Bulletin of Electrical Engineering and Informatics
Vol. 11, No. 2, April 2022, pp. 602~612
ISSN: 2302-9285, DOI: 10.11591/eei.v11i2.3172

Learning algorithm of artificial neural network factor forecasting power consumption of users

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Article Info

Article history:

Received Aug 9, 2021
Revised Jan 21, 2022
Accepted Feb 24, 2022

Keywords:

Algorithm
ANN
Projected power consumption factors

ABSTRACT

Seasonal fluctuations in electricity consumption, an uneven load of supply lines reduce not only the indicator of energy efficiency of networks but also contribute to a decrease in the service life of elements of power supply systems. Revealing the patterns of such fluctuations makes it possible to build models of power consumption, predict its dynamics, which in general will contribute to ensuring the energy efficiency of urban electrical networks and increasing the reliability of power supply systems. A computational, computer and neural network model is proposed that allows to increase the accuracy of the forecast of electricity consumption by household consumers. Based on the developed mathematical model, taking into account the obtained factor coefficients - t_i, h, c, s, k for 2020 for 9 cities of the Republic of Tajikistan, monthly coefficients characterizing the terrain conditions (α_i) were calculated. The results obtained using the proposed method was compared with the results of a computer and neural network model.

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1. INTRODUCTION

The increase in electricity consumption by household consumers in the absence of provision with other sources of energy (gas supply and heat supply) creates uncertainty for accurate forecasting, thereby creating the problem of maintaining the balance of capacities [1]-[5]. Known methods for predicting electricity consumption by household consumers are based on the presence of a combined source, i.e. the presence of electrical and thermal energy [1], [3], [4]. However, in conditions of inaccessibility (mountainous areas), the supply of gas and heat pipe, both from the point of economy and from the technical feasibility, is ineffective. The same problem manifests itself in residential consumers located in cities and deprived of these sources for some reasons. The proposed solutions to the problems of power supply to household consumers located in hard-to-reach places are based on the use of either a hybrid method of using a centralized and autonomous power supply or only autonomous power supply based on renewable energy sources (RES) due to the number of technically not possible to supply centralized power supply [6]-[12]. At the same time, heat-hot-water supply, depending on the sources, can be generated by the sources themselves (solar provide thermal energy) or through conversion by electric receivers (electric water heaters, electric heaters and electric stoves) when using a mini hydroelectric power plant or a wind farm (wind power plant) as an autonomous source. At the same time, the increase in the variety of household electrical receivers creates the complexity of forecasting in these terrain conditions.

It is known that an incorrect forecast leads to a decrease in the efficiency of both autonomous sources based on RES (due to the complexity of regulating the generated power) and combined sources associated with the complexity of synchronizing two or more autonomous sources with a centralized source (due to the appearance of additional power losses in the centralized network) [13]-[22]. The proposed various methods of improving energy efficiency based on modern means (semiconductor converters designed to improve the quality of electricity) and various methods of increasing energy efficiency due to correct forecasting are primarily applicable either with more or less typical meteorological conditions that do not take into account additional factors, height differences (location of consumers above sea level) and prosperity (the possibility of using more energy-efficient electrical consumers). Thus, to improve the accuracy of the forecast, it is necessary to take into account both the main and identified additional factors, the use of which will allow us to propose a forecasting method for household consumers. The proposed method should increase the efficiency of both autonomous sources based on renewable energy sources (due to the possibility of early planning) and combined sources (by reducing the loss and improving the quality of electricity in the centralized network by increasing the throughput of electrical installations). Regularization of the factorial forecasting of electricity consumption by household consumers is proposed to be carried out by the neural network algorithm, which will improve the forecasting accuracy due to the timely identification of weighted measured factors.

