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Forecasting the Energy Consumption of an Industrial Enterprise Based on the Neural Network Model

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Abstract: This research paper investigates the application of neural network models for forecasting in energy. The results of forecasting the weekly energy consumption of the enterprise according to the model of a multilayer perceptron at different values of neurons and training algorithms are given. The estimation and comparative analysis of models depending on model parameters is made.

Keywords: electrical loads, daily schedule, modelling, neural network, multilayer perceptron, MLP

1. Introduction

In the presence of the electricity market, the need to obtain forecast values of energy consumption is due to economic and technological reasons. Improving the accuracy of the forecast of electric loads allows to avoid overloading of generating capacities, to improve the quality of electricity, and to minimize its losses. Moreover, the projected loads significantly affect the market value of electricity, which is important both at the level of the individual industrial consumer planning its application for electricity, and at the level of the entire power system. High-level accuracy of power system planning allows to optimize the use of energy, distribute electrical loads between network facilities and meet the requirements for reliability and quality of electricity supply. This points to a great relevance and importance of the tasks related to modelling and forecasting of electrical loads for planning the optimal modes of operation of electricity consumers and power supply systems.

2. Analysis of recent research and publications

The quality and accuracy of the forecast depends on the chosen mathematical model. There are a large number of models and methods for loads prediction, which are usually based on the retrospective dynamics of power consumption and the factors that affect it, to identify a statistical relationship between model parameters and process characteristics. Ukrainian and foreign scientists, including V. Vynoslavsky, A. Prakhovnyk, V. Rozen, A. Voloshko, P. Chernenko, worked on the development of mathematical modelling and forecasting of electric loads (Vinoslavsky et al. 1974, Prakhovnik et al. 1985, Kalinchik et al. 2013, Voloshko et al. 2012, Chernenko et al. 2016).

In recent decades, the mathematical apparatus of artificial neural networks (ANN) has been successfully used for prediction, models based on which can establish a relationship between the output characteristics of the system and input factors using the learning procedure. The use of artificial neural networks allows to achieve forecast accuracy up to 96-97%, which will have a significant impact on the management of electrical loads. The choice of network type and its configuration depends on the specific task, available data and their volume.

At present, there are a significant number of classes of forecasting models (Tikhonov 2006). Moreover, some models and relevant methods relate to individual approaches to forecasting.

Speaking of the scientific works studying to the use of ANN in forecasting processes, we should mention the works by Yu. Zaigraieva, G. Shumilova, I. Chuchueva and others (Zaigraeva 2008, Sukhbaataryn 2004, Shumilova et al. 2008, Chuchueva 2012).

The principles of operation and options for the use of ANN were considered by the authors Haykin, Titterington, Picton, Dreyfus (Haykin 1999, Titterington 2009, Picton 2000, Dreyfus 2005).

The main requirements for forecast models include: sufficiently high accuracy of forecasting and simplicity of algorithms, which allows to minimise the decision time and volume of system memory; work in conditions of uncertain and insufficient information; ensuring the sustainability of management.

3. The goal of this paper

Is to develop a model for forecasting the electricity consumption of an enterprise using artificial neural networks to improve the accuracy of planning the operating mode and increase the reliability of the enterprise's estimates in making technical and economic decisions.

To achieve this goal, the following objectives are addressed in the paper:

- Building a structure and developing a mathematical model of ANN for power consumption forecasting.
- Investigation of neuromodels with different numbers of neurons to assess the effect of ANN configuration on prediction accuracy.

4. Presentation of the main research material

Interconnected neurons form a neural network. Network configuration is determined for each separate task. To solve some individual types of problems, there are already optimal configurations described in the academic literature on the construction and operation of neural networks (Komashinsky et al. 2002, Medvedev et al. 2002, Kruglov et al. 2002, Neural networks 2000, Haykin 2006).

