SHORT NOTES

MSC 93A30 DOI: 10.14529/jcem160406

ENERGY CONSUMPTION MODELLING USING NEURAL NETWORKS OF DIRECT DISTRIBUTION ON EXAMPLE OF RUSSIA UNITED POWER SYSTEM

V.G. Mokhov[1]**,** mokhov50@mail.ru**,**
T.S. Demyanenko[1]**,** oop_flp@mail.ru**,**
I.P. Ostanin[1]**,** deks1309@gmail.com
[1] South Ural State University, Chelyabinsk, Russian Federation

The article describes a model to estimate an electrical energy consumption on the basis of neural network of direct distribution. The model is tested on actual hourly data of both United energy system of Wholesale electricity market and power of Russia. An algorithm to train a neural network with different numbers of neurons in the hidden layer is described. We tested the obtained model and find that a forecast error is 2.13 % for a network with 72 neurons in the hidden layer. The designed scientific instrument is recommended in operating activities of electric power subjects, when main parameters of energy market are forecasted in order to reduce the penalties by improving the accuracy of forecasts.

Keywords: electric energy subjects; energy consumption; neural networks; activation function; wholesale market of electric energy and power, forecast.

Introduction

The wholesale electric energy market should provide sufficient power amount in order to coverage electric energy demand with regard to the necessary reserve of electrical power using the most effective resource-saving technologies. In this way, suppliers should to maintain the generating equipment ready for electric energy production. A system operator controls the timely and proper implementation of investment programs. Such programs of generating companies are formed as a result of power trading. The system operator also selects a power.

It is clear that errors of the forecast volume values appear regularly.

Market participants who have made mistakes in planning can buy or sell electric energy on the balancing market, but prices of the market are very disadvantageous.

It follows from the above that an accuracy of forecast of electric energy consumption and production is important [1].

Data of electric energy consumption volumes is time series. It is expedient to use neural networks in order to forecast the time series.

1. Method to Construct Neural Network Based on Multi-Layer Perceptron

The direct extension network is often used to forecast the time series. A signal in such network travels in only one direction: from input to output [2]. Multilayer perceptron is a subclass of direct extension networks. Such perceptron is a combination of several elements (see Fig. 1):
- an input layer (a set of input nodes),
- a set of n hidden layers ($n \in (1, N)$),
- an output layer.

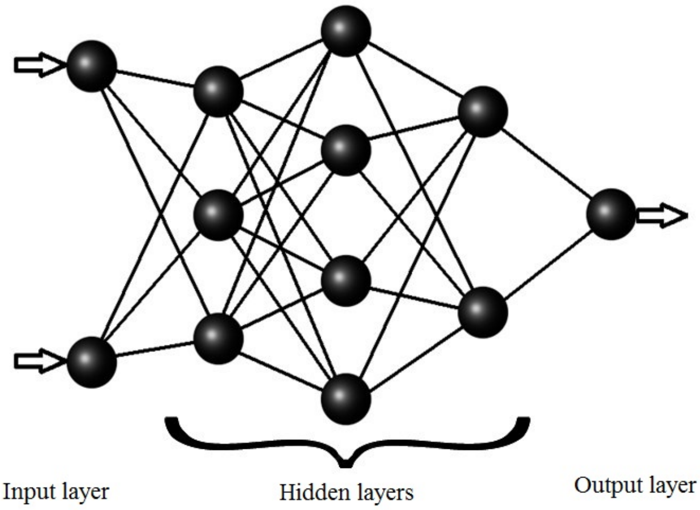

Fig. 1. An architecture of three-layer perceptron

The neurons of the hidden layers allow to train a network in order to decide more complex tasks. It is so, because such neurons consistent take the most important characteristics of the input vector.

All layers in the multilayer perceptron are highly connected. That is, each neuron of this layer is connected with each neuron of the next layer [3].

The output of each neuron of network is processed by nonlinear activation function. The training algorithm of an error backpropagation can be applied, if activation function is continuous, differentiable and monotonically nondecreasing. Also, the computations during training are more effective, if a derivative of the activation function can be found easily. More often an activation function is a function of sigmoid form [4]. One of such functions is the logistic function

$$f(x) = \frac{1}{1 + e^{-\alpha x}},$$

where α is a slope coefficient of sigmoid function. Let E be a function to calculate the error. Weights in the output layer change by gradient, which is calculated by the formula

$$\Delta W_0 = \eta \cdot O_N \times D_N,$$

where η is a firing coefficient (training speed), O_N is an output of the last hidden layer, D_N is an output layer error.

$$D_N = E(y, t) \cdot f'(y)$$

where y is an output of neural network, t is target output value, f is an activation function.

