Neural Network Prediction of the Electricity Consumption of Trolleybus and Tram Transport in Sofia City

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Abstract: A multilayer neural network with back propagation learning method used for prediction of the electricity consumption of the trolleybus and tram transport in Sofia city is presented in the paper. In the hauler "Transenergo" the Power Engineer has to declare necessary electricity consumption for every hour of the following week. The incorrect request affects the price of the electricity. Electricity consumption is a random process which depends on many factors. The Power Engineer has information for the following data: kilometers run, temperature, the kind of day and from this information has to declare the necessary electricity consumption. In this paper the property of neural networks to define the relation among a number of variables is employed for solving the problem of electricity consumptions prediction. The data for training of the NN are for the 2011-2012 period (17493 items). Testing data is for the 2013 year. The neural network has one input with five neurons, one hidden and one output layer with one neuron. The output is the electricity consumption. The accuracy, which is reached, is bigger than the Power Engineer has achieved in the real request for electric consumption.

Key-Words: - Neural network, electricity consumption, prediction, back propagation learning method

1 Introduction

Artificial neural networks (ANN) as an innovative approach have greatly enhanced the opportunities for analysis and treatment of information in different scientific and engineering areas. The great advantage of ANN is that they impose less restrictive requirements with respect to the available information about the character of the relationships between the processed data, the functional models, the type of distribution, etc. They provide a rich, powerful and robust non-parametric modelling framework with proven efficiency and potential for applications in many fields of science. The advantages of ANN encouraged many researchers to use these models in a broad spectrum of real-world applications. In some cases, the ANNs are a better alternative, either substitutive or complementary, to the traditional computational schemes for solving many engineering problems.

In many engineering and scientific applications a system having an unknown structure has measurable or observable input or output signals. Neural networks have been the most widely applied for modelling of systems [1-6]. Artificial neural networks, coupled with an appropriate learning algorithm have been used to learn complex relationships from a set of associated input-output vectors.

It is well-known that forecasting techniques based on artificial neural networks are appropriate means for prediction [7] from previously gathered data. The neural networks make possible to define the relation (linear or nonlinear) among a number of variables without their appropriate knowledge [8, 9, 10] Multilayer perceptron is usually used with forward or backward error propagation [11, 12] methods for analysis of temporal sequences (ARMAX, ARX) [7, 13, 14] as well as hybrid systems [15].

2 Problem Formulation

In the hauler “Transenergo” the Power Engineer has to declare the necessary electricity consumption for every hour of the following week. Incorrect request affects the price of electricity.

Electricity consumption is a random process which depends on many factors. The Power Engineer has information for the following data: kilometers run, temperature, the kind of day and from this information has to declare the necessary electricity consumption. The property of the neural networks to define the relation among a number of variables makes them suitable for solving this problem.

In this paper a multilayer perceptron with back propagation learning method is used for prediction of the electricity consumption of in trolleybus and tram transport in Sofia city.

3 Artificial neural network models used in the study-Feed forward back-propagation (FFBP) ANN

The Feed-forward (FF) or layered ANN is one of the first neural network architectures with typical structure shown in Fig. 1. It consists of several consecutive layers of nonlinear units called neurons. Connections are allowed only between neighbor layers directed from the first (input) to the last (output) layer. The specification of the FF model structure includes determination of the number of the input and the output neurons (depending on the specifics of the function that will be modeled); choice of the number of hidden layers and the number of neurons in each one of them and of the non-linear processing functions of all neurons (usually a kind of sigmoid-shaped nonlinearity). The “Neurons” in the first layer, indicated by squares, are not typical non-linear units. They only distribute the input vector to the first hidden layer (indicated by circles on the Fig.1). It is well known that usually one hidden layer is sufficient to model any complex nonlinear dependence between the input and output vector. The training algorithm of this type of neural networks is usually performed by applying the error back propagation (BP), from which their popular name has been shortened to FFBP.

