International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 23 (2017) pp. 13834-13842
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Method for Electric Power Load Forecasting Taking into Account Meteorological Factors based on Fuzzy Models

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Abstract

In this paper, we propose a method for electric power load forecasting based on fuzzy time series. The method is based on the decomposition of time series into trend and residual components and consists of the following stages: normalization of time series; decomposition of time series into trend and residual components; fuzzification of input trend variables; obtaining the result of fuzzy inference; defuzzification of output variables; getting the resulting forecast.

Keywords: Electric power load forecasting, fuzzy time series

Nowadays a large number of software tools for Electric Power Load Forecasting have been developed, which propose different methods and various prediction algorithms as well. To predict electrical loads it is important to determine a set of external factors that most significantly affect the process of electric power consumption. These factors are determined either by the method of expert evaluations, or by the use of factor analysis or dispersion analysis. [1] A characteristic set of factors influencing the consumption of electric power are [2]: air temperature, the beginning and the end of daylight hours and values characterizing the weekend and working days.

Influence of air temperature on electric consumption is presented in [1, 3].

There is a relationship between the consumption of electric load and air temperature. Figure 1 shows the graphs of the average daily consumption of electric loads and average daily temperatures for the Smolensk (Russia) electric power system during 2016-2017. According to the graphs presented here, the dependence of the electric power consumption on temperature is constructed for the power system for the period from January the 1-st to December the 21-st, 2015. These dependencies are shown in Figure 2.

The points of dependencies for the power system are approximated by a polynomial of the 6th degree:

$$W(\Theta) = -2\cdot 10^{-5}x^6 - 0.0009x^5 + 0.0438x^4 + 0.5941x^3 - 16.685x^2 - 249.48x + 19467.$$