Weights in hidden layer l change by gradient, which is calculated by the formula

$$\Delta W_l = \eta \cdot O_{l-1} \times D_l,$$

where O_{l-1} is an output of layer $(l-1)$, D_l is an error on layer l.

$$D_l = (W_{l+1} \times D_{l-1}) \cdot f'(O_l),$$

where W_{l+1} are weights on layer $(l+1)$, O_l is an output of layer l.

2. Algorithm Implementation

In the paper we use such high-level programming language as Python. We choose Python due to the following considerations:

– the software code is easy;

– there exists sufficiently large number of ready-made modules;

– a code fast executes.

We use hourly electric energy consumption data in order to create a training sample. The training sample is a set of N pairs (input, output), where the input is a vector of (48, 1) size, and the output is a vector of (24, 1) size.

The input vector includes electric consumption data for two days. The output vector includes electric consumption data for one day. In the paper we use a three-layer perceptron to forecast an energy consumption. The perceptron contains 48 neurons at the input layer, 72 neurons at the hidden layer and 24 neurons at the output layer, see Fig. 2.

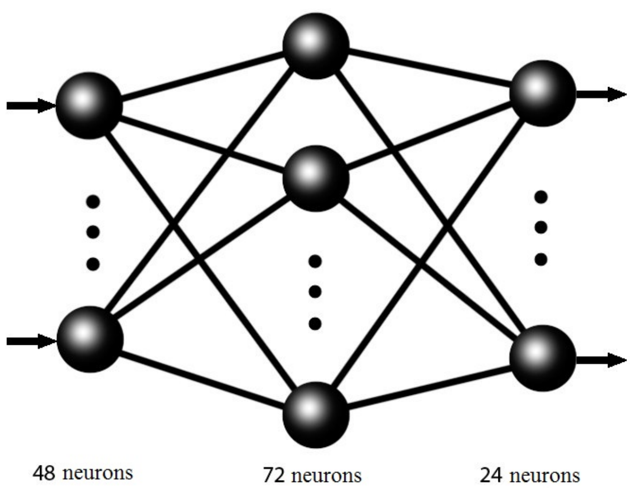

Fig. 2. Multilayer Perceptron

In the neural network in the input and hidden layers we use an activation function

$$tansig(x) = \frac{2}{1 + e^{-2x}} - 1.$$

The activation function does not apply to the output layer.

To calculate an output error of neural network we use a mean square error

$$E(y, \hat{y}) = \frac{\sum_{i=1}^{k} (y_k - \hat{y_k})^2}{k}.$$

For training we use the hourly data of electric energy consumption in Russia from 2009 to 2015. The data is taken from the official website of the System Operator of the United Energy system.

To evaluate the accuracy of forecast we use data of December 2015.

A parameter of model evaluating is MAPE (mean absolute percentage error)

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} |\frac{y_i - \hat{y}_i}{y_i}|,$$

where y_i is a theoretical value, $\hat{y}_i$ is a practical value.

Also, in order to find the optimal parameters of neural network, the tests with different number of neurons in the hidden layer are conducted. Namely, we test neural network having 24, 48, 72, 96 neurons in the hidden layer. The results are shown in Table.

The results of training a neural network
having different number of neurons in the hidden layer

Number of neurons	Error, %
24	11,83
48	4,52
72	2,13
96	2,24

Based on the training accuracy, we choose the network having 72 neurons in hidden layer.

To test the forecast we use hourly data of electric energy consumption in Russia for 2016. An average forecast error is 2.29 %. Graphical forecast image is shown in Figure 3.

Conclusion

In the paper we show that a multi-layer perceptron can to forecast electric energy consumption with sufficient accuracy. Several tests with different network parameters were conducted. The result of the tests are following. First, an optimum number of neurons in the hidden layer was identified. Second, sufficiently high forecast accuracy (97.71 %) was reached.