2. RESEARCH METHOD

To develop an algorithm for training a neural network of factorial forecasting of electricity consumption by household consumers, it is proposed [23], [24]:

– To identify and describe a mathematical model of additional variable factors (coefficient characterizing the terrain conditions) affecting the accuracy of the forecast in conditions of inaccessibility (elevation differences above sea level), the absence of other sources (gas supply and heat supply) and the welfare of consumers
– Taking into account the coefficient characterizing the conditions of the area, propose a method for predicting electricity consumption by household consumers;
– Build a computer model for predicting power consumption by household consumers in the MATLAB environment
– Choice of a learning algorithm for artificial neural network factorial forecasting of electricity consumption by household consumers
– Compare the results obtained by the method, computer and neural network model with the results of experiments.

2.1. Mathematical model of factorial (basic and additional) variables

The main, variable factors affecting power consumption can be attributed to the ambient temperature (meteorological), the number of connected power consumers (during maximum hours and in the remaining time) and operating modes (taking into account only the main factors lead to large differences between calculations and experiments for consumers located in difficult terrain). To predict power consumption by household consumers located in hard-to-reach places, accounting for forecasting only the main factors leads to an increase in inaccuracy. This is explained by the fact that with an increase in elevation above sea level at the same temperatures about the lowest elevation, the sensation of cold is high. This, in turn, leads to uncertainty (for example, the impossibility of using the developed standard load graphs for forecasts) associated with the fact that in difficult-to-access conditions, despite the low population density, due to sharp changes in ambient temperatures, electricity consumption has a distinctive character.

Therefore, it is necessary to propose such a mathematical model of the main and additional variable factors with the help of which it will be possible to take into account all the factors as much as possible. The resulting mathematical model should improve the accuracy of determining the actual and predicted power consumption of household consumers. Based on previous studies (using Pearson's goodness-of-fit test, factors of greatest significance were identified). The known main factor (temperature coefficient - t) and identified additional factors (accounting coefficient for height differences above sea level - h, coefficient of the structural performance of premises - c, consumer welfare, income analogue in the Tornquist function - s, and coefficient taking into account dynamics and seasonal fluctuations in consumer welfare - k). We represent the mathematical model in the form of a coefficient characterizing the conditions of the area.

$$\alpha_i = (((t_i \cdot h + c) \cdot s)/(s + k)), \tag{1}$$

The temperature coefficient is determined: at ambient temperatures from -3 °C and above,

$$t_i = \frac{|t_1|+|t_2|}{t_3}, \tag{2}$$

Where: t_1 is the ambient temperature at the user location (℃); t_2 is additional temperature (℃) (taking into account the difference between the temperature from the outside of the house and the temperature inside the room); t_3 is the ambient temperature on the 0 points above sea level (℃)
At an ambient temperature from -4 ℃ to -6 ℃,

$$t_i = \frac{|t_1|}{t_3}, \tag{3}$$

At ambient temperatures as,

$$t_i = \frac{|t_1|-|t_2|}{t_3}, \tag{4}$$

As can be seen from in (3), at an ambient temperature from -4 ℃ to -6 ℃, in the case of a construction of a residential building made of reinforced concrete, the additional temperature is not taken into account. This is explained by the fact that at a given ambient temperature, the design of a residential building does not affect the rise in temperature inside the room. If other heat-insulating materials are used, the dependence of the temperature coefficient on the ambient temperature must be determined either by in (2) or by (4). The coefficient of accounting for the height difference above sea level - *h* is determined by:

$$h = \frac{t_1}{t_2} \tag{5}$$

The coefficient of constructive performance of buildings of premises - *c* is determined by:

$$c = \frac{t_1}{t_4} \tag{6}$$

Where t_4: indoor temperature (apartment) (℃).

The welfare of the consumer, an analogue of income in the Tornquist function - s, and the coefficient taking into account the dynamics and seasonal fluctuations of the welfare of the consumer - k is determined using matrices of zero and one number (0 - correspondence of the minimum possibility of the consumer to use electrical consumers at the minimum and maximum ambient temperatures and the location of consumers, and 1 - corresponds to the maximum possibility of the consumer to use electrical receivers at the minimum and maximum ambient temperatures and the location of consumers).

