Electricity load forecasting using ANN

Ing. Dalibor Živčák

Department of Electrical Power Engineering, FEI Technical University in Košice, Vysokoškolská 4, 041 20 Košice, SR.
Fax : +421 55 633 6962, tel : +421 55 602 4149,
URL: http://www2.tuke.sk/tu/fei/kee/kee-a.html
E-mail: zivcak@tuke.sk

Abstract. The article presents the solution for tender of VSE a.s. The main addition of work is realized analysis of relation among given data more in details. Thereinafter is presented also algorithm for prediction the temperature base on approximate temperature normal and predicted value. A little bit was described methodology of input selection. Main ideas for particular job evaluation and predicted values of maximal electric load as results of all applied methods.

1 Introduction

The conditions of tender puts XX main task:

1. Processing of presented input.
2. Research of relation among data a as result of this selection of inputs.
3. Needed prediction model of temperature or its "normal".
4. Designed the input, selection of appropriate ANN and its architecture, evaluation of models.
5. Prediction of unknown 31 value of maximum electric load (1.1.-31.1.1999).

Main curve fitting models
There are many mathematic functions, which are suitable as representative function. Main methods to find the appropriate index of mathematic function is used mean square error. These methods are used to processing analog or discrete input
Most popular curve fitting models are:

Linear
This curve is representing linear dependencies (include constant) between two variables.

$$y = a.x + b,$$

where b is significant of value on y-axis for $x=0$ and a is gradient.

Exponentials
Usually is one-term and a two-term exponential model.

$$y = a.e^{b.x}$$

Exponentials are often used when the rate of change of a quantity is proportional to the initial amount of the quantity. If the coefficient associated with e is negative, then y represents exponential decay. If the coefficient is positive, then y represents exponential growth.

Fourier Series
The Fourier series is a sum of sine and cosine functions that is used to describe a periodic signal. It is represented in either the trigonometric form or the exponential form. The toolbox provides the trigonometric Fourier series form shown below

$$y = a_0 + \sum_{i=1}^{n} a_i.\cos(n.\varpi.x) + b_i.\cos(n.\varpi.x)$$

where a_0 is any "DC" offset of data ($I=0$), n is number of harmonics and ω represents frequency. Usually is speak about Fourier analysis and the fast Fourier transform

Gaussian model

The Gaussian model is used for fitting peaks, and is given by the equation:

$$y = \sum_{i=1}^{n} a_i.e^{-\left(\frac{x-b_i}{c_i}\right)^2} \quad ,$$

where a is the amplitude, b is the centroid (location), c is related to the peak width. To create the gaussian distribution with more peaks is realized by "sum", n is the number of peaks.

Polynomials

$y = \sum_{i=0}^{n} p_i x^n$, where n is polynomial degree.

Polynomials are often used when a simple empirical model is required. The model may be used for interpolation or extrapolation (unreliable), or it may be used to characterize data using a global fit. The main advantages of polynomial fits include reasonable flexibility for data that is not too complicated, and they are linear, which means the fitting process is simple. The main disadvantage is that high degree fits can become unstable. Additionally, polynomials of any degree can provide a good fit within the data range, but may diverge wildly outside that range.

Power series

Not so often occurred (shows the variety of data):

$y = a.x^b$, $y = a + b.x^c$,

$y = a.b.x^{b-1}.e^{-ax^b}$ - Weibull Distribution (used in reliability and life data analysis).

Rationals

Rational models can be defined as ratios of polynomials, then:

$$y = \frac{\sum_{i=0}^{n} p_i x^n}{x^m + \sum_{i=1}^{m} q_i x^m}$$

Like polynomials, rationals are often used when a simple empirical model is required. The main advantage of rationals is their flexibility with data that has complicated structure. The main disadvantage is that they become unstable when the denominator is around zero.

Sum of sins

The sum of sins model is used for fitting periodic functions, and is given by the equation:

$$y = \sum_{i=1}^{n} a_i.\sin(b_i.x + c_i)$$

where a is the amplitude, b is the frequency, and c is the phase for each sine wave term, n is the number of terms in the series. This equation is closely related to the Fourier series described previously. The main difference is the sum of sins equation includes phase information, and does not include a DC offset term.

Data analyzing was done using CurveExpert and Matlab.

