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HYBRID APPROACH TO THE FORECASTING OF ELECTRIC CONSUMPTION TIME SERIES FOR ORGANIZATIONAL MANAGEMENT IN THE WHOLESALE MARKET

Abstract: The improvement results of the hybrid approach to design of time series forecasting models with an uneven distribution of values of the electric consumption indicator in solving organizational management problems in the wholesale electricity market are presented.

Keywords: hybrid approach, time series forecasting, electric consumption processes, organizational management, wholesale electricity market.

Introduction

The problem of a significant increase in the energy efficiency of using electric energy - electric consumption is one of the main problems at the current stage of development of the electric power industry. The possibility of its effective implementation is directly related to the solution of the complex of tasks of managing electric consumption planning by electricity supplier companies - subjects of the organizational management system of the wholesale electricity market (WEM) [1].

These tasks also include the preparation of a daily schedule of electric consumption by wholesale suppliers, which they must submit to the WEM in the form of an hourly request for the amount of electric consumption in accordance with the regulations of its Rules. This schedule is used as input data for the sequential solution of subsequent tasks of the organizational and operational dispatch management aimed at ensuring reliable and cost-effective coverage of the declared volume of capacity by generating companies - electric power producers.

The technological process of electric consumption planning includes two levels. At the first level, planning is carried out directly by enterprises - end users. At the second level, planning is carried out by electric suppliers based on the use of data on the forecast of electric consumption received from enterprises of the first level. The plan of electricity consumption drawn up by them is drawn up in the form of an application and is submitted to the WEM at the time of day determined by the regulations.

The problem of planning electric consumption has been studied for many years in relation to enterprises in various industries. And in recent years, quite a lot of works has been devoted to solving this problem, as applied to the peculiarities of their functioning in market conditions [2-5]. The proposed methods of planning electric consumption are currently used in many industrial enterprises. Usually they are focused on a certain period of time during which no significant changes in production volumes occur in accordance with the prevailing conjuncture in the industry markets.

However, the peculiarity of market relations is that these changes may occur at different times in different industries. Therefore, to solve the problem of planning electric consumption, it is necessary to apply methods that use mathematical and information technological tools for the current assessment of electric consumption, taking into account the influence of market conditions on the functioning of enterprises [6]. The issues of systematization, analysis of existing methods of electric consumption planning at enterprises of various sectors of the economy and the creation of sound calculation methods that meet modern requirements for the accuracy of electric consumption planning is the subject of an self study. And in this paper they will not be considered.

The forecast data of electric consumption of a separate regional supplier constitutes the basic source information for carrying out all subsequent calculations in forecasting and planning deliveries by electricity producers to the WEM with the aim of forming trading and dispatching active load schedules for the «day-ahead» market [7].

1. Problem analysis and formulation of research objectives

In condition of operation of the electricity market, which received the meaningful name of the bilateral contracts market and the balancing market, mechanisms are provided to compensate for additional expenses in the power system by those suppliers whose declared volumes exceed the absolute value of the tolerances from actually volumes of consumed electricity. This circumstance should encourage electricity suppliers to use modern tools for modeling and forecasting electric consumption, used in the preparation of hourly planned electric consumption schedules for the next day to improve the quality of the forecast. Such hourly electricity planning based on the use of modern forecasting tools by suppliers is of interest not only for them, but also for large enterprises - qualified end-users of electricity.

When solving the problem of daily electric consumption planning at the level of electricity suppliers, certainly, a more detailed structure of electric consumption in the region of a particular supplier should be taken into account. According to various studies, it is the daily irregularity of electric consumption, along with seasonal irregularity, that largely determines the forecasting accuracy of electric consumption schedules [8].

The structure of the regional industries for a separate supplier is usually known. Planning of electric consumption by suppliers, taking into account the peculiarities of electric consumption in the production process by enterprises of these industries, is a rather difficult task [9]. Quite a large number of papers, the analysis of which is given in [10], are devoted to research related to electric consumption planning at the supplier level. Basically, they are designed to solve very important and complex tasks of medium-term and long-term forecasting of electric consumption. However, not always the data of such a forecast can be used to plan electric consumption for the coming day.