2.2. Method of forecasting electricity consumption by households, taking into account α_i

It is known that changes in daily and seasonal electricity consumption by household consumers are parabolic, while monthly and annual electricity consumption obeys a linear law. Consequently, the foregoing allows us to represent the dependence of electricity consumption by household consumers, taking into account the coefficient - α_i in the form of the following function.

$$f(\alpha_i, W) = W \cdot (1 - \alpha_i), \tag{7}$$

From (7) it follows that the variability of the curve shape depends on the coefficient α_i Taking into account the foregoing, we propose the following methods to control the current and predicted power consumption by household consumers.
- current

$$\mathrm{W}_{(\mathrm{act.})} = \mathrm{K} \cdot \mathrm{W}_{\mathrm{additional}}, \tag{8}$$

where the coefficient $\mathrm{K} = \frac{\mathrm{W}_{\mathrm{actually}}}{\mathrm{W}_{\mathrm{additional}}}$,
$\mathrm{W}_{\mathrm{actually}}$: actual power consumption, kWh
$\mathrm{W}_{\mathrm{additional}}$: permissible power consumption, kWh
- projected

$$\mathrm{W}_{(\mathrm{projected.})} = \mathrm{W}_{\mathrm{actually}} \cdot (1 - \alpha_i), \tag{9}$$

In (8) allows you to determine the effective power consumption using which in (9) you can predict the power consumption of household consumers. In (8) imply the need to establish the permissible power consumption. This need arises from the following considerations. Most of the countries with the location of electricity consumers in hard-to-reach places receive electricity from autonomous sources due to the limited capacity of these sources (changes in solar insolation during the day and seasonality, frost in the mountains and a decrease in water inflow, as well as the inconsistency of wind speed) cannot maintain the constancy of electricity generation. The problem of establishing permissible electricity consumption by household consumers in cities is possible in cases where consumers do not have other energy sources (except for electricity) and in the vast majority of cases use one source of energy, for example (hydraulic power plants). The Republic of Tajikistan can be attributed to such a country. In this country, most of the population is located at an altitude of more than 700 meters above sea level and is largely devoid of other sources of energy.

2.3. Computer model for forecasting power consumption

In the MATLAB program (which allows simulating physical processes), a mathematical in (1) was written, which allows, when specifying the necessary coefficients - t_i, h, c, s, k, to calculate the coefficient characterizing the terrain conditions - α_i. The results obtained are presented in the form of a block with control functions Figure 1 (at subzero temperatures) and Figure 2 (at positive temperatures) for the winter period when the consumer is located 750 m above sea level with a reinforced concrete structure of houses.

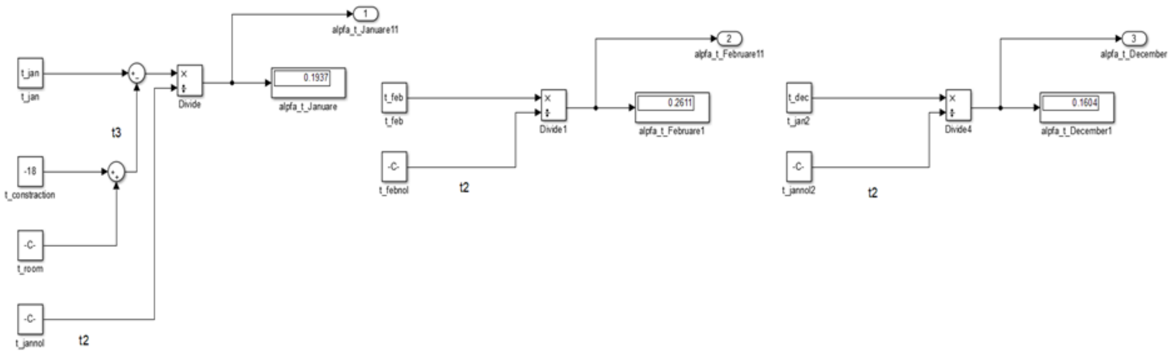


Figure 1. Block with control functions (minus temperature)

