Electricity Consumption Prediction System for the Public Transportation

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Abstract: A system for prediction of the electricity consumption of public transport in a city is presented in the paper. A multilayer neural network with back propagation learning method is the basic part of the system. In transport hauler the Power Engineer has to declare the 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. Dialogue system requires information for the month, type of day, time and temperature. The system provides information for the distributions of temperature, kilometers run and their joint distribution for the different periods. The system searches the kilometers run with similar parameters in the database and offers an average value. The Power Engineer compares this value with the planed kilometers run and decides the value for the request. Thereby formed query is the input vector to the neural network, which returns a value of electricity consumption. The neural network is previously trained with 26230 items for the past period. The neural network has one input with five neurons, one hidden and one output layer with one neuron. The output is the electricity consumption.

Key-Words: - Dialogue system, neural network, electricity consumption, prediction, back propagation learning method, copula, histogram, database

1 Introduction

Reducing energy consumption and eliminating energy wastage are among the main objectives of the European Union (EU). EU support for improving energy efficiency will prove decisive for the competitiveness, security of supply and the implementation of measures on issues related to climate change commitments under the Kyoto Protocol. There is significant potential for reducing consumption, especially in the energy-intensive sectors such as buildings, manufacturing, energy conversion and transport. Proper planning of the electricity consumption in the public transport contributes to energy efficiency.

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 [1-7]. 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 [8] 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 [9 - 11]. Multilayer perceptron is usually used with forward or backward error propagation [12, 13] methods for analysis of temporal sequences (ARMAX, ARX) [7, 14, 15] as well as hybrid systems [16].

In the late sixties of the last century Sklar [17] introduced a copula concept to separate the effect of dependence from the effect of marginal distributions in a joint distribution. The copula functions provide a natural way to study and measure linear and nonlinear dependencies between multiple random variables. Recently, the copula approach is widely used in various fields of sciences [18 - 24]. The procedures of copula approach are presented in details in the statistical literature [25 - 29].

2 Problem Formulation

In the transport hauler the Power Engineer has to declare the necessary electricity consumption for every hour of the following week. Incorrect requests affect the price of electricity.

Electricity consumption is a random process which depends on many factors. The Power Engineer has information for the following data: hour, month, the kind of day, temperature, planned kilometers run, and from this information has to declare the necessary electricity consumption. Because the kilometers run depends on several factors the engineer searches manually the kilometers run with similar parameters in the past database. It is necessary to automate this search.

The Power Engineer has obtained the temperature forecast for the next week, but this is not an accurate prediction.

Then for a given month, hour, kind of day, temperature and kilometers run the necessary electricity consumption has to predict.

In this paper a dialogue system for prediction of the electricity consumption of the public transport in a city, on the base of a neural network, is proposed.

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:

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

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

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

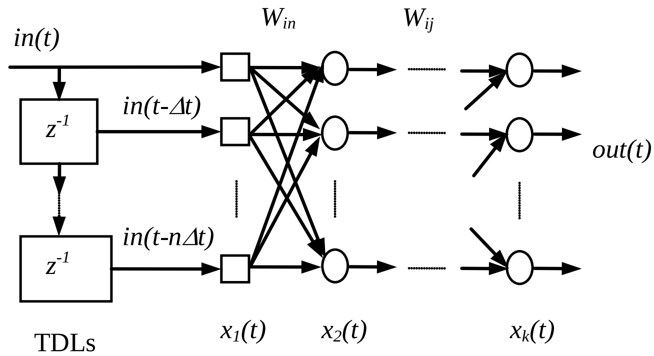

Fig. 1. Neural network with feed-forward back-propagation (FFBP) architecture.

