption by highlighting trend, seasonal, and noise components. For this purpose, methods of one-dimensional and multidimensional singular spectral analysis, wavelet analysis, etc. are often used. In general, taking into account seasonality in short-term forecasting is an important component of building an accurate forecast model. Therefore, the development of hybrid approaches that allow the identification of seasonality and trend and clear the initial series of noise is a promising area of research.

Table 2. Analysis of methods used in short-term forecasting of electricity consumption.

Method	Scope of Application	Forecasting Error		Identified Problems	Advantages of the Method	The Possibility of Using the Model to Solve Problems of Medium-Term Forecasting (i.e., How It Will Behave for Long Intervals)	Main Publications	Initial Dataset
		%	Estimation (+/−)					
Perceptron	Regional Dispatch Management	Weekly average 1.82 1.46	+	The need to retrain the network to account for the seasonality of data. Retraining the network.	The possibility of obtaining a reliable forecast in conditions of incompleteness of the initial data, a small complexity of the method.	More research is needed.	[26,47]	Hourly load values for the days preceding the predicted ones (24 values) and for the days a week ago (24 values). Initial network training: load data from two weeks ago. Accounting for the type of day (working, weekend, or holiday).
Fuzzy neural network	Regional Dispatch Management	Mean for a week 1.18 1.34	+	The complexity of the method, the need for an expert decision when choosing the necessary rules. The need for experimental selection of parameters.	The ability to add new rules.	It can be used for medium-term forecasting (for a month in advance) with a decrease in the accuracy of forecasting and, consequently, the need to re-evaluate the parameters of the model.	[26,47]	Hourly load values for the days preceding the predicted ones (24 values) and for the days a week ago (24 values). Initial network training: load data from two weeks ago. Accounting for the type of day (working, weekend, or holiday). Consideration of meteorological factors.
Hybrid model: multidimensional singular spectral analysis and fuzzy neural network	Regional Dispatch Management	1.3	+	The greater complexity of the method compared to the isolated use of a fuzzy neural network	The possibility of decomposing a number of power consumption into additive components: trend, seasonal (harmonic), and noise, which contributes to a better selection of signs supplied to the input of the neural network.	It can be used for medium-term forecasting (a month in advance) with a decrease in the accuracy of forecasting and, consequently, the need to re-evaluate the parameters of the model.	[47]	Daily schedules of electrical loads, meteorological factors (temperature, natural light)

Table 2. *Cont.*

Method	Scope of Application	Forecasting Error		Identified Problems	Advantages of the Method	The Possibility of Using the Model to Solve Problems of Medium-Term Forecasting (i.e., How It Will Behave for Long Intervals)	Main Publications	Initial Dataset
		%	Estimation (+/−)					
One-dimensional Convolutional Neural Network (CNN)	Sewage treatment plants	<5% (630 kWh standard error of the forecast)	+	The accuracy of the forecast can be higher if one adds data on the level of water pollution. However, there is a delay in obtaining the initial data: data on water level pollution is obtained through laboratory means, so the forecast of electricity consumption with these factors can be obtained only after a day.	Shorter forecast execution time and better generalizing ability of the method compared to the perceptron.	Additional research is needed.	[49]	Daily data on energy consumption. Data characterizing the volume of water flow at the entrance to treatment facilities and meteorological factors (25 factors, including temperature, humidity, wind speed, etc.). Open data of the wholesale electricity market and the total planned consumption capacity for the second price zone (zone Siberia).
Holt–Winters exponential smoothing model using a moving average to identify trends when smoothing graphs	Enterprises of the mineral resource complex located on the territory of Siberia	1.08	+	The complexity of the method. The complexity of the selection of model parameters.	Taking into account the trend and seasonality contributes to obtaining an accurate forecast. The model gives more accurate prediction results than the neural network model.		[5,45]	