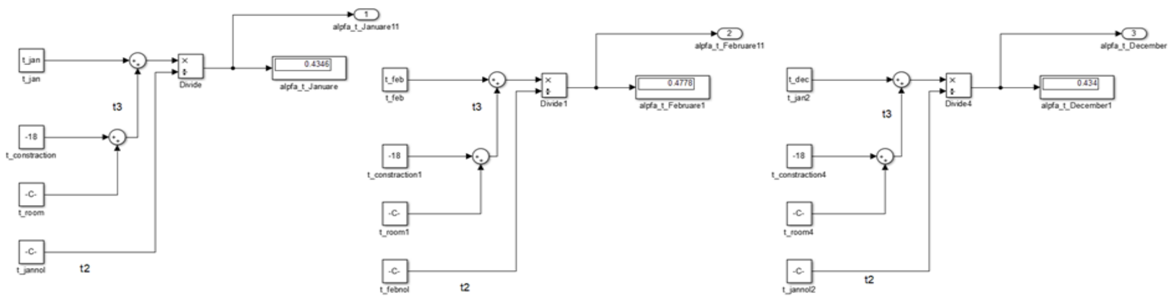


Figure 2. Block with control functions (positive temperature)

The resulting coefficients $\alpha_i$are transferred to in (9) written in MATLAB and represented as a block and a control function. The (9), in turn, consists of two terms, the first is the connection time of power consumers, the second is the difference $(1 - \alpha_i)$ as shown in Figure 3. The relationship of the two terms shows the values of the predicted power consumption by consumers. For further analysis of the results obtained in the constructed computer model, monthly forecasting of power consumption for a year was carried out. The model control function and the results of power consumption forecasting built in the MATLAB environment are shown in Figure 4.

2.4. The choice of the learning algorithm for artificial neural network factorial forecasting of electricity consumption by household consumers

There are several dozen different neural network architectures, and the effectiveness of many of them has been proven mathematically [25]. To solve forecasting problems, the following types of ANN are used: linear network, multilayer perceptron, network based on radial basis functions, generalized regression network [26]. The advantage of ANN is the possibility of factor forecasting. In this case, the network has X inputs, each of which corresponds to some factor that affects the forecasting parameter [27], [28]. The supply of significant factors (the value of the conductor current, cable temperature) to the network input together with the history of the temperature of the current-carrying conductor contributes to an increase in the accuracy of the forecast. At the same time, the network itself determines the dependencies between the factors, adjusting its parameters during training. Thus, fairly complex regression relationships can be modelled. To effectively solve the problem of factorial forecasting, it is necessary to select a suitable structure for an artificial neural network. Analysis of artificial intelligence methods intended for solving problems of factorial forecasting showed that a multi-layer perceptron can form an arbitrary multidimensional function at the output with an appropriate choice of the number of layers, the range of changes in signals and parameters of neurons. To solve the problem using an ANN, it is necessary to select a neural network configuration and create an environment in which this neural network will operate.