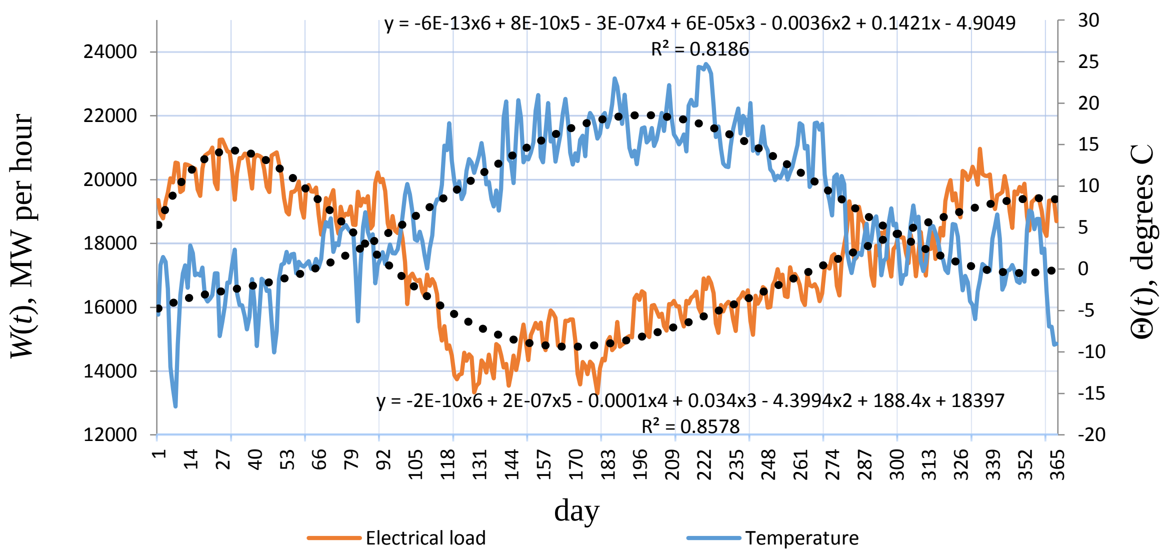

Figure 1: Graphs of daily consumption and average daily air temperature

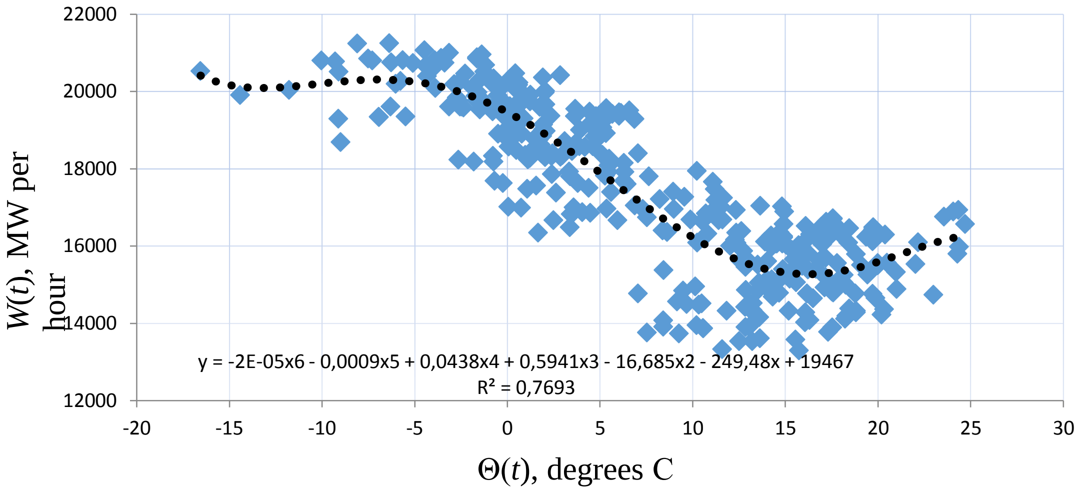

Figure 2: Dependence of daily energy consumption on the average daily air temperature

The relationship between power consumption and temperature can be estimated using the value of the coefficient of determination $R2$ ($0 \leq R2 \leq 1$), which also reflects the value of the approximation reliability. The calculated values of the coefficient of determination of the energy system: $R2$ = 0.77.

The value of the coefficient of determination $R2$ (not less than 0.75) indicates the relationship between power consumption and temperature. The relationship between power consumption and air temperature is explained by the "all-embracing" properties of this meteorological factor, because any changes in meteorological conditions (such as cloudiness, humidity, daylight hours, etc.) are resulted in changes in the daily air temperature flow [4]. All the factors influencing the air temperature affect the complex relationships, and that's why it is difficult to determine and separate the magnitude of the influence of the individual one.

However, thanks to long-term observations conducted for many years, scientists have proven the stable trends described in this section. And the inclusion of air temperature also eliminates the consideration of a number of additional meteorological factors.

The issue of the influence of air humidity on the consumption of electric power has not been sufficiently studied yet.

Figure 3 shows the graphs of the average daily consumption of electric load and average daily temperatures.

According to the presented graphs, the dependence of electric power consumption on humidity was constructed. And it presents the period from January the 1-st to December the 31-st of 2016 year. These indicators are shown in Figure 4.

The points of dependencies for the energy system are approximated by a polynomial of the 6th degree:

$$W(\Theta) = -9 \cdot 10^{-6} x^6 + 0.0036x^5 - 0.6273x^4 + 56.765x^3 - 2828.1x^2 + 7317x - 754248.$$