Determination, further study and consideration of the multifaceted influence of deterministic, quasi-deterministic and random factors on the results of electric consumption forecasting, in order to improve their quality, necessitates the development of new tools for mathematical and computer modeling based on the integration of statistical analysis methods, expert and artificial intelligence methods.

Therefore, the main objective of this paper is the development of mathematical modeling tools for dynamic, operational hourly forecasting for the coming day and planning electric consumption by electricity suppliers a day ahead in the wholesale market.

Currently, in many power systems of the world, when creating forecasting models, statistical methods are used to analyze dynamic time series, reflecting an ordered sequence of observations of a time-varying process [11]. Their practical implementation to reduce the error of calculations requires the collection, storage and further use of significant amounts of the original historical data of hourly actual electricity production. And to identify and correct errors, maintain a certain level of correctness, the implementation will require taking into account other factors that affect the forecast result, and as a result, the use of additional data.

An analysis of a number of studies carried out in [12] allows us to conclude that there is no universal method that could solve the problem of forecasting the characteristics of random processes of various natures. However, approaches have been developed, the use of which in solving specific applied problems makes it possible to build a prognostic model that provides reasonable reliability and accuracy for practice [13].

One of these is an approach based on the use of hybrid methods for constructing the forecasting models. To determine the numerical values of the predicted values at given points, an unformalized mathematical model of the required dependency is used, the constructing possibility of which is provided by applying a hybrid computational algorithm based on the joint use of the artificial neural network apparatus (ANN) and the genetic algorithm (GA). The experience of developing and applying such a technique for building the forecasting models is described in [14]. However, the quality of ANN application essentially depends on the completeness and reliability of the training sample, which is formed from the prepared initial retrospective data. Therefore, retrospective data must be first processed, i.e. filtering and normalization to ensure the specified conditions of use.

The aim of this paper is to improve the hybrid approach to the development of non-formalized mathematical models of electric consumption forecasting of a large regional supplier based on the combined use of modern information technologies deals with the ANN apparatus, GA and Kalman filters, which provide the required quality level of the forecasting process.

The need to improve the quality of forecasting the production and consumption of electricity is due not only to technological, but also economic reasons that are no less important in the conditions of market competition.

2. Time series formalization of electric consumption processes

As it is known, many authors [15] use the so-called additive form of the model to solve the forecasting problems of electric consumption and active load:

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$$P(t) = U(t) + V(t) + C(t) + E(t),$$

where $P(t) = (P^{act}(t_i^j) \mid i = \overline{1,N}, j = \overline{1,24})$ is a generalized time series of the actual hourly values of electric consumption (for *j*-th hour of the *i*-th day) of a regional company that supplies electricity for *N* days; $U(t)$ is a trend component; $V(t)$ is a seasonal component; $C(t)$ is a cyclic component; $E(t)$ is a random component of the time series.

The selection of interrelated trend, seasonal and cyclical components of the time series is a separate and very difficult task. The assumption of their additivity in the distribution, and further use of these components for solving problems of electric consumption forecasting, may introduce an additional error, which is difficult to take into account. Therefore, in this paper, in order to solve the problem of forecasting electric consumption, studies have been conducted of the possibility of using the time series model in the form:

$$P(t) = F(U(t), V(t), C(t)) + E(t),$$

where $F(U(t), V(t), C(t))$ is a unknown function of the three components.

To determine the numerical values of the predicted values at given hour points *j*, we will use a non-formalized mathematical model of the unknown function *F*, the possibility of constructing which is provided by applying a hybrid computational algorithm based on the sharing of the ANN apparatus, GA and Kalman filter.

Obviously, the members of the time series formed from the actual electric consumption data, in addition to the trend, seasonal, cyclical components, also contain a random component, which reflects the influence of hard-to-count factors on the electric consumption process. Its presence in the training sample data when building an ANN can significantly affect the result of network training, and, therefore, the quality of the forecast. Therefore, before using the actual data for the training process of a neural network, it is necessary to carry out their preliminary preparation as filtering, in order to eliminate the influence of random parts of the time series members on the training process.