Table 2. *Cont.*

Method	Scope of Application	Forecasting Error		Identified Problems	Advantages of the Method	The Possibility of Using the Model to Solve Problems of Medium-Term Forecasting (i.e., How It Will Behave for Long Intervals)	Main Publications	Initial Dataset
		%	Estimation (+/−)					
Recurrent neural network LSTM	Power systems of large federal districts of the Russian Federation	2.1	+	The complexity of the selection of model parameters. The difficulty of interpreting the forecast	Fast execution of the forecast. The presence of a memorization mechanism. Taking into account the nonlinearity of the source data. Lower susceptibility to outliers compared to classical methods (moving average, linear regression).		[52]	Data on the power consumption of federal districts for 13 years, meteorological data, information about the day of the week according to the production calendar, and features of industrial production in the relevant federal district (statistical information). Data for 3 days preceding the forecast period are sufficient for forecasting.
Linear regression	Power systems of large federal districts of the Russian Federation	3.3	+	Susceptibility to seasonal fluctuations. The need to retrain the model when using new data.	Easy to implement		[52]	

3.3. Medium-Term Forecasting

Medium-term forecasting of electricity consumption is necessary to substantiate the technical and economic performance of the energy company and its tariff policy, to draw up repair schedules for the main equipment, and for the process of making managerial decisions when planning electricity costs and developing strategies to minimize them. The aforementioned monograph [26] proposes two models similar to those developed for daily forecasting. This is a model based on ANN and FNN. The configuration of the model is described in detail in Ref. [26]. The ANN model contains one hidden layer with three neurons. The following data are fed to the model inputs: power consumption for the previous month, minimum and maximum monthly loads, average monthly temperature, day length, the number of holidays in the month preceding the forecast, the number of holidays, and forecast values of temperature and longitude for the forecast month. To train predictive models, data on the previous two months of the current and previous year were used. The authors note that the fuzzy neural network model gives a more accurate result, which confirms the effectiveness of the method due to the presence of a flexible decision-making mechanism.

The methods recommended in the reviewed work are not the only universal methods, including for short-term and operational forecasting of power consumption. There are other approaches in the literature [4–6,46–111]. Let us consider some of them in more detail.

The work Ref. [6] presented the forecasting of monthly electricity consumption using the feature extraction algorithm. This approach was based on the decomposition of the original power consumption series into a trend, a periodic component, and a stochastic series (noise) by applying a discrete wavelet transform. After removing the noise, the trend and harmonic series were modeled using the Gray model. As a result of the preprocessing of the series, the generalizing ability of the model was significantly improved and, as the authors of the developed model noted, it had advantages over the classical approaches used in China.

The study of forecasting the electricity demand in a city district using the example of six buildings was described in Ref. [95]. The authors developed a forecast taking into account climatic and social factors. To determine the level of the factors' influence on power consumption, analysis of principal components and multiple regression analysis were applied. The methods used in the study for forecasting were deep-machine-learning algorithms. The optimal network configuration was experimentally chosen and described in detail in Ref. [95]. The accuracy of forecast models was measured using the average percentage error for each season of the year separately, with the largest error obtained in the spring (8.82%) and the smallest in winter (4.51%).

Among the wide variety of classical and modern intellectual methods based on the use of neural networks and used in forecasting, an important place is given to the technocenological approach. According to this methodology, an object that consumes electricity (a large plant, a metropolis or another complex infrastructure object) is considered a technocenosis, an interconnected set of further indivisible individual technical products united by weak links and limited in space and time. Technocenosis is the central concept in the third scientific picture of the world proposed by Kudrin B.I., the founder of the technocenological direction in science (Figure 4).

To describe the structure of technocenoses and identify trends in their development and change, a special mathematical apparatus of hyperbolic H-distributions has been developed. Hyperbolic rank H-distributions are a decreasing sequence of parameter values, ordered in such a way that as the rank (serial number) increases, each subsequent number is less than the previous one.