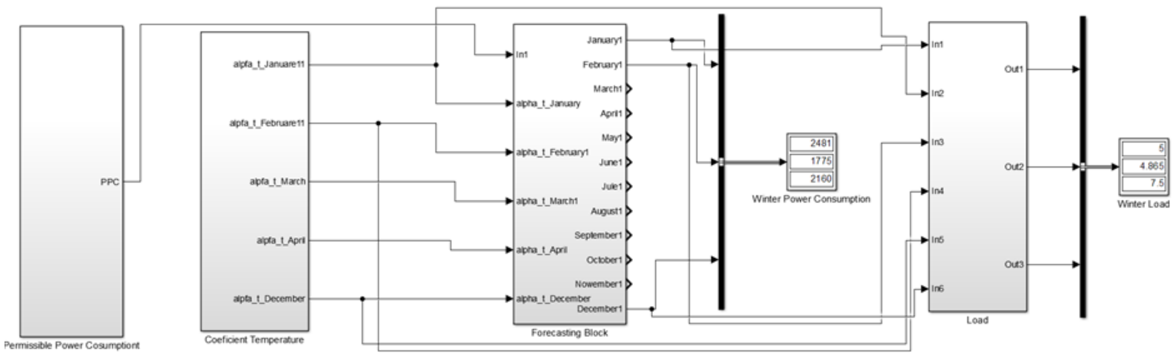


Figure 3. Block of results of predicted electricity consumption by household consumers

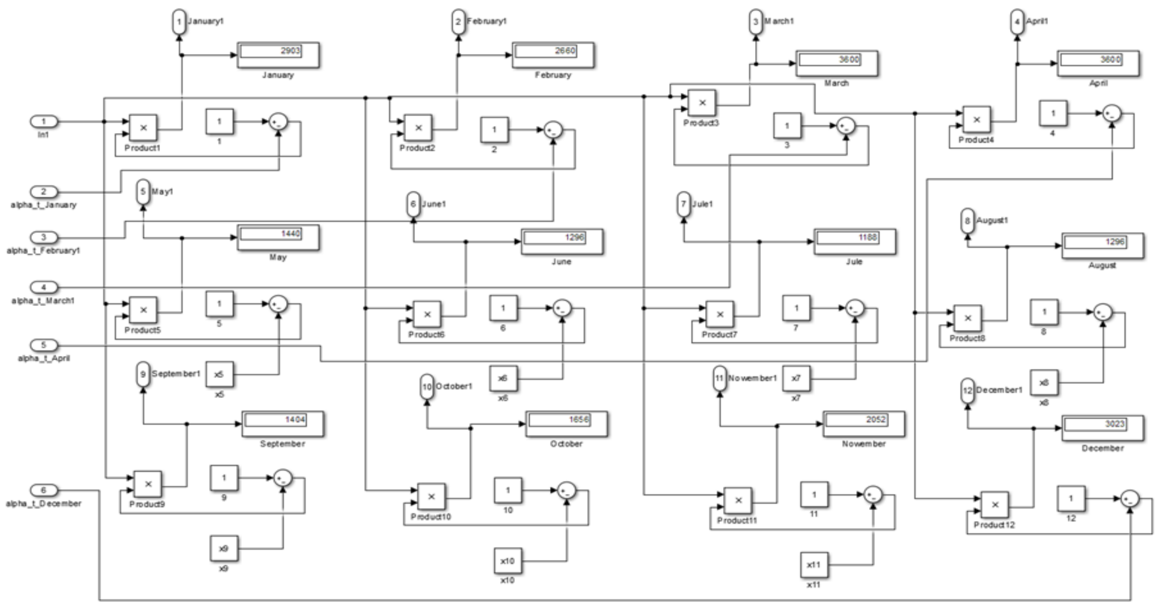


Figure 4. Control function and power consumption prediction results

Taking into account the problem posed and the analysis of the applicability of neural network models in the MATLAB environment, a nonlinear autoregressive neural network (NAR) was chosen, which allows when specifying one generalized indicator at the input (in our case, consisting of two terms (coefficient αi and the unit or total power of the electrical receiver with time of its connection) at the output, after choosing the number of layers and the learning algorithm, to obtain the predicted power consumption by household consumers. Figure 5 shows the architecture of a NAR.