It is known that the use of statistical methods for these purposes provides only the alignment of the time series components. At the same time, their random components are definitely distributed, but not separated from the main component. Therefore, at this stage of the study, a simplified version of the Kalman filter [16] was used to filter the time series members in order to precisely separate the random component of the time series components.

An example of the manifestation of a random component can be the case when an unknown value of the control action of the dispatch control of electric consumption leads to a deviation of the actual dispatching schedule of electric consumption from the planned one. We will carry out the further reasoning for a one-dimensional time series constructed for the *j*-th hour for *i* days of observations.

Let $X_j = (P^{act}(t_i^j) \mid i \in I)$ is the actual electric consumption data of the *j*-th hour for *I* days and $Y_j = (P^{pred}(t_i^j) \mid i \in I)$ is the forecast electric consumption data and $Z_j = (P^{plan}(t_i^j) \mid i \in I)$ is the planned schedule of electric consumption.

According to the WEM Rules, the planned schedule of electric consumption is compiled on the following day based on the data of the electric consumption forecast by large regional consumers and suppliers taking into account the meteorological conditions for the next day, current and retrospective weather conditions, actual data of electric consumption in previous periods and other external factors that may affect on electric consumption process. The actual schedule of electric consumption is implemented on the basis of the planned schedule by dispatch center during the implementation of the centralized operational and technological management of the integrated power system. Dispatch center on the basis of the online network status information and producers accident information should change the specified planned schedule. As a result, we present the forecast, planned and actual data of electric consumption in the following form:

$$Y_j = F^Y(U_j, V_j, C_j),\ Z_j = F^X(Y_j) + E_j^X,\ X_j = Z_j + D_j,$$

where F^X, F^Y are the values formed from the main components of the time series of the actual and forecast electric consumption schedules, E_j^X is the random component of external factors affecting the electric consumption process, D_j is the random component of the deviation of actual dispatch schedule from the planned one.

It is necessary to select time series of actual data, the filtered components of which do not contain random components. Denote this data as $X_j^{main} = X_j - E_j^X - D_j$, which will be used for training the neural network.

To form the series X_j^{main}, we will use the simplified Kalman filter of the following form:

$$X_{j+1}^{main} = K * X_{j+1} + (1-K) * X_j^{main} \tag{1}$$

The coefficient K must be determined from the condition $\min |X_{j+1}^{main} - X_{j+1}|$. At the same time, we will take into account the fact that the actual electric consumption data is much more accurate than the forecast one, although they contain a random component. Based on the same considerations, we assume that $X_1^{main} = K * X_1 + (1-K) * X_1 = X_1$. And all the following components of the desired series are determined by the formula (1).

3. Technique for constructing a non-formalized hybrid forecasting model

In general, the electric consumption forecasting model is represented by the following dependency:

$$P^{pred}(t_i^j) = F\left(P_{main}^{act}(t_{i-1}^j), \ldots, P_{main}^{act}(t_{i-n}^j), T_i\right),$$

where $P^{pred}(t_i^j)$ is the forecast value of electric consumption, $P_{main}^{act}(t_{i-1}^j), \ldots, P_{main}^{act}(t_{i-n}^j)$ are the filtered actual values of electric consumption for $n \in N$ previous days of observations, T_i is the set of external factors affecting electric consumption.

The use of external factors in forecasting improves the accuracy of the forecast. In this case, the more factors taken into account, the higher the accuracy of the forecast. The categories of groups of days of the week, temperature and climatic factors, seasonality, etc. are considered as external factors.