A distinctive feature of the technocenosis is the specificity of the connections between the individual technical elements. Technocenosis is optimally managed through the implementation of rank analysis procedures.

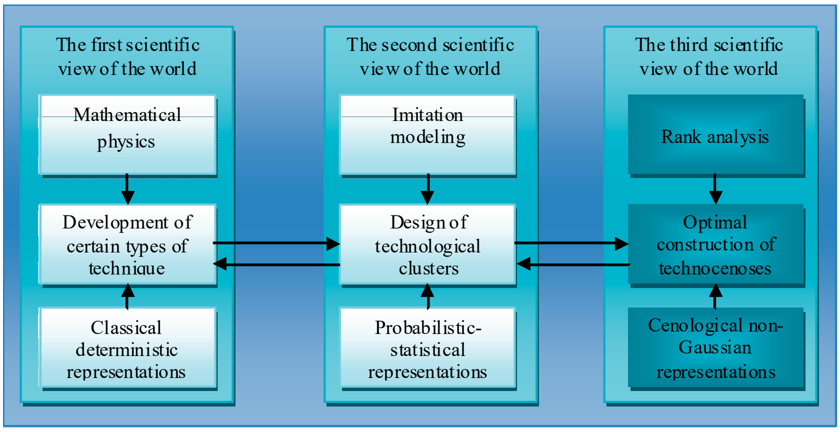

Figure 4. Methodological levels of understanding technical systems within three main scientific views of the world Ref. [96].

The rank analysis procedures used in forecasting include the forecasting G-method, forecasting Z-method, and GZ-analysis. G-methods are based on classical Gaussian mathematical statistics and time series theory. This class of methods allows considering the individual properties of objects functioning in the technocenosis. Z-methods are based on Zipf's mathematical statistics and the theory of structural topological dynamics of rank parametric distributions. When predicting based on Z-methods, the system properties of technocenosis objects are taken into account. GZ-methodology involves taking into account individual and system properties when predicting power consumption by technocenosis objects. In general, the rank analysis methodology is among the promising methodologies, allowing for the power facility properties in a comprehensive manner, and is used in medium-term and long-term forecasting of the facility's power consumption. These forecasting methods are described in detail in Ref. [96]. Figure 5 shows the GZ-analysis scheme, in which the following conventions are introduced: ARMA (autoregressive moving-average) model, TVRD time series decomposition model, time series SSA (singular spectrum analysis) model, BPT model without a fixed first point, SPT model with a fixed first point, and DCZ model divided into caste zones.

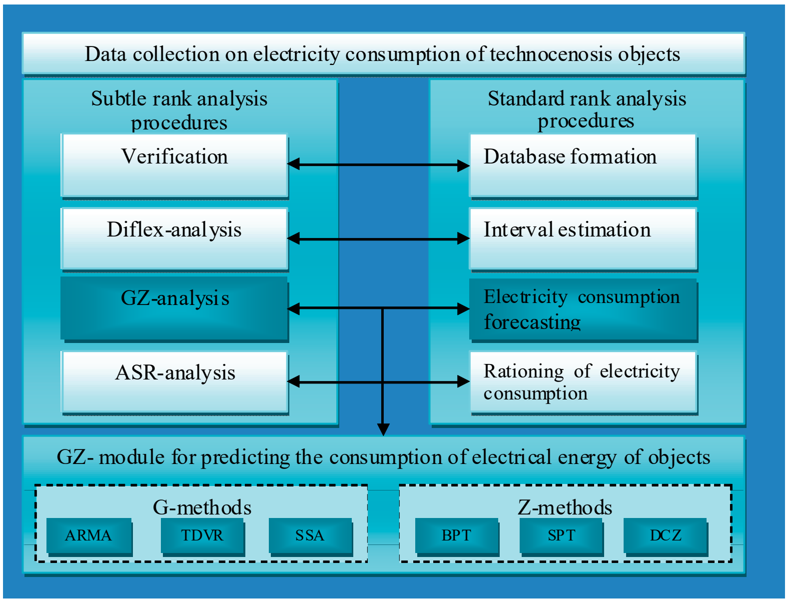

Figure 5. Standard and subtle rank analysis procedures.