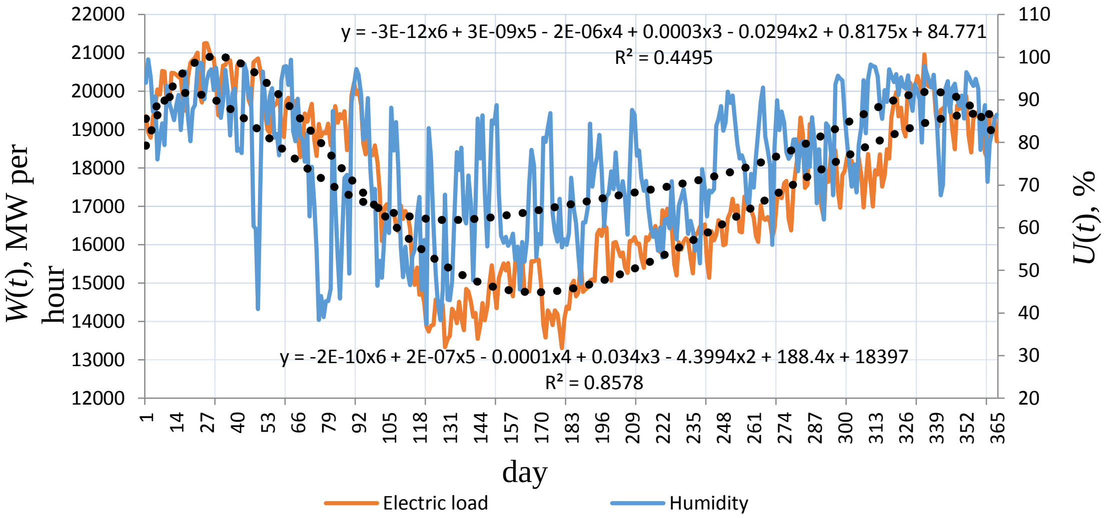

Figure 3: Graphs of daily consumption and average daily air humidity

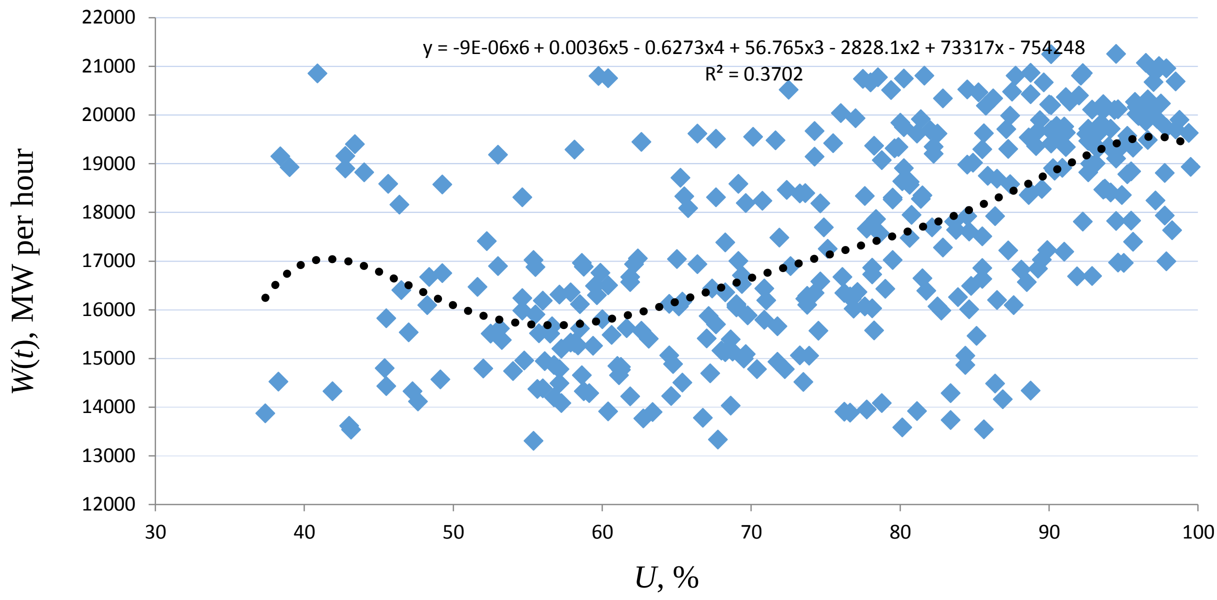

Figure 4: Daily electric power consumption versus daily average air humidity

The relationship between power consumption and humidity can be estimated using the value of the coefficient of determination *R*2 (0≤ *R*2 ≤1), which also reflects the value of reliability. The calculated values of the coefficient of determination of the energy system were made for 2015: *R*2 = 0.37.

The value of the coefficient of determination *R*2 (less than 0.75) indicates the lack of a close relationship between electric power consumption and humidity, at the same time the value of the coefficient *R*2 (more than 0.25) indicates the presence of a connection, the value of which is difficult to establish using statistical models.

A detailed regression analysis of this relationship showed mixed results. More specific results on the relationship between electric power consumption and humidity can be obtained using intelligent prediction models. When solving problems of forecasting electric loads, the object of forecasting is the electric power consumption as a set of processes of consumption of electricity by the entire spectrum of consumers. After determining the method for electric power load forecasting under conditions of uncertainty using classical methods, previously unknown parameters of the predictive model are determined – the dependence of the output parameters on the input parameters of the model.

The vector of the input parameters of the forecast model is the values of the electric power consumption by hours or days, or the values of the consumed electricity for a certain period of time, or the parameters that affect the amount of electric power consumption.

The following requirements are to be applied to the method of electric power consumption forecasting [5]:

- to meet the requirements of adaptability, i.e. to ensure that a wide range of changes, additional data can be taken into account and that the required accuracy is provided;
- to ensure work with a large number of input parameters, the number of which can be changed during the operation;
- to provide the required depth of forecasting;
- to provide for the possibility of verification of data in accordance with the actual consumption of electrical loads.

A perspective direction for solving these problems is the creation of hybrid models which combine the accuracy of the statistical approach with the flexibility and versatility of intellectual methods.

It is often impossible to make an approximation of satisfactory accuracy over the entire area of determining the predicted parameters under abrupt changes in loads in case of the variable nature of forecasting process. So, it is recommended, based on the determination of the moments of change of the selected parameters, to split the entire range of the parameter definition into several local sections, and to build its forecasting model for each such region [6].