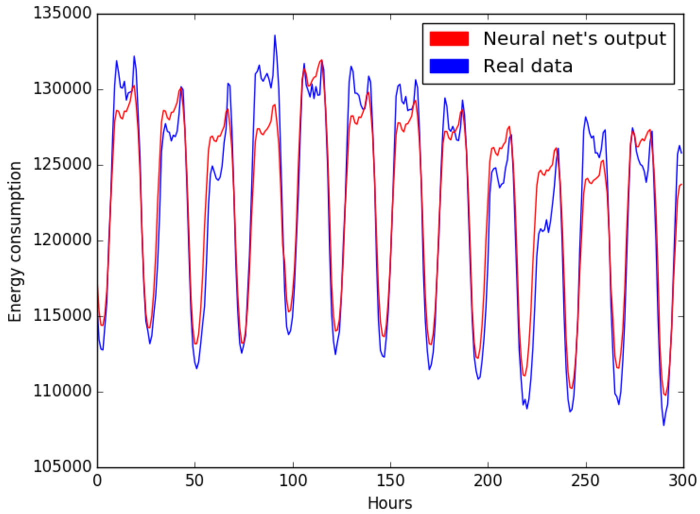

Fig. 3. Forecast of neural network

References

1. Mokhov V.G., Demyanenko T.S. Modeling of the Time Series Digressions by the Example of the UPS of the Ural. *Bulletin of the South Ural State University. Series: Mathematical Modelling, Programming and Computer Software*, 2015, vol. 8, no. 4. pp. 127–130. doi: 10.14529/mmp150412

2. Kriesel D. *A Brief Introduction to Neural Networks*. Germany, 2007.

3. Haykin S. [*Neural Networks: A full course*]. Moscow, Williams, 2006. (in Russian)

4. Osovsky S. [*Neural Networks for Information Processing*]. Moscow, Finance and Statistics, 2002. (in Russian)

Veniamin G. Mokhov, DSc (Economics), Professor, Department of Mathematical and Computer Modelling, South Ural State University, (Chelyabinsk, Russian Federation), mokhov50@mail.ru

Tatyana S. Demyanenko, Senior Tutor, Department of Mathematical and Computer Modelling, South Ural State University, (Chelyabinsk, Russian Federation), oop_flp@mail.ru

Ilya P. Ostanin, Under Graduate, Department of Mathematical and Computer Modelling, South Ural State University, (Chelyabinsk, Russian Federation), deks1309@gmail.com

Received December 7, 2016

УДК 519.248 DOI: 10.14529/jcem160406

МОДЕЛИРОВАНИЕ ЭНЕРГОПОТРЕБЛЕНИЯ С ПОМОЩЬЮ НЕЙРОННЫХ СЕТЕЙ ПРЯМОГО РАСПРОСТРАНЕНИЯ НА ПРИМЕРЕ ОЭС РОССИИ

В.Г. Мохов, Т.С. Демьяненко, И.П. Останин

В статье рассмотрена модель прогнозирования объемов потребления электроэнергии на основе нейронной сети прямого распространения. Модель протестирована на фактических почасовых данных Объединенной энергосистемы Оптового рынка электроэнергии и мощности России. Описан алгоритм обучения нейронной сети с разным количеством нейронов на скрытом слое. При тестировании полученной модели была достигнута ошибка прогноза 2,13 % для сети с 72 нейронами на скрытом слое. Разработанный научный инструментарий рекомендуется в операционной деятельности субъектов электроэнергетики при прогнозировании основных параметров энергетического рынка для снижения штрафных санкций за счет повышения точности прогнозов.

Ключевые слова: субъекты электроэнергетики; энергопотребление; нейронные сети; активационная функция; оптовый рынок электроэнергии и мощности; прогнозирование.

Литература

1. Мохов, В.Г. Modeling of the Time Series Digressions by the Example of the UPS of the Ural / В.Г. Мохов, Т.С. Демьяненко // Вестник ЮУрГУ. Серия: Математическое моделирование и программирование. – 2015. – Т. 8, № 4. – С. 127–130.
2. Kriesel, D. A Brief Introduction to Neural Networks / D. Kriesel. – Germany, 2007.
3. Хайкин, С. Нейронные сети: Полный курс / С. Хайкин. – М.: Вильямс, 2006.
4. Осовский, С. Нейронные сети для обработки информации / С. Осовский. – М.: Финансы и статистика, 2002.

Мохов Вениамин Геннадьевич, доктор экономических наук, профессор, кафедра математического и компьютерного моделирования, Южно-Уральский государственный университет, (г. Челябинск, Российская Федерация), mokhov50@mail.ru

Демьяненко Татьяна Сергеевна, старший преподаватель, кафедра математического и компьютерного моделирования, Южно-Уральский государственный университет, (г. Челябинск, Российская Федерация), oop_flp@mail.ru

Останин Илья Павлович, магистрант, кафедра математического и компьютерного моделирования, Южно-Уральский государственный университет, (г. Челябинск, Российская Федерация), deks1309@gmail.com

Поступила в редакцию 7 декабря 2016 г.