Taking into account the fact that on different days of the week, electric consumption schedules may differ significantly, we select from the series $P(t)$ the following sample of values for groups of days of the week, during which daily consumption schedules can be taken such that they have approximately the same, both quantitative and qualitative changes:

1) $X^M = \left(\left(P_{main}^{act}(t_i^j) \mid i \in I^M \right) \mid j = \overline{1,24} \right)$ is an array of 24 time series for mondays and before holiday days I^M;

2) $X^W = \left(\left(P_{main}^{act}(t_i^j) \mid i \in I^W \right) \mid j = \overline{1,24} \right)$ is an array of 24 time series for working (regular) days I^W;

3) $X^H = \left(\left(P_{main}^{act}(t_i^j) \mid i \in I^H \right) \mid j = \overline{1,24} \right)$ is an array of 24 time series for weekends and holidays I^H.

A distinctive feature of the proposed technique for building a hybrid forecasting model is that for each selected group of days, a separate sample of 24 daily-hour time series is constructed on actual historical data on electrical consumption for a certain number of days, which is determined by the forecast quality requirements. Moreover, a mathematical model of the total daily consumption $\widetilde{Y}^r = \left(\sum_{j=1}^{24} P_{main}^{act}(t_i^j) \mid i \in I^r \right), r \in \{M, W, H\}$ for each of the days of the selected group’s r is being built simultaneously.

The idea of building such a horizontal-vertical structure (Fig. 1) of a mathematical model of a time series system was used in [17, 18]. The choice of just such a method of forming a sample of initial data is due both to the technological features of the wholesale electricity market operation in its purchase mode for the day ahead, as well as the methodological features of building a neural network model when choosing an activation function and the need to check the adequacy of network training in the hourly and daily consumption for each selected groups of days.

Thus, for the purpose of forecasting electric consumption of a regional supplier, it is necessary to form three groups of time series X^r - training samples of 24 representative hourly series in each, as well as three series $\tilde{X}^r$ - daily volumes of actual electric consumption for training in the corresponding neural networks.

Next, the GA is used to search for a solution to the optimal ANN topology in order to accelerate the process of its learning. Using the GA, a population of neural networks is distinguished in which each individual represents a separate ANN [19]. During population initialization, one half of the individuals are randomly assigned. The genes of the second half of the population are defined as the inversion of the genes of the first half of the individual (genome). This allows to evenly distributing the bits "1" and "0" in the population to minimize the likelihood of early convergence of the algorithm.

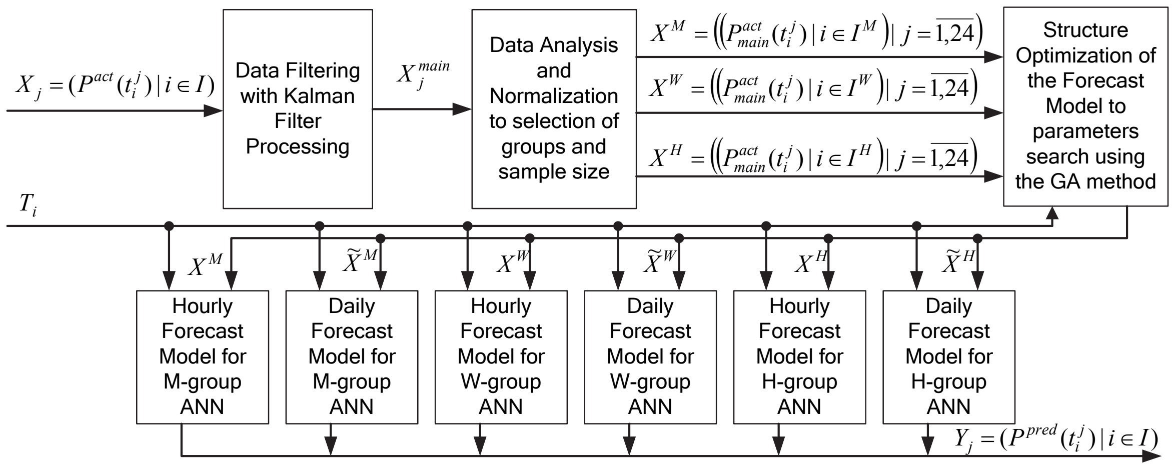

Fig. 1 Hybrid scheme of a complex of mathematical tools for constructing generalized nonlinear multifactor models