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 system

First the system asks for the month, kind of the day and the temperature. Power Engineer has the temperature forecast for the next week, but this is not an accurate prediction. For this reason he uses a histogram of distribution of the temperature for the previous month, for the same month of the previous years, to choose the exact temperature for this hour. To help him resolve the problem, the system includes searching in the database for the temperature of the same day and hour for the previous years. To give the exact value for kilometers run the system searches in the database for such kind of days and the same temperature or close to it. The histogram of temperature and the joint histogram of the temperatures and kilometers run for the different periods help to choose how close to the predicted temperature to search and the exact value of kilometers run. In Fig. 2 the probability density function of temperatures and kilometers run for 2011 and 2012 years is shown. It is obtained by copula [25-29]. The dependency between the values of the temperature and the kilometers run and the values between 0 and 1 in Fig.2 are known to the user.

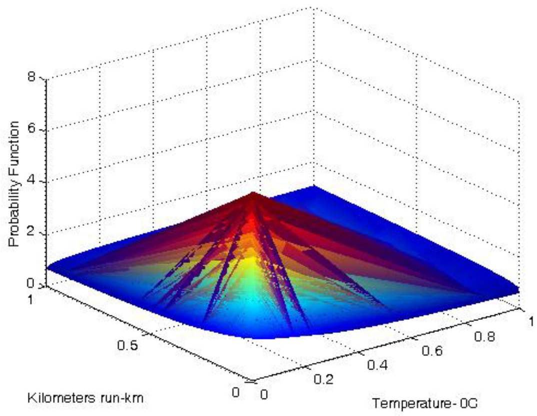

Fig.2

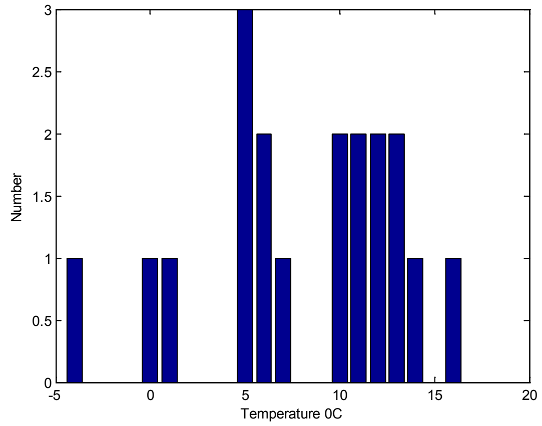

Fig3.

In Fig.3 the histogram of the temperature for the work days in the March from 11:00 to 12:00 is shown.

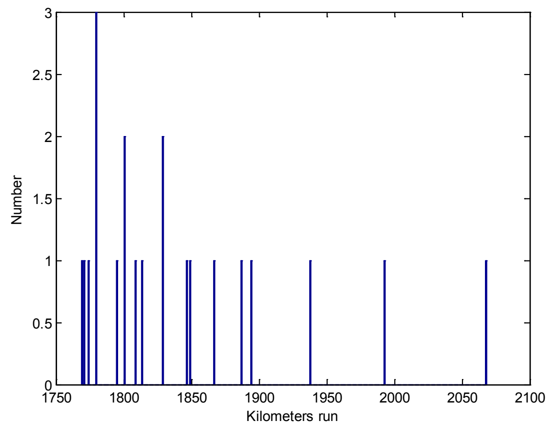

Fig.4

In Fig.4 the histogram of kilometers run in the month of June from 10 :00 to 11:00 is given.

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 layer is determined by the criterion of the minimum squared error and the highest correlation coefficient between the observed and predicted data sets. The number of neurons in the hidden layer is 31. The output is the electricity consumption.

6 Results

The calculations are made in MATLAB environment. The neural network is trained with 26230 items. The unit of electricity consumption is MW. The results from the testing with the new data for 2014 are given in Fig. 5, 6 and 7.

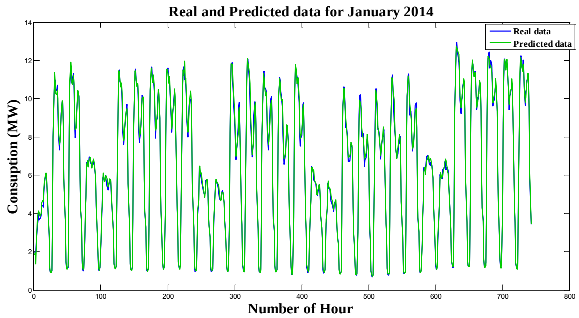

Fig. 5

Fig. 5 shows the real data and the prediction of electricity consumption for January 2014. The error for the entire month of January is 0.5%.

