ESTIMATION OF THE ELECTRICAL ENERGY CONSUMPTION

C. Volosencu

Departamentul de Automatica si Informatica Industriala
Facultatea de Automatica si Calculatoare
Universitatea "Politehnica" din Timisoara, Romania

Abstract: This paper presents a simple example of design, modelling and simulation of a model of the electrical energy consumption based on feedforward neural networks. A database with electrical energy consummated on a year is used to train and to test the neural network. Levenberg-Marquardt method from the neural network toolbox of Matlab was used for training. Good quality criteria were obtained for a prediction for a short term with a simple neural network with only a hidden layer and a reduced number of neurones.

Keywords: measurement of electrical energy, power systems, estimation, feedforward neural networks, Levenberg-Marquardt method, Matlab

1   INTRODUCTION

In the last years neural networks were developed, different training methods appeared and they were used in a large number of applications [4, 6, 8, 9, 10]. The estimation of the electrical energy consumption for the power distribution stations is a possible application of the neural networks. Other methods are used for this purpose with their advantages and disadvantages [2 3]. The users of the neural networks hope to obtain a simpler implementation of the estimation model with less estimation errors. In this paper design considerations of a simple estimation model for the electrical energy consumption for short term based on neural networks are presented.

2   DATA BASE

The database for developing the estimation model covers an eight months period and it contains the records of the daily electrical energy consumption from 15 to 15 daily consumption schedules. From the date base we may notice some aspects as follows. The daily consumption curves keeps the same form from a day to another day. There is an important difference in the working days from the free days (Saturday and Sunday), as is shown in Fig. 1.
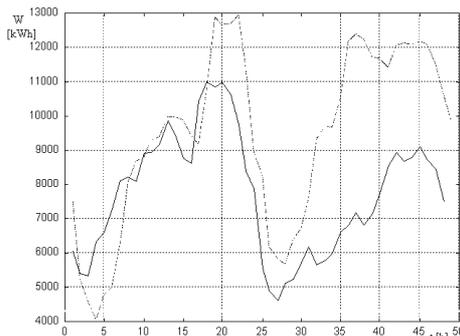
There are some major differences sometimes in the consumption curves for the same day of the week in different weeks and months. This observation is illustrated in Fig. 2 and 3, for two Tuesdays from two consecutive weeks. In some situations there are anomalies in the consumption curves, due probably to some abnormal events, which happen in the power network –records of zero values. In these cases the consumption curves were adjusted at the general forms of the consumption curves for the same days from other weeks. There are also differences in the weekly consumption curves, illustrated in Fig. 4 and 5.

Figure 1. The consumption for working days (Monday, Tuesday) __ and for the free days ...

From these observations, the only fact, which can affect substantial, the precision of the estimation of the electrical energy consumption is the correct recording of the data. From the data base used, that contains records of the electrical energy consumption from 15 to 15 minutes, a modified data based was built with consumption from one hour, by summation of the of the consummated energies from one hour on the all period of time. The electrical energy consumption curve is presented in Fig. 6.

The values of the consummated energy were scaled in the domain [-5, 5]. The scaled data based was used to train and to test the neural network. Records from the period of time from 20 of February '98 to 12 of October '98 were used to rain the neural network. And records from the period of time from 13 of October '98 to 16 of October '98 were used to test the neural network.
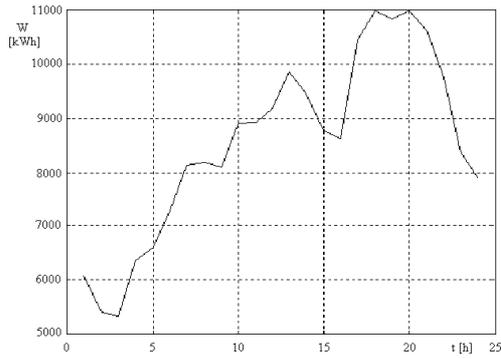
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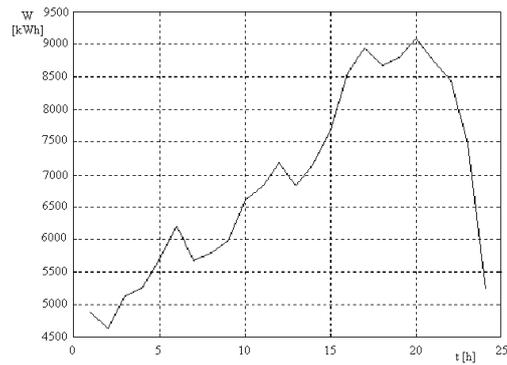**Figure 2.** The consumption from a Tuesday