Let us consider the GZ-analysis in more detail. This method is a combination of G-methods and Z-methods. For forecasting using G-methods, moving average autoregression models, variations of methods based on the analysis of the singular prectra of the time series trajectory matrix are used. When forecasting using Z-methods, technocenosis objects are clustered into castes of rank parametric distribution (noah, pointer, locust) for further forecasting of each caste zone separately. When determining the boundaries of caste zones, the equal distribution criterion of resources between caste zones is usually used [96]. To predict the power consumption of the noah caste, which includes objects with the highest power consumption, a polynomial selection technique is used that best approximates the initial data. For each object of the noah caste, the optimal degrees of the polynomial are determined. Forecasting the power consumption by the objects of the technocenosis pointer and locust castes is similar and occurs by extrapolating the time series of regression coefficients of the hyperbolic two-parameter form parameters of the rank distribution of the studied technocenosis objects. Using the least squares method, the regression coefficients are determined and, using extrapolation, the predicted values of the rank coefficient and the first point are obtained.

Table 3 shows the results of a comparative analysis of various methods used in medium-term forecasting.

Medium-term forecasting is relevant both at the regional and state levels for planning the operation modes of energy systems for individual enterprises and power plants. Monthly average electricity consumption forecasting is a complex and important process since micro- and macroeconomic indicators influence monthly electricity consumption.

Medium-term forecasting of electricity consumption is complicated by the volatility of macroeconomic conditions and social development. Therefore, when performing monthly forecasting, it is necessary to identify and take into account the trends in monthly electricity consumption using data for a continuous series of years Ref. [25]. In addition, monthly data on electricity consumption are a complex aggregate indicator influenced by many poorly formalized factors. Therefore, for medium-term forecasting, periodic components must be considered. To do this, the literature recommends using wavelet analysis, one-dimensional and multidimensional singular spectral analysis, the Gray method, and others to decompose the original series into additive components: trend, seasonal, and random (noise). Such analysis allows extracting features, which are then fed to the input of the models (usually neural or fuzzy neural), allowing significant improvement of the predictive model's accuracy compared to the option of supplying a preprocessed initial series. The classical methods (for example, moving average) have such disadvantages as the possibility of losing information about the periodicity due to the smoothing of the time series, significantly worsening the forecasting results compared to wavelet analysis and other methods listed above. In comparison, disposing of these disadvantages will allow the elimination of the noise component without a loss in quality and great improvement of the prediction results.

In addition to deep-machine-learning algorithms, rank analysis of technocenoses is used for medium-term forecasting. This methodology makes it possible to achieve sufficiently accurate forecasting results while having only retrospective data on the power consumption of a large infrastructure facility and without considering additional factors.

Table 3. Analysis of methods used in the medium-term forecasting of electricity consumption.