The output of each hidden layer of neurons is calculated by nonlinear dependence of the linear combination of outputs of the neurons in the previous hidden layer:

$$x_j(t) = f\left(W_{ij} x_i(t)\right) \qquad (1)$$

For the input and the first hidden layer the dependences are:

$$\begin{aligned} x_1(t) &= \left[in(t) \quad in(t-\Delta t) \quad \cdots \quad in(t-n\Delta t)\right]^T \\ x_2(t) &= f\left(W_{in} x_1(t)\right) \end{aligned} \qquad (2)$$

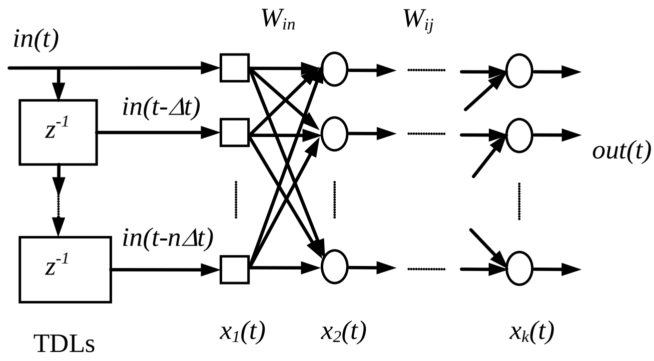

Fig. 1. Neural network with feed-forward back-propagation (FFBP) architecture.

Here t denotes a discrete moment in time, Δt is the (sampling) discretization step and f is a monotonically increasing function, usually nonlinear sigmoid (logistic sigmoid or hyperbolic tangent), in the case of hidden layers and usually linear for the output layer of the network.

This architecture models a static dependence between its input and output vectors of the network. In order to be able to model a dynamic process dependence, lines of time delay elements (briefly TDL) are inserted at the network input that keep “memory” of the past states of the modelled process.

4 The data

The data are provided by Transenergo IRP, Sofia. They contain for every hour of the day: the date (day and month), the hour, the kind of the day (whether the day is weekday or weekend), kilometres run, the temperature and electricity consumption in MW. The data for training of the NN are for the 2011-2012 period (17493 items). Testing data is for the 2013 year.

5 Choice of neural network structure

The neural network has one input with five neurons, one hidden and one output layer with one neuron. The input parameters are the date (day and month), the hour, the kind of the day (whether the day is weekday or weekend), kilometers run and temperature. The number of neurons in the second

ISBN: 978-960-474-375-9

layer is determined by the criterion of the minimum squared error and the highest correlation coefficient between the observed and predicted data sets. The output is the electricity consumption.

6 Results

The calculations are made in MATLAB environment. The neural network is trained with 17943 items. The number of neurons in the hidden layer is determined by the criterion of the minimum squared error and the highest correlation coefficient between the observed and predicted data sets after many experiences with different number of neurons. The results from the testing with the new data for 2013 are given in Fig. 2, 3 and 4. Fig. 2 shows the real data and the prediction of electricity consumption for January 2013.

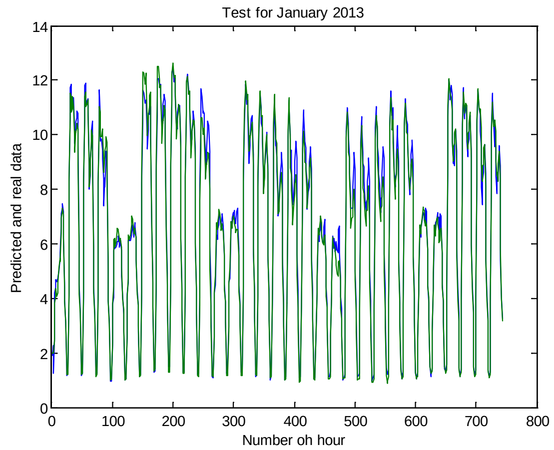

Fig. 2

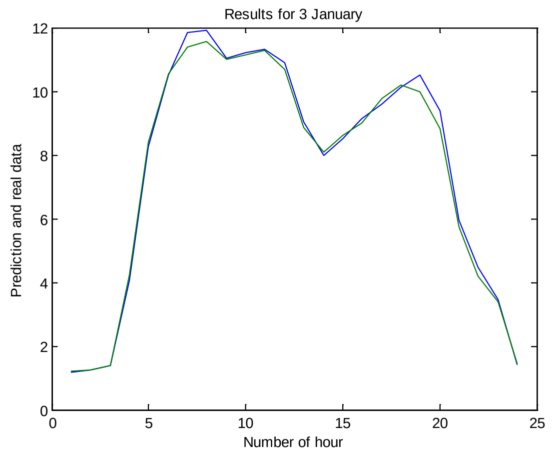

Fig. 3

The results for the 3rd of January are in Fig. 3. The results for the 1st of September are displayed in Fig. 4. The unit of electricity consumption is MW. The error for the entire month of January is 1%. In Fig. 5 there is a histogram of the error. It is evident that the predictions with big positive and negative errors are very few. Fig. 6 shows the decrease of the error for the training, validation and testing processes. The best validation performance is achived at the 313 epoch. In Fig. 7 the regression coefficients for training, validation and testing are shown. They are very big, biger than 0.996.