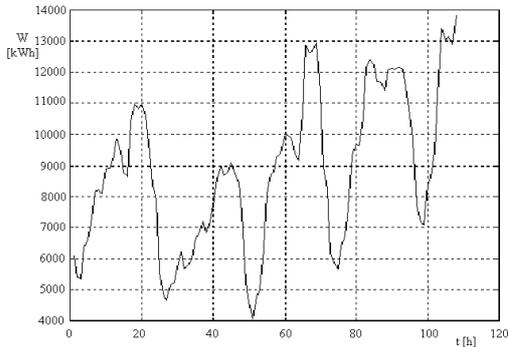**Figure 3.** The consumption for the next Tuesday

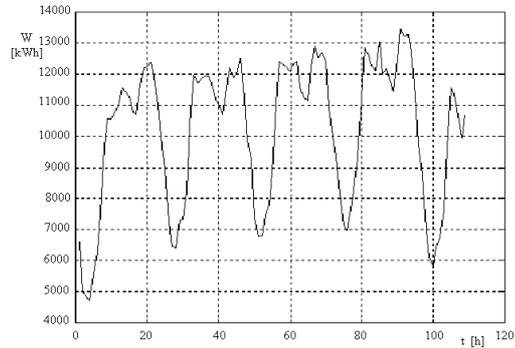**Figure 4.** The consumption for a certain week

Figure 5. The consumption for the next week
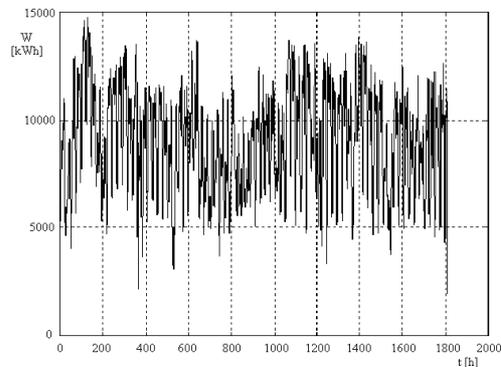

Figure 6. The training set

3   DESIGN OF THE NEURAL NETWORK

3.1   Generalities

In the design procedure of the neural network the following parameters were chosen: the inputs of the network; the number of hidden layers and the number of its neurones and the number of output neurones [4, 5, 6, 7, 8, 9, 10].

A feedforward neural network with continuous values was chosen [9]. Only one hidden layer was used [5]. Different structures were tested, with a different number of neurones on the hidden layer. As the activation functions for the hidden layer the hyperbolic tangent was used and for the output layer the linear function was used.

The sum square error was computed for the each structure. The structure was chosen after a compromise made between the output error and the number of the neurones on the hidden layer.

Also, in the training process the consummated computer's memory and the training time were important impediments, created by the available computing resources [9].

The training sets were built using only a part of the database. So, if on the inputs of the neural network are used data from the past consumption, the first hours can be used only for the inputs and not for the outputs. Also, data from the last week were used to test the network after its training. These data was not used in the training process.

3.2 Correlation analysis

To choose the inputs of the neural network an auto-correlation analysis was made on the database between the electrical energy consummated at the different time moments [2, 3]. The basic principal of the auto-correlation analysis consists in computing the coefficients of auto-correlation for each ordinate pair of energies (W_t, W_{t+1}), at two consecutive time moments. The auto-correlation coefficient estimated of the observation at separated time moment k, for the same time series is r_k. The coefficient r_k are statistical values determined for samples from database. It is a statistical measure of the dependence between two random variables. It has values in the interval [-1, 1]. The value −1 means a perfect negative correlation and the value 1 means a perfect positive correlation. If $r_k = 0$, then W_{t+k} and W_t are not correlated. The error in sampling can produce values for r_k different from 0 even in the case of non-correlation between two values.