After initial initialization, networks without hidden neurons are encoded in the genes of all individuals. Moreover, all input neurons are connected to each output neuron. That is, at first all presented ANNs differ only in weights of interneuron connections. In the evaluation process, based on the genetic information of the individual being considered, a neural network is first constructed, and then its performance is checked, which is determined by the individual's fitness. After evaluation, all individuals are sorted in order of decreasing fitness. A more successful half of the sorted population is allowed to cross. And the best individual immediately goes into the next generation. In the reproduction process, each individual is crossed with a randomly selected individual from among the selected individuals for crossing. Two formed descendants are added to the new generation. After the new generation is formed, the mutation operator starts working. Since the selection made by cutting significantly weakens the diversity within the population [20] and leads to the early convergence of the algorithm, the probability of mutation about 15-25% is quite large. If the best individual in the population does not change for more than 7 generations, the algorithm is restarted. During the restart, the entire population is reinitialized and the process of finding a solution starts from the beginning. Thus, there is a way out of local minima due to the relief of the objective function, as well as a large level of individuals in one generation [21].

A distinctive feature of this algorithm is that the number of hidden neurons is theoretically unlimited, unlike the one proposed in [21, 22]. To regulate the size of the resulting networks, two coefficients are used, which allow, at the mutation stage, to adaptively choose which type of structure transformation is more suitable for this network.

In practice, several methods are used to encode information about the neural network in the individual’s genotype [23]. The presented algorithm uses link coding. In addition, each gene contains information about the indices of the initial and final neuron of the link, as well as the weight of their link (Fig. 2).

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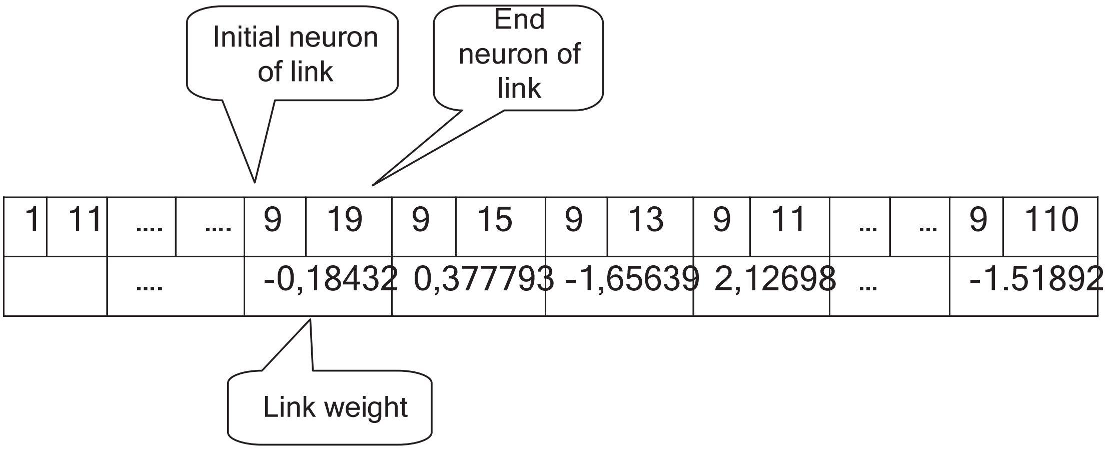

Fig.2 ANN Coding

It is obvious that the chosen coding technique requires special genetic operators that implement crossing and mutation. When performing the crossing, two parents are used, which produce two descendants. Common neurons and links are inherited by both descendants, and the value of links in the network of descendants is formed using a two-point crossover [24]. ANN elements that differ are distributed among descendants. The example of crossing is shown in Fig. 3. The solid lines show the common neurons and links, the dotted ones are those that differ. An important feature is that neurons with the same indices are considered identical, despite the different placement and number of links in the network. It is also important that one of these neurons may have a different index, which will change as a result of the correction of the indices after mutation.