Using Curvefit were found

1.2 Processing of temperature

To do right prediction of expected electric load (maximum value) is necessary to analyze also others factors. The most important is outside temperature. Temperature also reflect other weather condition as cover of sky, daylight… Fig. 1 a) shows the counted average temperature of given data. How its see the distribution of temperature has gaussian character.

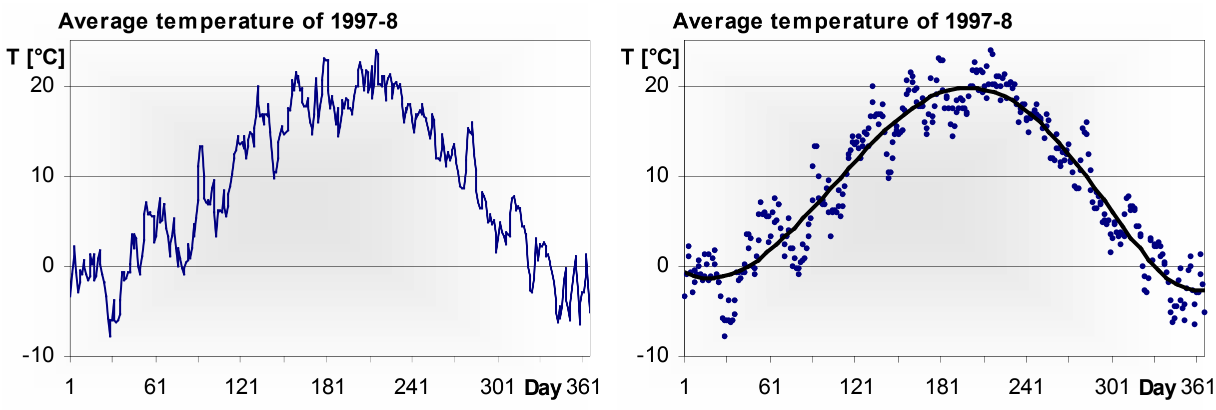

Fig. 1 a) Average temperature of year 1997-8 **b) Multi-nominal fitting**

Fig. 1 b) shows the fitting polynomial of 5th degree (p_0=-0,6359, p_1=-0,0811, p_2=-00024, p_3=-5,92.10^{-6}, p_4=-1,61.10^{-8}, p_5=4,36.10^{-11}) with standard deviation *S=2.59* and correlation coefficient *0.95*. Fig. 2 shows the gaussian distribution of temperature.

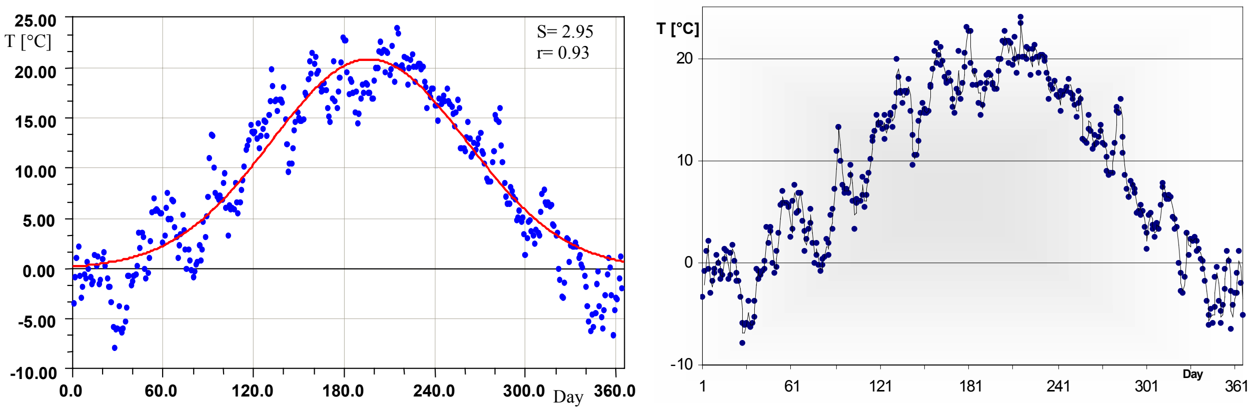

Fig. 2 a) Gaussian fitting **b) Moving average fitting**

The index for gaussian curve are: *a= 20.85, b= 196.04, c= 64.85.*

In this case, that the each day during the year cannot exceed the number of day for whole year is possible to use polynomial curve as "normal". To compute normal from array of 2 years measurement is not correct (usually the normal is computed for more than 20 years). But our experiences confirm competence of used method. The temperature normal has gaussian distribution, with some exception at the edge. The periodicity of temperature is very good to see at all figures above. Next goal was prediction of temperature periodicity and find hidden relation in input. To get reliable prediction of expected temperature behavior is needed bigger array of input and results of other observation. The reached error was about 2.5 % for one day ahead model, but with increasing time interval, the error was moving and the prediction was not reliable. The error of prediction for 4 weeks grow over 50 %. The result is that for useful prediction of temperature for bigger time interval is needed more data and others parameters. This failure shift the prediction of electric load to next level…