The problem of determining the boundaries of such local regions is known as the problem of detecting "disruption". "Disruption", as a rule, is understood as a change in the probable properties of a random process – for example, mathematical expectation or variance. However, for technically complex receivers, such a criterion may give inaccurate estimates of the moment of the disruption.

In such case, it is recommended to use the apparatus of fuzzy time series, which makes possible to divide the time series into trend and residual components.

Trend is a stable change of a parameter over time. The tendency of a time series of electrical load, as a rule, is expressed by some non-random function. The numerical format of the presentation of trend is not always convenient for the expert and does not allow interpreting data in terms of a domain. The residual component (the result of subtracting the trend from the original series) is the discrepancy between the actual and calculated values, which can't be taken into account when forming a trend. The residual component, depending on the nature of the series, can be of a random nature (in this case it is considered as an error, noise), and reflect the influence of factors not taken into account in the trend. In the latter case, the residual component is significant and can also be partially described by a functional dependence.

Due to the mentioned above and based on the classical model of decomposition of the time series, a model of the time series of electrical load consumption is proposed:

$$\langle G, F, U \rangle,$$

where G – is the name of the time series; F – the trend of the local area of the original time series, which can be represented as $F = \langle f(t),\ f(t-1), ...,\ f(t-n) \rangle$, $f(t)$ – the elements of the trend component of the time series; n – the number of elements in the time series; U – residual component of the local area of the initial time series, which can be represented as $U = \langle u(t), u(t-1), ..., u(t-n) \rangle$, $u(t)$ – elements of the residual component of the time series; n– the number of elements in the time series.

The trend is selected using fuzzy or *F*-transform (Fuzzy transform). The fuzzy approximation method has been developed [7], has good approximating and filtering properties, stability related to initial conditions.

Experimental studies show that the residual component of the time series of electrical load often carries some deterministic component.

Varying the step value when using a fuzzy transformation, you can determine the cyclic or seasonal component. Each consumption reading of the electrical load is proposed to be represented as:

$$P(t) = f(t) + u(t),$$

where $P(t)$ – is the predicted value of the time series; $f(t)$ – is an element of the trend component of the time series; $u(t)$ – is the residual component of the time series.

Based on the described time series model, a method for analyzing and predicting the electric load is proposed. The model for forecasting the consumption of electrical loads, determined on the basis of (1), is represented by a triple:

$$TR = \langle T, F, B \rangle.$$

Here is T – the method of decomposition of the time series of electric load, which can be represented as:

$$T = \{T_f, T_b\},$$

where $T_f = \{tf_1,\ ...,\ tf_n\},\ n = [\overline{1,\ N}]$ – is the trend component that can be extracted from the source series using the method of least squares, artificial neural networks, fuzzy transformations, etc.; $T_b = \{tb_1,\ ...,\ tb_n\},\ n = [\overline{1,\ N}]$ – a series of residual components obtained by subtracting the trend component from the original series; N – is the number of elements in the series.

$F = \{A, R, D\}$ – fuzzy rule-based model of type ANFIS for forecasting the trend component[11].

$B = \{A, R, D\}$ – fuzzy model for predicting the residual component. The composition is similar to the neural-fuzzy model for forecasting the trend component. Differences in models are in the set of linguistic terms of output data and output variables and the basis of fuzzy rules.

$A = \{A_1, .., A_n\}$ – a set of input linguistic variables which are located in the first layer and are characterized by a set of linguistic terms: $A_j = \{a_1, .., a_v\}, v = [\overline{1, V}]$, where V – is the number of terms of the j-th linguistic variable; $a_i,\ i = [\overline{1, V}]$ – linguistic term characterized by the membership function.

The membership function can be any function that allows to calculate the degree of belonging of an arbitrary element of a universal set to a fuzzy set [8, 9]. The most commonly used triangle and bell-shaped functions belong to fuzzy sets. The correspondence between the numerical value of the input variable of the fuzzy inference system and the value of the membership function of the corresponding term of the linguistic variable is called the fuzzification process [10].

R – fuzzy rules base, located in the second layer and showing the influence of factors of input variables on the set of logical statements of the type: "IF *x* is *a*, THEN *y* is *B*".

With the help of conjunctions and disjunctions, the fuzzy rule base can be represented as:

$$\bigcup_{p=1}^{k_j} \left[\bigcap_{i=1}^{n} \left(OP_1(x_i, a_i^{jp}) \right) \right] \rightarrow y_p = OP_2(\beta_p,\ d_p),\ j = [\overline{1, m}],$$

where a_i^{jp} – is the linguistic term by which the variable is estimated X_i; OP_1 – is the operator for estimating the membership of the variable x_i to κ for a fuzzy set a_i^{jp}, OP_2 – is the operator of accumulation of conclusions β_p, for each rule p, and the value of the fuzzy term d_p; k_j – the number of conjunct lines, in which the output is estimated by a fuzzy term d_j, $j=[\overline{1, m}]$; m – the number of terms used for the linguistic evaluation of the output parameter y.