On each cycle, all training observations are sequentially fed to the network input, the initial values are compared with the target values, and the error function is calculated. The values of the error function, as well as its gradient, are used to adjust the weights and offsets, after which all steps are repeated. The initial values of the ratios and biases of the network are chosen randomly. The learning process is terminated either after a certain number of cycles, or when the error decreases to a sufficiently small level or ceases to decrease.

Suppose a given multilayer perceptron with a smooth activation function (Surovtsev at al. 1994) (Fig. 1).

Its work is set by the equations:

$$NET_{ijl} = \Sigma w_{ijl} \cdot x_{ijl} - \Theta \tag{1}$$

$$OUT_{jl} = F(NET_{jl}) \tag{2}$$

$$X_{ij(l+1)} = OUT_{il} \tag{3}$$

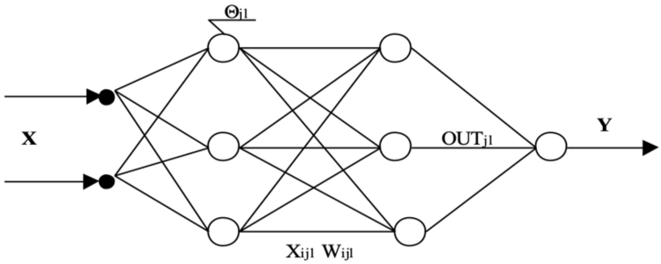

Fig. 1. Multilayer perceptron

We accept the total quadratic error as the objective function:

$$E = \frac{1}{2} \cdot \sum_j \sum_s \left(y_j^s - d_j^s\right)^2. \tag{4}$$

The network is defined by its parameter vector – a set of weights and threshold levels of

$$P = \binom{W}{\Theta}. \tag{5}$$

where W is a vector, the components of which are the weights of the network, Θ is the vector of network threshold levels.

Therefore, if we consider the training set as given, the network error depends only on the vector of parameters:

$$E = E(P) \tag{6}$$

During training on each iteration, the parameters in the direction of antigradient E will be adjusted:

$$\Delta P = -\varepsilon \cdot \nabla E(P). \tag{7}$$

The model of the object of research is realized on the basis of ANN. Preliminary preparation of the input data vector reduces the duration of the learning process, which is important for large amounts of data in the case of multicomponent systems. The mathematical apparatus of the ANN for the implementation of the model is selected based on the fact that the network of such a structure can simulate a function of almost any degree of complexity, and the number of layers and the number of elements in each layer determine the complexity of the function. MLP network has the ability to extrapolate data and high performance after training (Kalinchik et al. 2016).

The paper predicts the schedule of active power consumption for the day ahead on the basis of data on electricity consumption for the previous days. The total sampling consists of 168 observations (24 hourly observations per day during a week) and is provided in the form of a table and graph (Fig. 2). To verify the accuracy of the forecast, the forecast will be based on 144 observations, and the data of the last day will serve as a control sequence. The accuracy of the model will be assessed by the average value of the relative error in the control sequence and the value of the relative error in determining the daily power consumption.

A multilayer perceptron was adopted as a model for prediction. The number of perceptron inputs is determined by the length of the load schedule (24 observations per day). To obtain the predicted value, one source element is sufficient. The number of neurons in the hidden layer is set from 2 to 20 and will be adjusted depending on the accuracy of the model, which will be determined by the performance on the training and test sequences. Threshold activation functions may take linear, hyperbolic, exponential values. Network learning algorithm is BFGS.