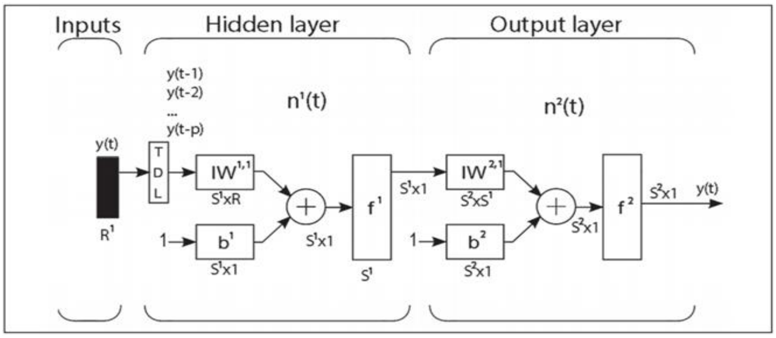
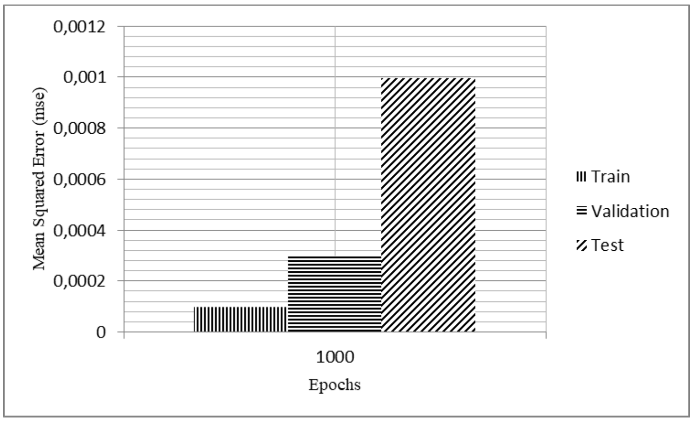
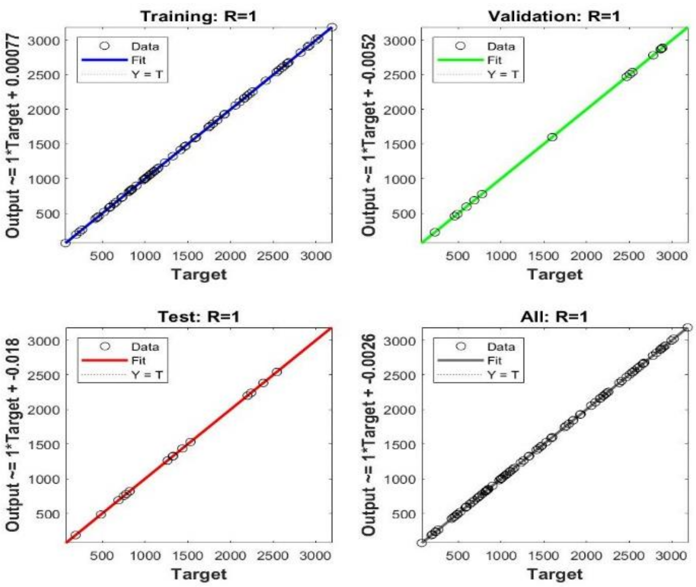


Figure 5. The architecture of the NAR

Of the three learning algorithms: i) Levenberg - Marquardt; ii) Bayesian regularization; iii) Conjugate gradient method. To solve the tasks we set, the first algorithm turned out to be the most effective, showing the greatest convergence of the results both in terms of training and the nonlinear autoregression of the trained neural network (NAR) (Figure 6). As can be seen from Figure 6(a), the degree of learning of the NAR is in the range of 10^{-2}-10^{-4}, and in Figure 6(b), the nonlinear autoregression of the trained neural network (NAR) does not go beyond the boundaries, which confirms the rather high efficiency.



(a)



(b)

Figure 6. Results of applying the neural network model (a) trainability, convergence, error and (b) nonlinear autoregression of the trained neural network (NAR)

3. RESULTS AND DISCUSSION

Based on the developed mathematical model, in (1), taking into account the obtained factor coefficients - t_i, h, c, s, for 2020 for 9 cities of the Republic of Tajikistan, monthly coefficients characterizing the terrain conditions (α_i). were calculated. The initial data of the calculated coefficients were determined:

- Temperature coefficients - t_i (ambient temperatures were taken from the data of the Agency for Hydrometeorology);
- Coefficient - h (from the data of the Statistics Agency);
- Coefficient - c (from the date of the Construction Agency).