D – is the output variable of the fuzzy product model, which is characterized by terms: $D=\{d_1,..,d_m\}$, where m– is the number of terms of the output variable; $d_j = c_{0j} + \sum_{i=1}^{n} c_{ij} \cdot x_i$ – the value of the linguistic term, depending on the input variables x_i; c_{ij} – coefficients of linguistic terms.

The output value of the fuzzy model can be represented as:

$$Y = \sum_{i=1}^{m} y_i ,$$

where m – is the number of terms of the output variable; $y_i = \beta_i \cdot d_i$ – each rule's conclusion ; β_i – normalization of the prerequisites of each rule from the set R.

The linguistic terms of the input and output variables, as well as the rules base, are formed during the learning process, which is described in [11].

It is difficult to assess precisely the influence of factors on the consumption of electric load. Using forecast values in a fuzzy form allows experts to make well informed and weighted decisions, as well as to identify dependencies that can not be determined at first glance.

Nevertheless, it is important for experts a precise value of the electrical load during the selected "horizon" of prediction. Forecasted fuzzy values lead to clarity, applying the defuzzification operation.

The predicted value of the electrical series on the basis of the above presented model in numerical form can be represented by the expression:

$$P_{k+1} = F_k + B_k + \varepsilon_k ,$$

where F_k – is the defuzzification value of the trend component of the time series of the electric load; B_k – is the defuzzification value of the residual component of the time series of the electric load; ε_k – is a random error of prediction.

Based on the time series model, here is a method proposed for analyzing the forecasting of the time series of electrical load consumption, which involves spliting the series into local areas and further working with the current local area. The local trend of the local area with the presentation of data in a linguistic form is predicted. Also in the resulting forecast, the residual component is taken into account, the forecasting method and its parameters are determined on the basis of the characteristics of the current region.

The structural scheme of the forecasting method is shown in Figure 5.

Figure 6 presents the proposed method for analyzing and predicting the values of the time series of electric load consumption. The method is split into several stages.

At the first stage, the data is normalized, which affects the accuracy of predicting the electrical load. Normalization is necessary for the adequate application of mathematical models and computer calculations related to large and small quantities. For the uniform distribution of time series elements, their values are represented in the range [0, 1].

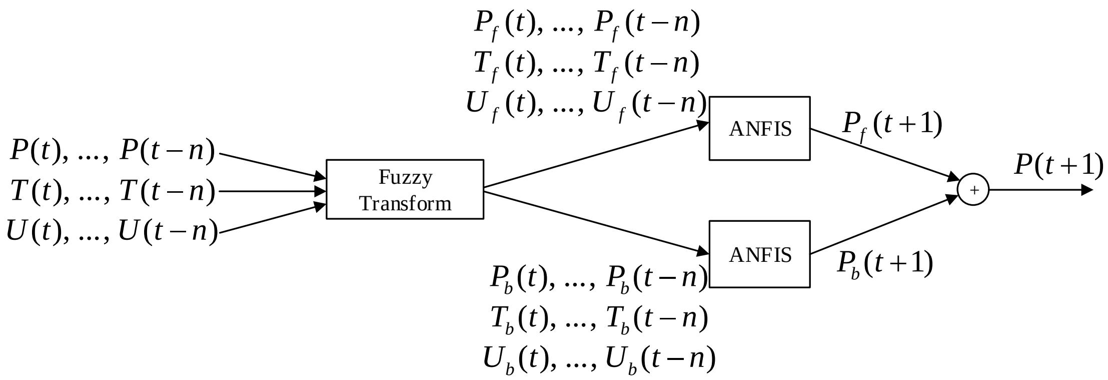

Figure 5: Structural scheme for predicting electrical loads based on fuzzy time series