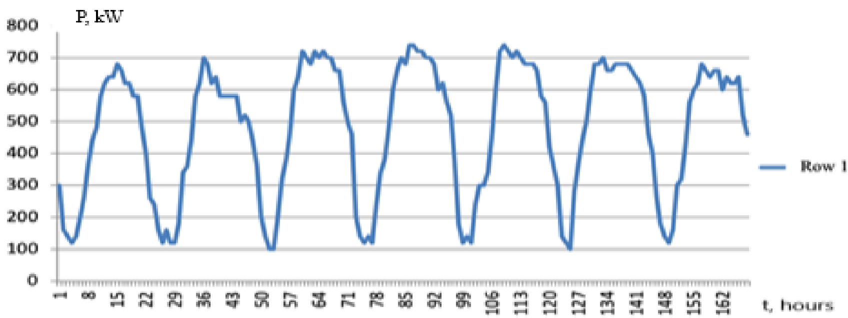

Fig. 2. Weekly schedule of energy consumption of an enterprise

When training networks under given conditions, the best 2 results out of 50 options have the characteristics shown in Table 1. The two networks with the best performance (the smallest absolute error in the training and control sequence) were used to build forecasts for the day ahead (Fig. 3). The quality of the models was assessed by relative error indicators for the predicted values of electricity consumption and the total amount of electricity consumed in Table 2. The average error in forecasting the current values of active power consumption for MLP 24-16-1, MLP-24-14-1 and MLP 24-1-1 networks was 9.7%, 9.9% and 9.5%, respectively. When estimating the total amount of energy consumed, the error was 1.8%, 1.6% and 4.1%.

Table 1. Characteristics networks

№	Net	Training perf.	Test perf.	Training error	Test error	Training algorithm	Hidden activation	Output activation
1	MLP 24-20-1	0.960162	0.981960	1319.822	708.0249	BFGS 5	Identity	Identity
2	**MLP 24-14-1**	**0.974301**	**0.983437**	**804.850**	**646.3876**	**BFGS 12**	**Logistic**	**Identity**
3	MLP 24-14-1	0.973262	0.982999	836.882	763.7459	BFGS 13	Tanh	Exponential
4	MLP 24-20-1	0.962599	0.982751	1210.119	872.7152	BFGS 8	Exponential	Exponential
5	MLP 24-14-1	0.974809	0.982893	789.723	750.9171	BFGS 11	Identity	Logistic
6	MLP 24-2-1	0.968802	0.982306	1004.553	735.2150	BFGS 12	Sine	Sine
7	MLP 24-4-1	0.961010	0.982408	1279.481	715.6567	BFGS 7	Identity	Identity
8	MLP 24-5-1	0.965437	0.982536	1113.829	703.7486	BFGS 29	Sine	Sine
9	**MLP 24-16-1**	**0.975561**	**0.982711**	**752.883**	**740.1567**	**BFGS 11**	**Identity**	**Logistic**
10	MLP 24-11-1	0.973378	0.982453	826.363	758.3667	BFGS 12	Identity	Logistic