For longer time horizont of prediction is sufficient temperature "normal". Creation of temperature "normal" was describing above.

Fig. 4 shows justness of using the temperature to improve prediction. Figures show the value of electric load as function of temperature. There are also plotted alternate curves. Of course multi-nominal reached higher correlation coefficient, but multi-nominal is good for interpolation not for extrapolation, which caused uncertainty at the borders. This was solved using sigmoid function.

Thereinafter is discussed the designed of prediction model and particularly the input to ANN (artificial neural networks). Usually were used ADALINE and Back-propagation ANN to prediction. There is not describe the processing of input for ANN.

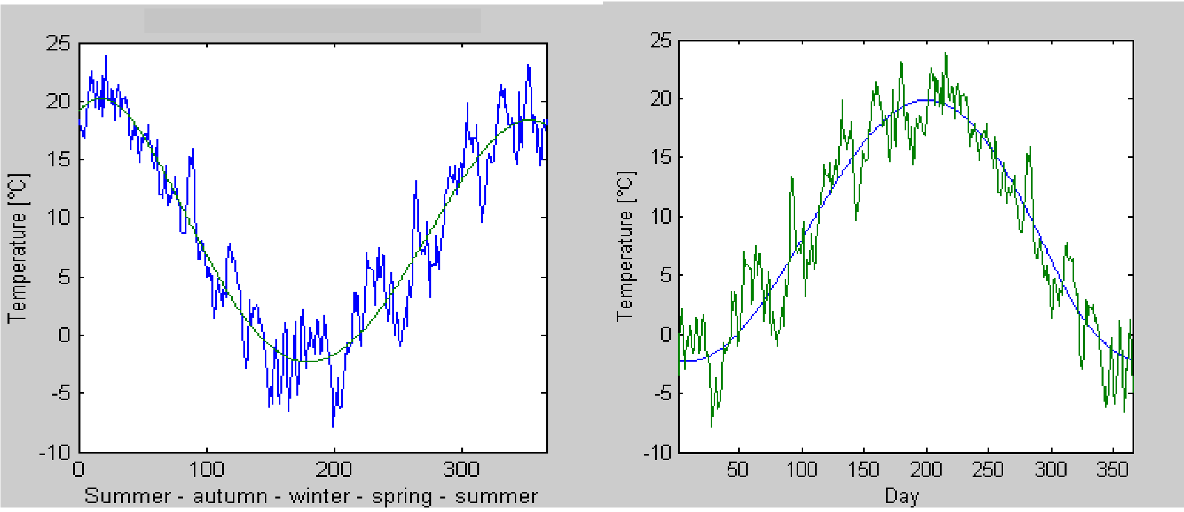

Fig. 3 a) Divided year **b) Result ant temperature “normal”**

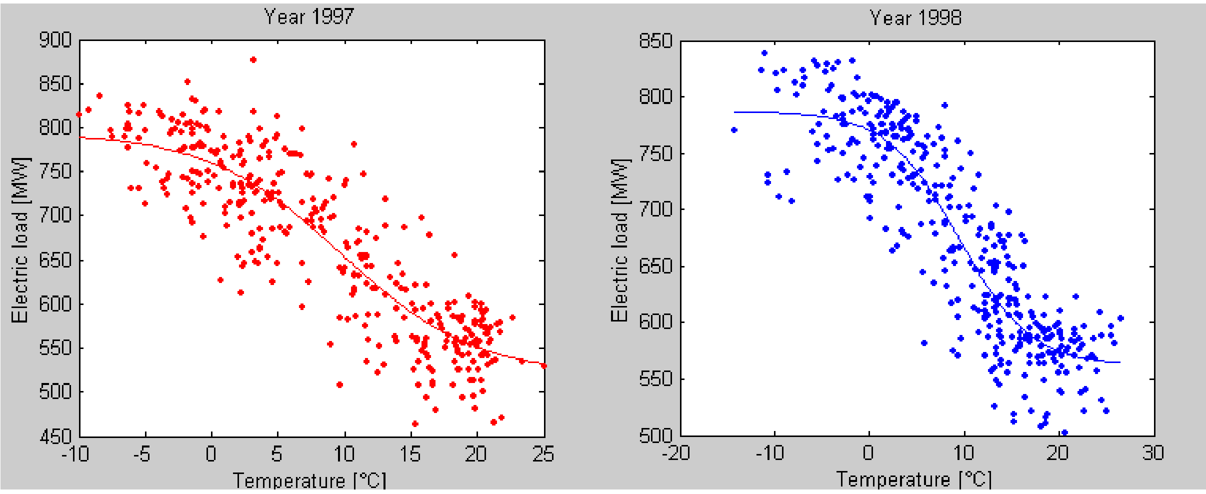

Fig. 4 a) Gaussian fitting **b) Moving average fitting**

1.3 Prediction of temperature

There were two main types of predictors:

1. The temperature was predicted only from known data from one till 31 day ahead. The prediction was very unstable and uncertainty. The error was allowed for one sometimes for two week ahead. With bigger time interval was better as expected value take counted temperature normal.

2. The temperature was predicted one day ahead and the predicted temperature in day *D* was served as input to predict next value (recurrent predictor, the output is in next step bring as input). Using this method was reached error on testing area about 50 %, but for one week the error was under 7 %.

Base on these results I decide to utilize as tempeature normal, also predicted temperature (describe later).

1.4 Feast day and holydays

Next very important factor is affect of feast. Processing of data confirm this idea. The electric load is during the weekend (Saturday and Subday) lower about 6 % and 11 % as average for work days. Also during the feast as eastern, Christmas… The electric load is greatly lower and the form of curve is also changing (now not so important for prediction of maximum electric load).

The input, which interpret the type of predicted day from side of feasts, where create data with emphasis on character of predicted day as day in week, feast and also type of its neighbors.

2 Prediction model of maximum electric load

Prediction of maximum electric load is at present recently occurred problem. This problem gets importance with approaching of privatization of power engineering and price liberalization of electric energy.

Train and test array