The statistical analysis was made for three different time periods: 1) from 23 of April to 18 of August 1998; 2) from 09 of January to 22 of April 1998 and 3) from 9 of January to 18 of August 1998. The values of the auto-correlation coefficients are presented in Tab. 1, for the electrical energy consummated at the moment t and at different time moments from the past t-k. Electrical energy consumption with 12 hours before the prognoses hour, consumption with one day before (with 23, 24 and 25 hours before) and the consumption with one week before (with 191, 192 and 193 hours before).

Table 1. The auto-correlation coefficients

k	r_k		
[h]	23.04 -18.08 1998	09.01 -22.04 1998	09.01 -18.08 1998
1	0.804	0.872	0.894
2	0.486	0.607	0.738
3	0.260	0.541	0.694
4	0.108	0.341	0.382
5	0.008	0.140	0.300
6	0.046	0.029	0.265
7	0.053	0.017	0.313
8	0.003	0.156	0.313
9	0.137	0.124	0.396
10	0.288	0.460	0.297
11	0.373	0.331	0.347
12	0.389	0.220	0.200
23	0.591	0.731	0.773
24	0.756	0.845	0.865
25	0.582	0.732	0.771
168	0.763	0.845	0.819
169	0.600	0.761	0.741
191	0.460	0.620	0.649
192	0.622	0.759	0.740
193	0.462	0.677	0.664

From the analysis of the Tab. 1 we may say the following conclusion. The most powerful correlation of the energy consumption at the prognosis time is related to the first, second and third hours last hours. After the examination of the other time periods we may say the fourth moments until the prognosis is also important. The auto-correlation coefficients for the last 23, 24 and 25 have also important values. For the history of the estimation of the energy consumption for long term the important correlation are for the last 24, 168, 169 and 192 hours before the prognosis.

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For a estimation for short term the inputs of the neural network were chosen the energies at five times before the prognosis: $W(t)$, $W(t\text{-}1)$, $W(t\text{-}2)$, $W(t\text{-}3)$ and $W(t\text{-}4)$.

3.3   Network design

Only one hidden layer is enough for the estimation model for short-term [5]. The main reason of this consideration consist in the fact that the intermediate neurones which are not connected directly with the output neurone will have very little variations of their weights and they will learn very slowly. Another reason for choosing this structure is its simplicity. Using of two ore more hidden layers is necessary for a model for estimation for a long term. The only way to determine the number of the neurones from the hidden layer is to do iterative training for different neurones and to compare the resulted square sum error [9]. In practice for a large number of problems one hidden layer is enough [5].

The training of the neural network was made using Levenberg-Marquardt method from the Matlab's neural network toolbox [1, 7].

To choose the number of neurones from the hidden layer some iterative training were done from 1 to 10 neurones. The values of the prediction error are presented in Tab. 2 for all the tested structures.

Table 2. The prediction error

n	1	2	3	4	5
E	4,9	4,2	4,1	3,7	3,6
n	6	7	8	9	10
E	3,6	3,5	3,4	3,3	3,3

We may notice that increasing the number of neurones the error decreases. After this test a network with only 7 neurones on the hidden layer was chosen.

The final structure of the neural network is presented in Fig. 7. The output of the neural network is the estimated energy at the time t+1: $W(t+1)$.