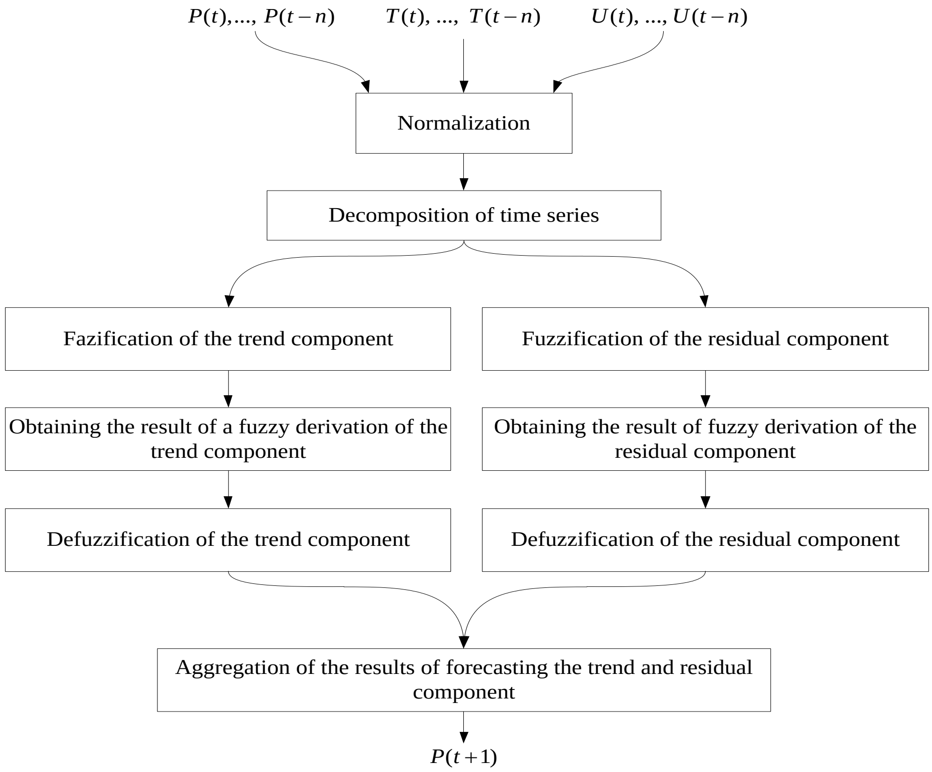

Figure 6: Method for predicting electrical loads based on fuzzy time series

At the second stage, the decomposition of a number of electrical loads into the trend and residual components is performed by the fuzzy splitting.

At the third stage, the input variables of the trend selected in the second stage and the residual component are fuzzificated. The process of fuzzification consists in relating the input variable and the membership function from a certain set of terms to a linguistic variable. The linguistic variable is set directly by the expert or adaptively, when learning on the basis of the training sample.

At the fourth stage, the result of a fuzzy inference is obtained in 3 steps. At the first step, aggregation of sub-conditions is performed, which consists in determining the degree of truth for each rule of the fuzzy inference model. At the second step, the transition from the conditions to the sub-conclusion (activating the sub-conclusion) is performed. For each sub-conclusion, there is a degree of truth. The third step is the accumulation of conclusions. At this stage, a fuzzy set is obtained for each of the input variables.

At the fifth stage, the output variables are defuzzificated. At the defuzzification stage the fuzzy value obtained at fuzzy inference is converted into a precise one. The defuzzification stage is considered complete when for each of the output linguistic variables the final quantitative values will be defined as a real number.

To predict the remainder of the time series of the electric load, a fuzzy conclusion model is constructed, which allows us to take the deterministic component into account.

The number of input neurons determines the required prediction horizon. Depending on the long-term forecast, the input receives information about the current power consumption and power for l previous days $P(t), ..., P(t-l)$ and the index indicating the prediction hour i (1, ..., n), where n = 24, 48. Also at the inputs of the artificial neural network the conditional values characterizing the day are given: working or output. [12] In order to make possible to take into account meteorological factors, the information is sent about current temperature $\Theta(t)$ and humidity of air $U(t)$, temperature and humidity for l preceding days $\Theta(t), ..., \Theta(t-l), U(t), ..., U(t-l)$ as well as their forecast values $\Theta(t+n)$ and $U(t+n)$ accordingly.

At the sixth stage, the resultant forecast is obtained. Summing up the results of the trend forecast and the residual component:

$$P(t+1) = F(t+1) + B(t+1),$$

where $P(t+1)$ – is the predicted value of the electrical load; $F(t+1)$ – predicted value of the trend component of the electric load; $B(t+1)$ – the predicted value of the residual component of the electrical load.

To compare the results of the forecast, artificial neural networks [ANN], neural-fuzzy networks [NNS], real data and the proposed method were used.

To assess the effectiveness of the proposed method for electrical load forecasting on the basis of fuzzy time series, the following tasks are selected:

- operational forecast (see Figure 7);
- short-term forecast (see Figure 8);
- long-term forecast (see Figure 9).