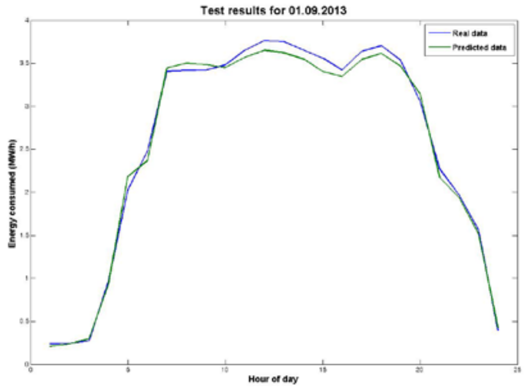

Fig. 4

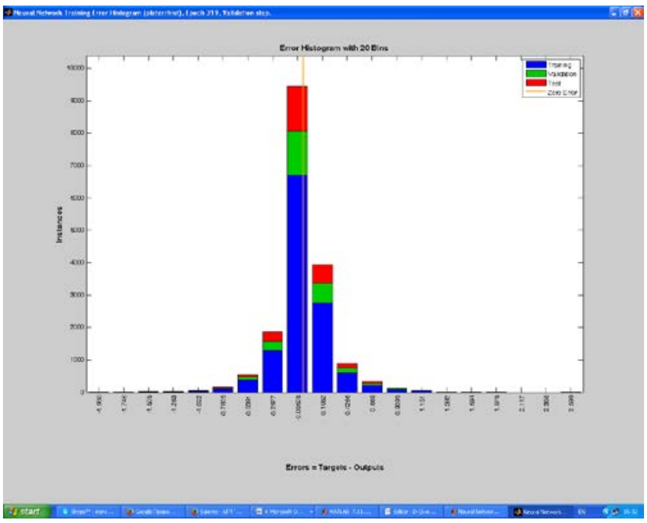

Fig. 5

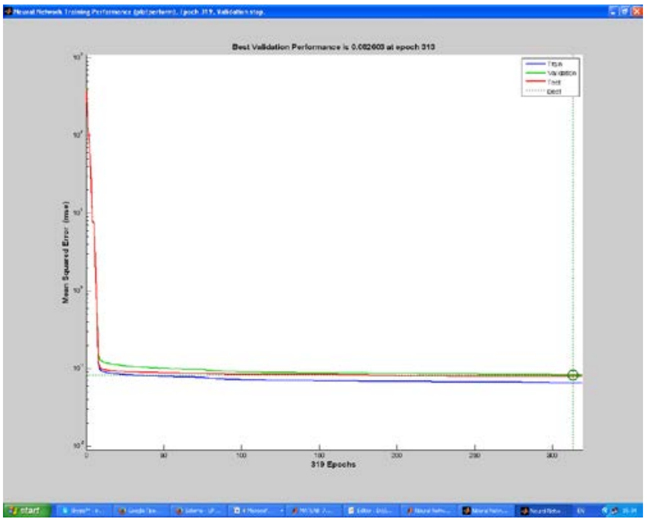

Fig. 6

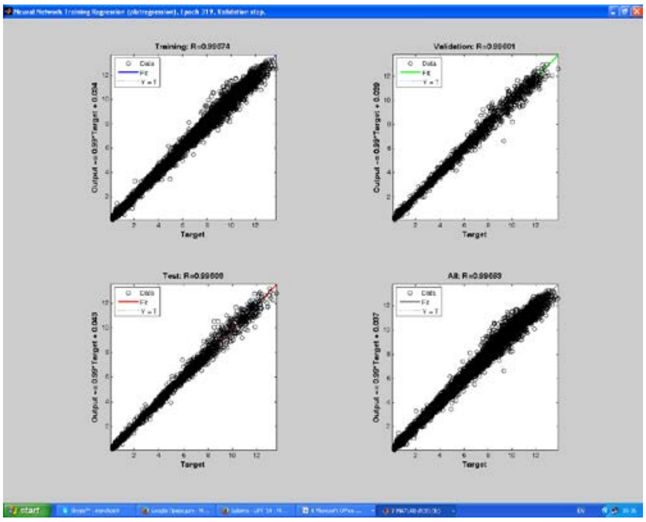

Fig. 7

7 Conclusion

The applicability of the neural network for prediction of electricity consumption is studied in this paper. The ability of the neural networks to define the relation among a number of variables without their appropriate knowledge is proven again. The neural network extracts the relation from a big number of available real data and predicts for new data with small error. The accuracy, which is reached, is bigger with our model, than the Power Engineer has achieved in the real request for electric consumption. His deviation is 6%, whereas the error of our model is between 1 and 2%. In the future, the prediction with neural network will be included in a real system for electrical consumption request.

References:

[1] Thibault, J., Feedforward neural networks for identification of dynamic processes, J.Chem. Eng. Comm 105, 109-128, 1991.

[2] Thibault, J., V.V. Breusegem and A.Cheruy, On line prediction of fermentation variables using neural networks, J. Biotechnol. Bioeng. 36(12), 1041-1048, 1990.

[3] Thibault, J. and A.Cheruy, A comparison of GMDH and neural networks for modeling of a bioprocess. In MIM-S^2 Imacs Annals on computing and applied mathematics proceedings, Sept., Brussels, 1990.

[4] Koprinkova, P., M.Petrova, T. Patarinska and M. Bliznalova, Neural networks modeling of fermentation process 29(3):303-317, 1998.

[5] Petrova, M., Koprinkova P., T. Patarinska and M. Bliznalova, Neural networks modeling of fermentation process. Specific growth rate model. J. Cyber. and Systems 29:303-317,1998.

[6] Grancharova, A. and S. Vasileva , Neural model-based optimization of brewing yeast production process. 4th International Scientific-Technical Conference on Process Control, Koutynad Desnou, Ches Republic, 2000