Method	Scope of Application	Forecasting Error		Identified Problems	Advantages of the Method	The Possibility of Using the Model to Solve Short-Term/Long-Term Forecasting Problems (i.e., How It Will Behave for Sort Intervals)	Main Publications	Initial Dataset	Performance (Forecast Execution Time, s)
		%	Estimation (+/−)						
Perceptron	Large residential buildings in 6 districts of China	13.29 (average for 6 buildings)	+	Network overfitting. The complexity of the method implementation. The complexity of obtaining the source data.	The principal component method and multiple regression analysis are used to analyze factors, which increases the accuracy of the model. The Levenberg–Marquardt algorithm was chosen as the neural network learning algorithm. There is an analysis of the application of the method by season: the best forecast in winter (error 4.51%), the worst in winter (8.82%).	The model is applicable to solving hourly forecasting problems.	[26,95]	Load on the power grid, social factors (employment): twelve input data: month, day, hour, minute, outdoor air temperature, outdoor air humidity, outdoor air pressure, wind speed, wind direction, visibility, number of people under the age of fifteen (for example, zero, one, two, three and etc.), and current power consumption	No information available
CatBoost Gradient Boosting	A small industrial enterprise	7.95%	+	The model does not take into account the data of the technological process.	The performance of the model. Automated selection of hyperparameters. Resistance to emissions.	The model can be used for short-term forecasting. Additional studies are needed to evaluate the application in the long term.	[98]	Monthly power consumption for 5 years by divisions of the enterprise with a division into technical needs and lighting. Monthly average weather data (humidity, wind speed, temperature, dew point temperature).	50
Autoregression of the integrated moving average ARIMA	A small industrial enterprise	15.92	−	Insufficient level of model accuracy due to the complexity of the selection of model parameters.	A well-developed mathematical apparatus. Ease of implementation.	More research is needed.	[98]	Monthly power consumption for 5 years by divisions of the enterprise with a division into technical needs and lighting. Monthly average weather data (humidity, wind speed, temperature, dew point temperature).	70

Thus, as well as for short-term forecasting of power consumption, the use of classical and intelligent approaches is typical for the medium-term. Hybrid approaches with the allocation of trend, harmonic, and noise components are also relevant. It is worth noting that when making a forecast from a month to a year in advance, researchers use different sets of retrospective data depending on their frequency. That is, in some studies, daily data were used to predict the aggregated indicator for the month; in other parts of the studies, monthly data on electricity consumption and monthly average data on factors affecting the amount of electricity consumption (for example, meteorological factors) were used. Therefore, when choosing a model, it is worth considering the frequency of data in the original dataset for forecasting. Thus, monthly or quarterly electricity consumption over several years is sufficient for the application of rank analysis, and when using machine learning algorithms, the accuracy of the forecast, as a rule, increases with the use of more detailed source data.

3.4. Long-Term Forecasting

Long-term forecasting is necessary to developing most strategies. Data on planned industrial production directly affect the GDP level and a number of macroeconomic and microeconomic indicators. In addition, an accurate forecast involving different scenarios of input parameters (for example, production volume) affects the development level of the country as a whole. Long-term forecasting is also relevant when making managerial decisions at industrial enterprises and other facilities, as it allows the modeling of an object's change in the long term according to various scenarios and the making of informed management decisions when developing strategies for its (enterprise or other object) progress. Long-term forecasting, like other forecasting types, plays an important role when implementing economically profitable strategies but can also contribute to solving environmental problems or developing recommendations for their solution. For example, when forecasting electricity consumption, it is necessary to take into account the industry decarbonization strategy and other factors that affect the consumption and production of electricity in the long term.

The researchers note that in order for the forecast of electricity consumption to be reliable, the forecasting horizon should be no more than three or five years, which is described in works Refs. [4,111–128] devoted to long-term forecasting.

One of the best ways to obtain an accurate forecast of electricity consumption for a year or several years is to use the rank analysis methodology described earlier. The rank analysis advantages include the fact that the initial time series of power consumption are sufficient for forecasting, and they do not require additional factors affecting power consumption. This feature makes this methodology unique in solving such problems. Let us consider a study consisting in long-term forecasting of the power consumption of a complex system considered to be a technocenosis.

In Ref. [111], the study consists of predicting the power consumption of objects of socioeconomic systems based on the rank norm values. The author has developed an algorithm for predicting power consumption based on the rank norm values as developing the methods of the vector rank analysis theory. In the first stage, the initial power consumption data are imported, sorted, and verified and a tabulated rank distribution, which is then presented in a vector rank space, is formed. The next step is the calculation of the rank norm. According to Ref. [111], "a rank norm is a non-negative functional given in a vector rank space, generalizing the concept of a vector length or an absolute value of a parameter". Next, a matrix of rank norms is constructed for each radius vector of the vector rank distribution used in forecasting. At the end of the algorithm, the reverse recovery procedure of predictive rank norms for the values of power consumption is performed. The average relative annual errors of the algorithm for predicting the values of rank norms for 2017, 2018, and 2019 are significantly lower (by 2.7%, 3%, and 3.3%, respectively) than when using the forecasting method with a fixed first point Ref. [111]. Thus, the results of this study confirm the effectiveness of the rank analysis algorithm in predicting the power consumption of objects of socioeconomic systems.