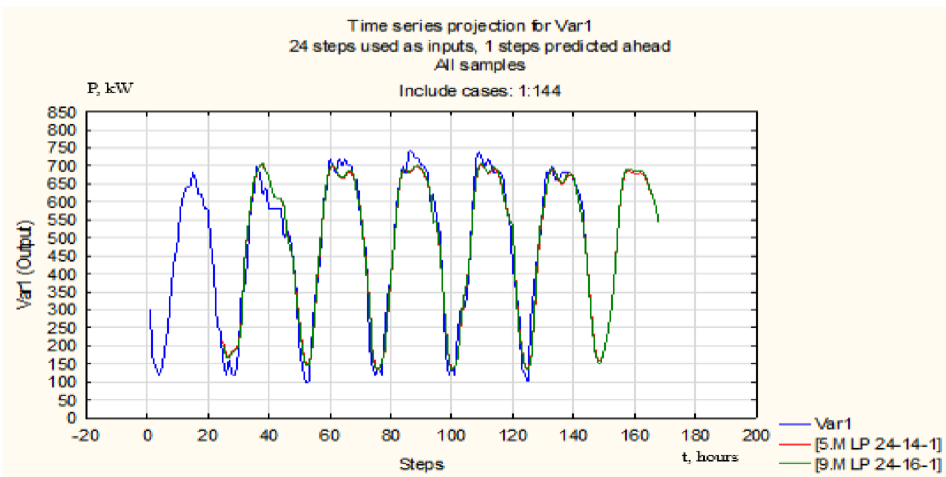

Fig. 3. Graphs of energy consumption by the original sequence and ANN models

Table 2. Estimation of accuracy of models

	Dimen-sion W	24"16"1	24"14"1	Error	Error	24"1"1	Error
1:00	400	364.8682	369.8831	0.08783	0.075292	347.7334	0.130666
2:00	260	263.5233	271.1761	0.013551	0.042985	249.8743	0.038945
3:00	180	184.6158	191.9261	0.025644	0.066256	170.9807	0.050107
4:00	140	153.2481	159.4724	0.094629	0.139089	147.3600	0.052571
5:00	120	153.0187	157.3944	0.275156	0.311620	167.1893	0.393244
6:00	160	186.0898	188.3890	0.163061	0.177431	237.1377	0.482111
7:00	300	228.1412	228.5293	0.239529	0.238236	313.9695	0.046565
8:00	320	281.0085	281.0490	0.121849	0.121722	404.3978	0.263743
9:00	420	350.9698	352.1839	0.164358	0.161467	495.7506	0.180358
10:00	560	456.1922	456.8315	0.185371	0.18423	577.6940	0.031596
11:00	600	575.1257	572.1859	0.041457	0.046357	633.2087	0.055348
12:00	620	654.7844	648.0695	0.056104	0.045273	656.2832	0.058521
13:00	680	687.5770	680.9111	0.011143	0.00134	661.0392	0.027883
14:00	660	690.9127	684.9339	0.046837	0.037779	649.6118	0.015740
15:00	640	687.9962	682.8616	0.074994	0.066971	642.9487	0.004607
16:00	660	684.3566	679.8348	0.036904	0.030053	642.3883	0.026684
17:00	660	683.8430	678.9896	0.036126	0.028772	646.9048	0.019841
18:00	600	686.2046	680.1743	0.143674	0.133624	658.9881	0.098313
19:00	640	681.8390	675.1215	0.065373	0.054877	671.7496	0.049609
20:00	620	664.0817	658.0634	0.071100	0.061393	675.4060	0.089365
21:00	620	637.2844	633.5488	0.027878	0.021853	663.2066	0.069688
22:00	640	611.4985	610.2385	0.044534	0.046502	625.3585	0.022877
23:00	520	584.7224	584.8978	0.124466	0.124803	556.1733	0.069564
24:00	460	541.7731	542.5004	0.177768	0.179349	458.3088	0.003676
	Amoun W	**Amoun W**	**Amoun W**	**Error**	**Error**	**Amoun W**	**Error**
	11480	11694	11669	0.018612	0.016478	11953	0.0412598

5. Conclusions

Operation of the enterprise has a cyclical change of loads, repeated daily during the week. Operation of the enterprise is characterized by hours of minimum load (from 0 to 8 hours) and hours of work with a nominal load of 600 to 700 kW. To build a mathematical model of the function of changing the electrical load, it is advisable to use a multilayer perceptron.

The daily load schedule with hourly data recording determines the observation period and the required number of neurons (24) in the input layer, because predicting a decrease in the number of neurons will worsen the quality of the model due to period mismatch, and increase will complicate the model.

For the proposed prediction model, a network with one hidden neuron provides a more accurate prediction for individual observations, but for predicting total power consumption over a set period, networks with more hidden neurons are more accurate. The biggest forecasting errors are observed at the time of changing the operating mode.

The error of the forecast values for operation at rated mode from 10 to 17 hours (minimum value 0.4%, maximum value 5.8%) and 4.1% error of forecast daily consumption indicates sufficient accuracy of the ANN model applied for forecasting daily loads of the enterprise.

The capability of processing large data sets, self-learning based on the given data sequences, and the high accuracy of the models confirm the feasibility of using artificial neural networks to solve problems of forecasting electrical loads.