[7] Benvenuto F., A. Marani, 2000, Neural Networks for environmental problems: data quality control and air pollution nowcasting., Global Nest:the Int. J. Vol. 2, N 3, pp. 281-292.

[8] Gardner M. W., Dorling S. R., 1998, "Artificial Neural Networks (the Multilayer Perceptron) A Review of Appl. in the Atmospheric Sciences", Atmospheric Env., 32(14), pp. 2627-2636.

[9] Popova S., I. Videnova, D. Nedialkov, 2002, Using Neural Network modelling for forecasting air quality parameters. BiioPS'02. October., 28-29, p. II.7 - II10.

[10] Rankinen K, M. Forsius, M. Holmberg, A. Lepisto, 2000, NoLIMITS Report 3. Using Models in NoLIMITS.

[11] Cichocki, A. and R. Unbehauen. Neural networks for optimization and signal processing, John Wiley and Sons, New York, 424-478, 1993.

*[12] Pashova L., S. Popova, Daily sea level forecast at tide gauge Burgas, Bulgaria using artificial neural networks, Journal of Sea Research, **66**, 154–161, 2011*

[13] Koprinkova-Hristova, L. Pashova, S. Popova, Application of two neural networks for gap filling of geodata,, J. Aut. and Inf 4/2012, 7-13

[14] *Pashova L., Koprinkova-Hristova P., Popova S., Gap filling of daily sea levels by artificial neural networks, 10 th International Conference on Marine Navigation and Safety of Sea Transportation, Gdynia 19-21 June, 2013, - International Journal on Marine Navigation and Safety of Sea Transportation, Vol 7 Nu 2 June 2013 pp. 225-232*

[15] *Zimmermann H.J., 1991, Fuzzy set theory and its applicaions. Second Edition, Kluwer Academic Publishers.*

Acknowledgments

This study is financially supported by the Bulgarian Ministry of Education, Youth and Science under the Project BG051PO001-3.3-05/0001 „Science and business”, financed by Operational Programme “Human Resource Development”, European Social Fund.

The authors are grateful to Dr. Maya Dimitrova for her help in the preparation of the paper.

ISBN: 978-960-474-375-9