In Ref. [112], the results of predicting the electricity consumption by industry using the Gray correlation analysis model were presented. The authors developed a predictive model that produced forecasts for three sectors of the Chinese economy: primary, secondary, and tertiary industries. The authors noted that the Gray model allowed the construction of a forecast in the presence of a small amount of data, thereby surpassing classical forecasting methods (autoregressive, etc.). The researchers emphasized the importance of having an accurate forecast when planning strategies for the effective development of industrial production. The model developed in Ref. [112] took into account socio-economic factors affecting industrial production, such as the volume of gross domestic product per capita, the total population of the country, the level of urbanization (%), the share of the primary industrial sector (%), the share of secondary industrial industry (%), share of tertiary industry (%), and total carbon emissions (billion tons). When modeling various scenarios for China's development, socioeconomic indicators were considered. For each such scenario, forecasts for 2021–2030 were created separately for each sector of the economy. The power consumption data on industry and socioeconomic indicators for the period from 2011 to 2020 were used to forecast.

The study Ref. [113] describes the power consumption modeling using classical machine-learning algorithms (support vector machine SVR, Random years RF) and deep learning (nonlinear autoregressive exogenous neural network (NARX) and LSTM)). According to [100], the forecast was built for 2019 based on hourly power consumption data for 2010–2018 and meteorological data. To assess the forecast accuracy in Ref. [113], the determination coefficient, the root mean square error (RMSE), and the mean absolute error in percent (MAPE) were used. Using the NARX model, the most accurate forecast was obtained; MAPE was 4.2%. However, the researchers noted the need for additional research to be able to recommend the constructed model as the best of the four considered.

The work Ref. [114] proposed a model for predicting annual electricity consumption using a hybrid model. The authors developed a model based on the least squares support vector machine (LSSVM) algorithm. To find the optimal parameters of the LSSVM algorithm, the evolutionary fruit fly optimization algorithm (FOA) was used. The model obtained by the authors in Ref. [114] had an advantage over regression models, the LSSVM model without additional application of metaheuristic approaches to parameter optimization, and other methods. FOA is a powerful evolutionary approach to solving the problem of finding the optimum of a function with a continuous domain of definition, also confirmed in the study described in Ref. [114].

The authors in Ref. [115] demonstrate study results consisting of long-term forecasting of electricity demand in Azerbaijan. The authors note that since the country is rich in energy resources (oil), real (non-oil) GDP data are used to study the electricity demand. In Ref. [115], electricity demand up to 2025 is modeled based on data for the period from 2006 to 2010. According to researchers, the results obtained should be taken into account when developing strategies for the state development.

Of particular interest is the expert analysis using the Delphi method carried out in Ref. [126]. The authors conducted scenario modeling of the sustainable development of energy supply in the Arctic until 2035. The simulation results show that in all scenarios, up to 50% of the energy balance in 2035 will be accounted for by gas, but the role of carbon-free energy sources will increase. The main objects considered in the study, the power consumption of which must be provided, are: military bases, hydrocarbon deposits, and deposits of rare earth metals, settlements (single-industry towns), research bases, logistics clusters, medical bases, agricultural complexes, tourist bases, and data processing centers.

The mathematical model made it possible to predict the demand for energy types of individual types of consumers, which makes it possible to determine the vector of development and stimulation of certain types of resources for energy production in the

Arctic. The model allows us to take into account not only the growth but also the fall in demand for certain categories of consumers under various scenarios Ref. [126].