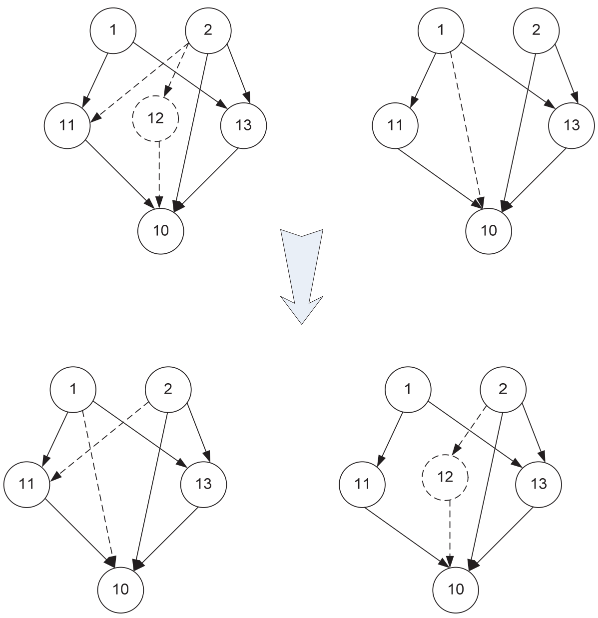

Fig.3 Example of Crossing

Mutation can be of several types:

- adding a hidden neuron with the assignment of the index [*N*-1], where *N* is the number of hidden neurons in the network after the addition;
- deleting a randomly selected hidden neuron along with all input and output links;
- adding a link;
- deleting a randomly selected link;
- changing in the weight of a randomly selected link by a random value from the range [-0.5; 0.5].

Thus, using a mutation, one can change the parameters of the ANN structure point by point. Accidental addition or removal of neurons and links can lead to situations where there will be many neurons and few links in the network. Therefore, it will be more logical to apply different types of mutations depending on the characteristics of the network architecture that an individual represents after a mutation. To do this, you must enter the coefficients that regulate the size and direction of network change.

One of them characterizes the degree of "connectivity" of neurons in the network and is calculated by the formula:

$$f_C = \frac{N_C}{2^{FB-1}\left[N_N(N_N-1) - N_I(N_I-1) - (1-FB)N_O(N_O-1)\right]} \tag{2}$$

where N_C is the number of links in the network; N_I, N_O, N_N are the number of input and output neurons and the total number of neurons in the network, respectively; FB is the flag indicating the presence ($FB = 1$) or absence ($FB = 0$) of feedback.

It is worth noting that links from hidden neurons to output neurons may appear randomly. Thus, the smaller the coefficient f_C, the more likely a new link will be added as a result of the mutation.

The use of the second coefficient is based on the assumption that the more elements as a result in the input and output vectors of the training sample (input and output neurons), the more likely it is that a more complex network will be required to solve the problem. The second coefficient is calculated by the following formula:

$$f_N = \frac{N_I + N_O}{N_N} \tag{3}$$

Thus, the more neurons in the network, the lower the coefficient f_N will be, and, consequently, the less likely the mutation will be chosen, which will add a new hidden neuron.

The algorithm uses a pack of coefficients $f_N * f_C$ in order to take into account the degree of connectivity of already existing neurons.

Deleting links in the ANN generates a side effect: “hanging” neurons may appear that have no input links, as well as “dead-end” neurons that do not have output links. In such cases, when the value of the neuron activation function is not zero for a zero weighted sum of its inputs (for example, logistically and sigmoid function), the presence of “hanging” neurons provides the ability to adjust the neural displacements. On the other hand, it should be noted that the removal of links can help to remove some non-informative or little informative input attributes (neurons) and thus optimize the structure of the ANN and improve the quality of its learning.

Conclusion

As show analysis of the use of modeling methods in solving the problem of choosing and building a model for forecasting electric consumption confirms the thesis that it is impossible to build a universal prognostic model devoid of the shortcomings of individual modeling methods. As a result, preference is given to the approach to the hybrid use of a complex of mathematical tools based on the apparatus of ANN, GA, Kalman filters for constructing generalized nonlinear multifactor models, which will increase the efficiency of the process of their construction and subsequent use for searching both short-term and long-term forecasts.

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