The square sum error resulted after the final training is presented in Fig.. 8. The neural network was implemented using the neural network toolbox from Matlab [1, 7].
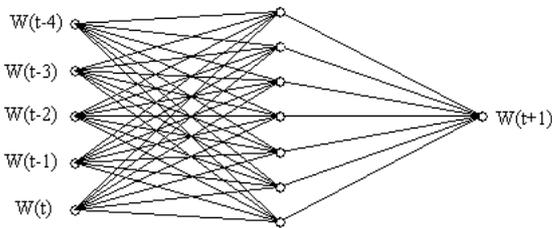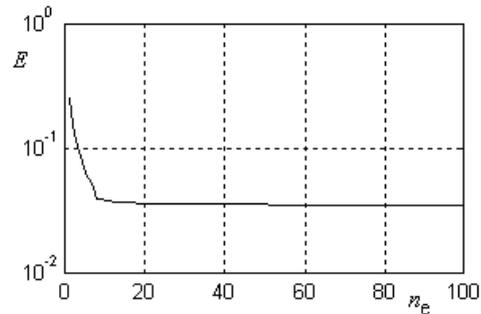

Figure 7. The neural network

Figure 8. The sum square error

4   TEST RESULTS

The neural network was tested with different testing sets from the database. The prediction error obtained is in the interval [-1, 1]. The results of a test are presented in Fig. 9. Records from 72 hours (3 days) are used.

The values of the weights, taken from Matlab's workspace are presented as follows. The weights from the input layer to the hidden layer are clustered in the matrix w_1:

$$w1 = \begin{bmatrix} -0{,}2583 & 1{,}2440 & -1{,}0725 & -0{,}6133 & 1{,}1676 \\ 0{,}3144 & 0{,}2904 & -0{,}7054 & 0{,}1553 & 0{,}5939 \\ -0{,}3143 & -1{,}1923 & -0{,}1671 & 0{,}1787 & 1{,}0811 \\ 0{,}0917 & 0{,}7393 & -0{,}7916 & -1{,}2877 & 1{,}5702 \\ -1{,}1274 & 1{,}0680 & -0.5490 & 0{,}2128 & 0{,}0546 \\ -0{,}8218 & 1{,}7400 & -0{,}2459 & 0{,}3776 & -0{,}9060 \\ -1{,}2062 & 0{,}3624 & 0{,}6883 & -0{,}3507 & -0{,}8657 \end{bmatrix}$$

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The weights from the hidden layer to the output layer are clustered in the matrix w_2:

$$w2 = \begin{bmatrix} -1,96 & 2,78 & -0,58 & 1,15 & -1,01 & 0,98 & 0,70 \end{bmatrix}$$
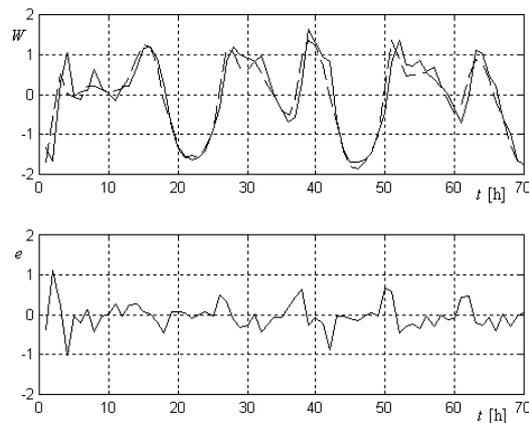

Figure 9. Up: the actual time series … and the
desired series : Low: the estimation error

Analysing the weights we may not clean or reduce the network connections or neurones because all the weights have important values.

5   CONCLUSION

In this paper a simple model for estimation of the electrical energy consumption for short term was designed and tested. This model is based on a feedforward neural network with continuous trained with Levenberg-Marquardt's method. The structure of the neural network is given. The neural network was trained using a database with values from 10 months. The inputs of the network were determined after an auto-correlation statistical analysis. The estimation model was tested with different sets of consummated energies for 70 hours. The estimation errors are in the interval of the scaled values of the consummated energies.

In the future a larger neural network may be developed with a more powerful computing capability for estimation for a long term.

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AUTHOR: Dipl.-Ing. Constantin VOLOSENCU, Departamentul de Automatica si Informatica Industriala, Facultatea de Automatica si Calculatoare, Universitatea "Politehnica" din Timisoara, Bd. V. Pârvan, nr. 2, Timisoara, 1900 România, Phone: 4 056 244877(698), Fax 4 056 192049
E-mail: cvolos@aut.utt.ro