Table 4 shows the results of a comparative analysis of some methods of long-term forecasting.

Thus, all long-term forecasting methods can be divided into those that use different development scenarios (individual industry, region, state), taking into account economic indicators, and those for which there is enough data on electricity consumption for previous years. The first category includes models based on using various architectures of neural networks, including hybrid models, using Gray correlation analysis, etc. These methods assume the presence of GDP, GNP, and other macroeconomic and microeconomic indicators, which in turn are also predictive values. Therefore, usually with the help of such models, a series of forecasts is obtained, taking into account various development scenarios. The second category of methods includes power consumption modeling when using the rank analysis apparatus. A static model of power consumption is built based on retrospective data and then on a dynamic model of power consumption. With the help of a dynamic model, a long-term forecast for developing a large infrastructure facility, considered to be a technocenosis, is obtained. The forecast is obtained according to two scenarios: taking into account the implementation of energy saving measures and without taking energy-saving measures. To build dynamic and static models of power consumption, a number of specific rank analysis procedures are performed, described in detail in Ref. [96].

It should be noted that both categories of methods conventionally separated by us are actively used in long-term forecasting and are a prospect for further research.

Long-term forecasting takes into account a number of indicators of socio-economic, technological development, etc., which, in turn, are themselves forecasted values. Therefore, modeling based on several scenarios is an important tool in making strategically important management decisions. In addition, the methods of expert assessments (Delphi, questionnaires, etc.) in modeling such scenarios are decisive since they allow us to determine the vector of development of electricity consumption from the point of view of the opinions of highly competent specialists.

Thus, when analyzing the methods used in long-term forecasting of electricity consumption, there is, firstly, a significant share of the influence of a human expert on the production of the forecast and secondly, the need to apply a systematic approach when taking into account factors affecting the annual amount of electricity consumption of objects of different scales (states, regional power systems, large industrial facilities or organizations, etc.). Therefore, it is unacceptable to use poorly interpreted methods, such as the use of neural networks (without building additional models explaining the results of neural network modeling) for long-term forecasting of power consumption. The creation of hybrid expert forecasting systems that support a human–machine interface is promising. A large share of human participation in determining scenarios for the development of energy consumption allows, based on these data and taking into account retrospective development scenarios, the development of a forecast using modern forecasting methods (numerical methods, neural networks, etc.).

Table 4. Analysis of methods used in long-term forecasting of electricity consumption.

Method	Scope of Application	Forecasting Error		Identified Problems	Advantages of the Method	The Possibility of Using the Model to Solve Problems of Medium-Term Forecasting	Main Publications	Initial Dataset	Performance (Forecast Execution Time, s)
		%	Estimation (+/−)						
A method based on the values of rank norms	Socioeconomic systems of the regions of the Russian Federation	4.87	+	The complexity of the mathematical apparatus. The need for competencies in the field of rank analysis of technocenoses.	Obtaining a reliable forecast without the need to take into account factors affecting power consumption.	The model can be applied for medium-term forecasting.	[111]	Monthly data on regional electricity consumption Russia for eleven years from 2009 to 2019	No information available
Deep Neural Network with Fuzzy Wavelets	Urban Buildings	–	+	The complexity of the mathematical apparatus. The complexity of evaluating the results of forecasting.	A small number of rules and less complexity of the model compared to a fully connected neural network.	The model can be applied for medium-term forecasting.	[120]	Electricity consumption in Tehran, Mashhad, Ahvaz, and Urmia from 2010 to 2021	50
Delphi	The Arctic Energy System	–	+	Subjectivity of expert opinions. The complexity of evaluating the results of forecasting.	There are three reasonable scenarios of development: positive, negative, and neutral. Taking into account many risks when developing scenarios. Analysis of consumers by energy consumption level.	More research is needed.	[126]	Expert assessments	No information available
Gray Model	China's Industries	–	+	The complexity of evaluating the results of forecasting.	A small amount of the initial sample is necessary for forecasting. Consideration of socio-economic development scenarios.	Not applicable	[112]	Data on the level of production, urbanization and socioeconomic development for 2011–2020	No information available
Nonlinear autoregressive exogenous neural network	Regional municipalities	4.2	+	The complexity of selecting hyperparameters of the model	Prediction accuracy. The possibility of using the method for other prediction intervals. The ability to scale the model taking into account new factors.	It is possible to build a forecast for the short and medium term.	[113]	The dataset includes hourly load demand data for nine years for Bruce County, Ontario, Canada combined with climate information (temperature and wind speed) for 2010–2018 (forecast made for 2019).	960