References

Chernenko, P.O. (2016). Peculiarities of short-term forecasting of electric load of power system with essential component of industrial power consumption / P.O. Chernenko, O.V. Martyniuk, V.O. Miroshnyk // Proceedings of the Institute of Electrodynamics of the National Academy of Sciences of Ukraine. 43. 24-31.

Chuchueva, I.A. (2012). Model for forecasting time series based on a sample of maximum similarity: dissertation of the PhD: 05.13.18 / Chuchueva I.A. Moscow, 153.

Dreyfus, G. (2005). Neural Networks. *Springer*, 386.

Haykin, S. (1999). Neural Networks: A Comprehensive Foundation, 2nd Edition, Prentice-Hall.

Kalinchik, V.P. (2013). Forecasting of indicators of energy consumption, generation and cost of the received energy / Kalinchik V.P., Kokorina M.T.: NTUU “KPI” N.-i. Institute of Automation and Power Engineering "Energy". Kiev, 14: bibliographic illustrations: 7 – deposit in SSTLU Ukraine 22.07.13, 35 Uk.

Kalinchik, V.P. (2016). Energy-efficient control of the "crusher-mill" mechatronic complex using artificial neural networks / Kalinchik V.P., Rosen V.P., Shevchuk S.P., Meita A.V. // Energy: economics, technology, ecology, 3, 45-50.

Komashinsky, V.I., Smirnov, D.A. (2002). Neural networks and their application in control and communication systems: Moscow: Hotline – Telecom, 94.

Kruglov, V.V., Borisov, V.V. (2002). Artificial neural networks. Theory and practice. Moscow. Hotline – Telecom. 382.

Medvedev, V.S., Potemkin, V.G. (2002). Neural networks. MATLAB 6. – Moscow: Dialogue, MIFE, 496.

Neural networks. (2000). STATISTICA Neural Networks. – Moscow: Hotline – Telecom. 182.

Picton, P. (2000). Neural networks. *New York: Palgrave, 195*.

Prakhovnik, A.V. (1985). Energy-saving modes of power supply of mining enterprises / A.V. Prahovnik, V.P. Rosen, V.V. Degtyarev. – Moscow: Bosom, 232.

Shumilova, G.P. (2008). Prediction of electrical loads in the operational control of electric power systems based on neural network structures / G.P. Shumilova, N.E. Gotman, T.B. Startseva. *Syktyvkar: RAS, 78*.

Sukhbaataryn Munkhzhargal. (2004). Development and research of neural network algorithms for short-term forecasting of the load of the central electric power system of Mongolia: dissertation of the PhD: 05.14.02 / Sukhbaataryn Munkhzha. – Novosibirsk, 177.

Surovtsev, I.S., Klyukin, V.I., Pivovarova, R.P. (1994). Neural networks. *Voronezh: HSU, 224*.

Tikhonov, E.E. (2006). Forecasting methods in market conditions: textbook / E.E. Tikhonov – Nevinnomyssk: North Caucasian GTU, 221. ISBN 5895710778.

Titterington, M. (2009). Neural networks. *WIREs Computational Statistics, 2*(1). 1-8.

Vinoslavsky, V.N. (1974). Forecasting the power consumption of industrial facilities / V.N. Vinoslavsky, A.V. Prakhovnik, A.F. Bondarenko // *Energy and electrification, 5*, 30-31.

Voloshko, A.V., Lutchin, T.M., Kladko, O.M. (2012). Short-term forecasting of electric load graphs based on wavelet transforms. Energosberezhenie, vol. Energy. *Energy audit., 6*. 35-42.

Zaigraeva, Yu. B. (2008). Neural network models for assessing and planning energy losses in electrical systems: author. dis. for a job. scientific. degree of Cand. those. Sciences: spec. 05.14.02 "Power Plants and Electric Power Systems" / Zaigraeva Yulia Borisovna; Novosibirsk state technical university – Novosibirsk, 20.