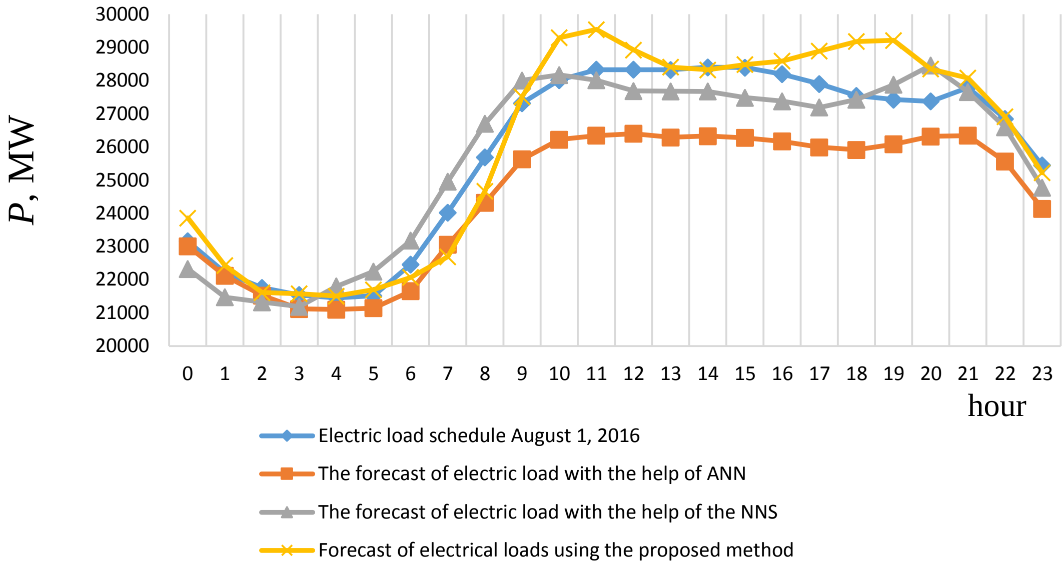

Figure 7: Graphs of electric load forecasts on August the 1-st

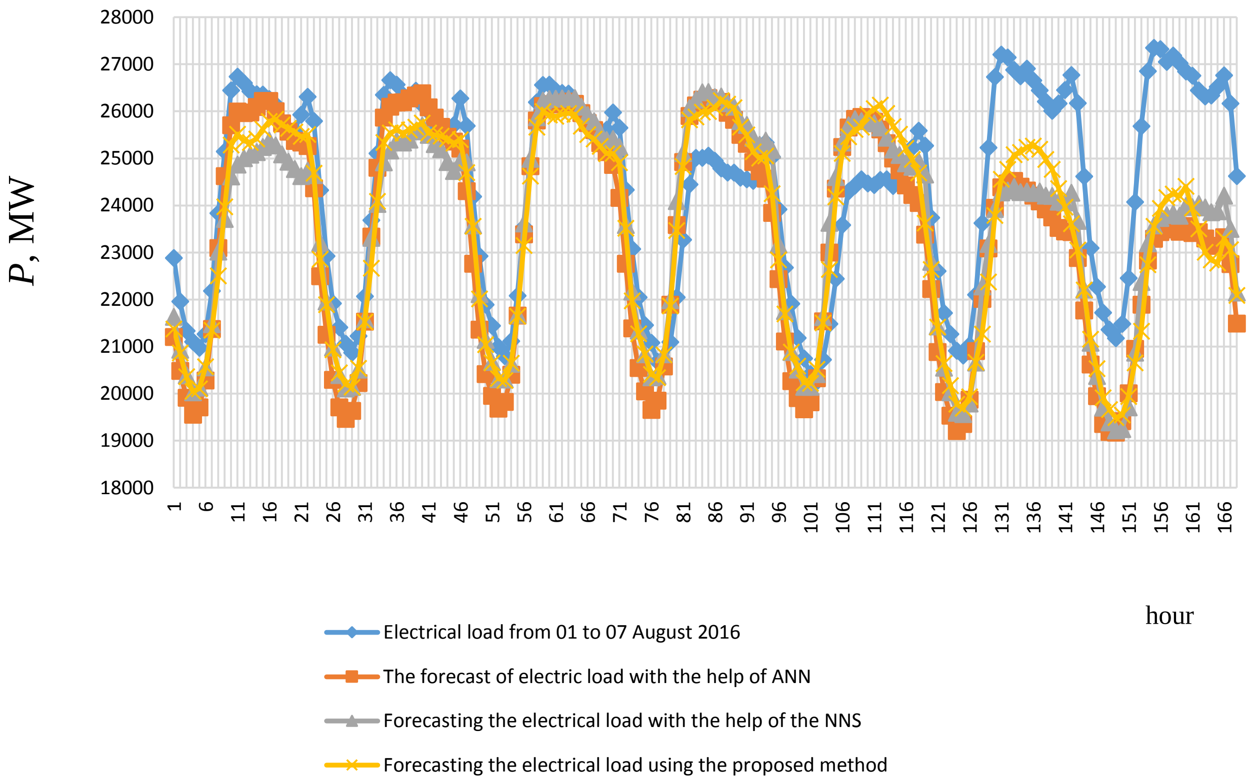

Figure 8: Charts of electric load forecasts from August the 1-st to August the 7-th