4. Conclusions

As a result of the literature review, a large number of sources have been analyzed, reflecting the current state of the problem of electricity forecasting for various subject areas of electricity use. The methods used in forecasting electricity consumption have been studied, taking into account their classification according to the anticipation period.

As the introduction states, there are no universal methods that guarantee an accurate forecast of electricity consumption without considering the initial data specifics and factors affecting electricity consumption. It has been revealed that modern methods, such as machine-learning algorithms, do not always give better results compared to classical forecasting approaches. It is also worth noting that the involvement of researchers in the work on the task of forecasting power consumption for a variety of objects is growing, such as from office buildings to regional or state forecasting. Moreover, the task is relevant for all areas—production, consumption, and services.

According to many scientists, there are more than 200 methods for predicting electricity consumption, of which only a small number are original methods used in isolation from each other. The rest of the methods are a combination of several approaches or a modification of existing methods. This is due to the fact that each specific task of forecasting power consumption has a number of specific parameters and that it is necessary to adjust the existing methods or develop new ones to obtain a reliable forecast. Therefore, hybrid forecasting models, intelligent data processing technologies, rank analysis, and a combination of other methods are currently quite widespread.

For almost a century, researchers have been working on the problem of forecasting electricity consumption, and this field of study has not been yet exhausted. On the contrary, there is a significant increase in the number of studies in this area. Forecasting the consumption of electrical energy is relevant at all levels of management (strategic, tactical, and operational). This causes interest in improving the methods used for operational, short-term, medium-term, and long-term forecasting of power consumption.

When analyzing the forecasting methods at all relevant levels, there is a tendency towards the active use of neural networks. This trend has arisen because neural networks allow the taking into account of the non-linear nature of power consumption data and finding non-trivial dependencies in them. All this allows improvement of the accuracy of operational, short-term, medium-term, and long-term forecasting of electricity consumption.

The systematization of methods for forecasting electricity consumption based on forecast anticipation period allowed us to identify the following patterns. Firstly, for operational and short-term forecasting, intelligent methods (fuzzy logic, neural networks, various methods of time series decomposition, and probabilistic forecasting methods) are most often and actively used. This makes it possible to notice that for these prediction classes, the requirement for interpreting the result is quite low. That is, the forecast itself, and its accuracy, are more important than its mathematical justification. In these types of forecasting, there are many publications confirming the idea that machine learning algorithms cope with the forecasting task better than an expert or traditional approaches, such as linear regression and moving average. Therefore, we consider the use of models of the so-called "black box" relevant and promising for operational and short-term forecasting. On the other hand, in the medium- and long-term forecasting, there is also a large proportion of the use of intelligent methods. At the same time, however, the degree of interpretation of the results obtained in forecasting is very high. Therefore, expert opinion regarding the results of the forecast, and often for the preparation of initial data for the forecast (in the case of long-term forecasting), is decisive.

The analysis of the data has shown that at present, sufficient analysis is not provided, specifically for industries. At the same time, there are examples of buildings, sewage treatment plants, and mining quarries, but there are no classifications proving that certain methods are better for a particular industry. Each method is selected and configured individually according to the source data. In this regard, it is extremely important to conduct analytical research in this direction in relation to the fundamental industries.

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