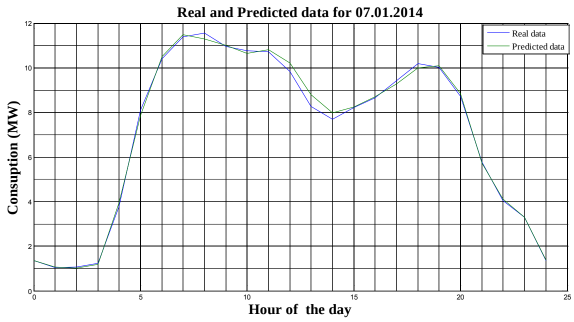

Fig. 6

The results for the 7th of January are in Fig. 6.

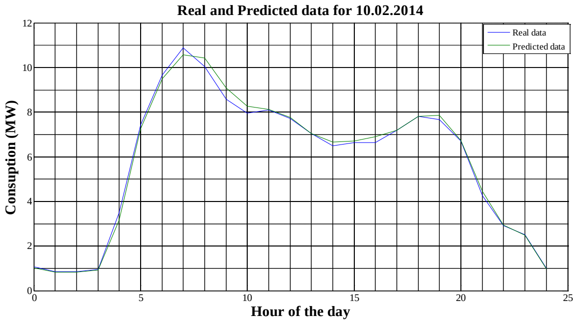

Fig. 7

The results for the 10th of February are displayed in Fig. 7.

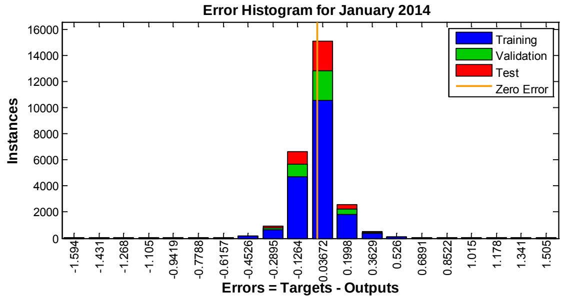

Fig. 8

In Fig. 8 there is a histogram of the error. It is evident that the predictions with big positive and negative errors are very few.

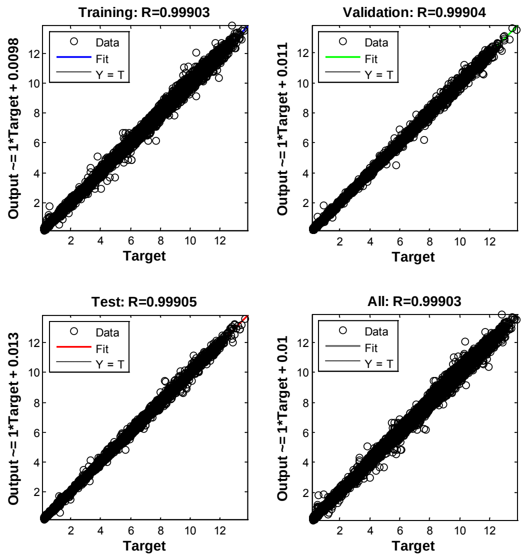

Fig. 9

In Fig. 9 the regression coefficients for training, validation and testing are shown. They are very big, biger than 0.999.

7 Conclusion

A real system for prediction of electricity consumption is studied in this paper. The dialogue system helps the Power Engineer to choose the parameters which are inputs for the neural network. To choose the exact values, the user searches in the database and uses histograms and joint distribution provided by the system. 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. For prediction of electricity consumption other methods, such as time series analysis [30, 31] instead or together with a neural network, will be studied for use in the future.

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