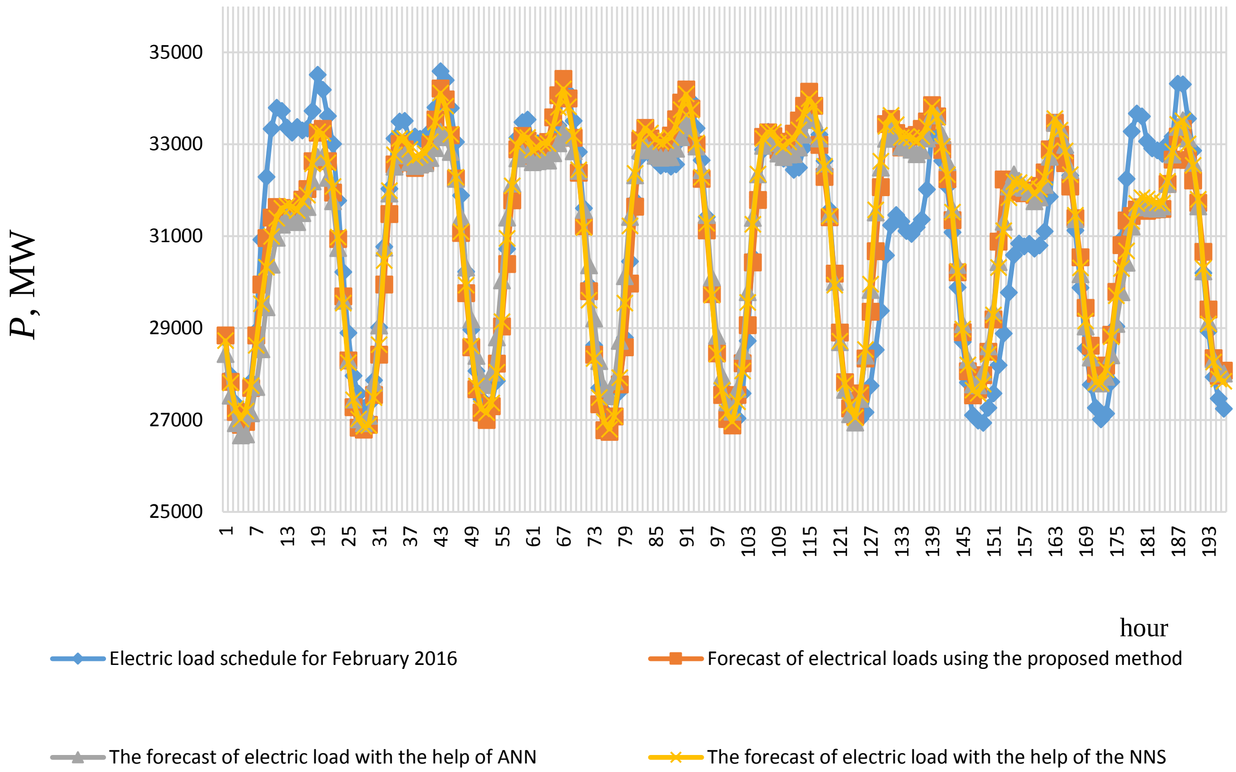

Figure 9: Graphs of electric load forecasts

The results of Electric load forecasting on the basis of various intelligent models are presented in Table 1.

Table 1: Error predicting electrical loads based on intelligent models

The depth of the forecast	Predictive error MAPE, %		
	NNS	ANN	The proposed method
24 (1 day)	4.70	2.36	2,20
168 (7 days)	4.47	4.70	4,44
744 (31 days)	2.73	2.56	2,60

CONCLUSION

The results of the conducted experiments showed that the proposed method allows us to improve the accuracy of operational and short-term Electric Load Forecasting in comparison with the known neural network and neuron-fuzzy prediction models. However, it should be taken into account that the evaluation results can be affected by the characteristics of the estimated electric power systems.

ACKNOWLEDGEMENT

The reported study was funded by Russian Science Foundation, according to the research project No. 16-19-10568.

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