The calculation results are shown in the form of the dependence of the coefficient - α_i on the number of cities in Figure 7.

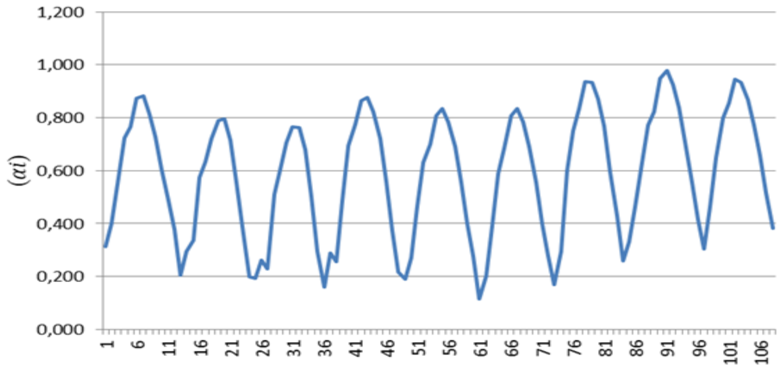


Figure 7. Results of modelling the coefficient αi for 9 cities for 2020

To check the adequacy of the proposed models, the results obtained were compared with the results of experimental data. For experimental data, the readings of electricity metering devices for groups of household consumers were taken. The comparison results are presented in Table 1.

Table 1. Comparison of experimental results with simulation results

December			January			February		
Mathematical model	Computer model	Experimental	Mathematical model	Computer model	Experimental	Mathematical model	Computer model	Experimental
2950	3023	3000	2880	2903	2850	2580	2660	2700
				Error				
1.7%	0.8%	-	1%	1.8%	-	4%	1.4%	-

The results obtained are shown in Table 1 show high convergence (errors not exceeding 5%). Thus, it can be argued about the high forecast accuracy when using the proposed method (9). To compare the results obtained based on (9) with the results of the selected and trained neural network model, the dependences of the electricity consumption of household consumers on the considered number of cities for the 2020 period were constructed, Figures 8 and 9. The results obtained as shown in Figure 9, showed a high convergence with the results obtained by the proposed method (9).

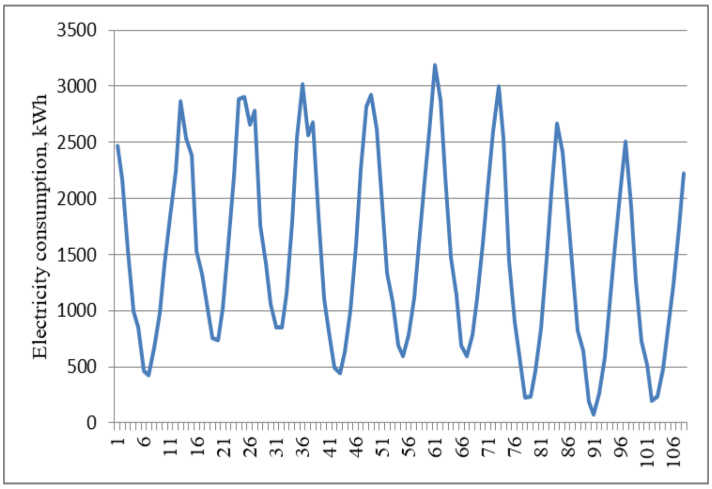


Figure 8. Results of modelling by the proposed method (9)

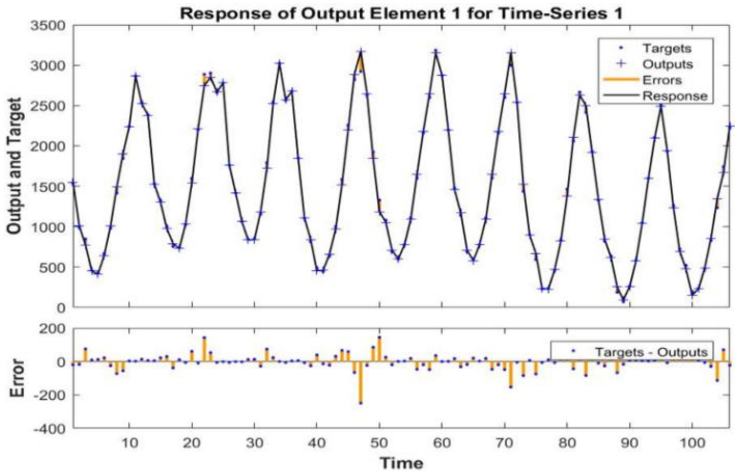


Figure 9. Results of modelling in a neural network model

Thus, after comparing the results of a computer, neural network model, experimental data with the proposed methods, it can be argued about the high accuracy of forecasting power consumption when using the method. However, given the transition from semiautomatization to fully automated control and management of autonomous sources of the implementation of a neural network model to control the actual and offer the forecast, we believe it is necessary to offer an algorithm that can allow, due to the high accuracy of the predicted power consumption, to reduce power losses and increase the service life of renewable energy sources. Figure 10 shows a learning algorithm of artificial neural network factor forecasting electricity consumption of household consumers. As seen from Figure 10 the proposed algorithm under any conditions has the opportunity to constant retraining thereby allowing to increase prediction accuracy.

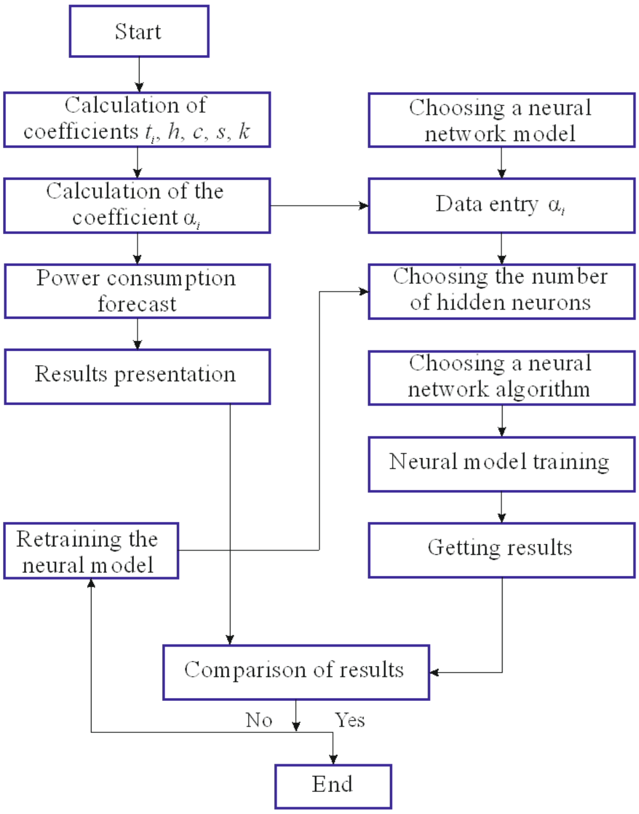


Figure 10. The algorithm of artificial neural network learning factor forecasting electricity consumption of household consumers

4. CONCLUSION

Models and a method are proposed to improve the accuracy of forecasting power consumption by household consumers. To minimize participation in the control and management of electricity generation from renewable energy sources, an algorithm for learning artificial neural networks for factorial forecasting of electricity consumption by household consumers is proposed. The use of which (due to the possibility of continuous learning) will improve the accuracy of the forecast. Confirmation of this is the high convergence of the results obtained based on the proposed models and method. Confirmation of this is the high convergence of the results obtained based on the proposed models and method.

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