The test and train array were selected randomly but the most important were the beginning of year (1997 or 98). This was also problem because of decreasing the more important input.
The error were counted likewise are defined condition for evaluation of results published on web page.
Note: the send results were not tested and training array was whole input (both years).

2.1 Models of prediiction

As first was done prediction of maximum electric load for one day ahead. The best results were moving about 1.4 %. The input to ANN consist of (number in parentheses indicate the size of variable):
Week type (7) feast type(3) feast temperature (2) min. load D-1 aver. load D-1 max. load D-8 max load D-2 max load D-1 Max-min Load D-1
The output was always value of appropriate maximum electric load. For this input (with little adjustment) were attempts to find the best ANN and its architecture.

Prediction models of 31 days ahead
Than base on experiences was designed model of inputs to predict maximum electric load from one till 31 days ahead. Inputs:
Week type (7) feast type(3) feast temperature (2) max. load D-(i+8) max load D-(i+2) max load D-(i+1)
The input was change to adjust it for conditions. Except min., aver. and differences of electric load, because of inaccessibleness of this data for bigger time interval.
For each time delay (one two…31 days ahead) were designed and training particular ANN. The best results was reached about 6.5 %. in
In both cases was realized prediction with and without predicted temperature or temperature “normal”. The prediction when input was without predicted temperature (prediction of temperature for January 1999) reach better and more reliable. But on other side the error for one week ahead was usually better with model, where input contain also predicted temperature.

Recurrent prediction models
This model similarly as model for prediction of temperature use to predict next value of electric load as input previous predicted values. Fig. 5 and Fig. 6 show the effect of temperature to maximum load for prediction model also is very good to see effect of feast days the three Magi. Fig. 5 a) and Fig. 6 a) is very good see as with growing temperature the electric load is falling down.

Model 1
Back-propagation ANN with two layers was selected. Output layer has one neuron and number of neuron in hidden layers was from 15 till 50. the transfer function was “*sigmoig*”.
Input:
Week type (7) feast type(3) feast temperature (2) max. load D-8 max load D-2 max load D-1
Where temperature consists only of counted temperature “normal”.

Model 2
The same as Model 1, except that the temperature input consist of counted temperature normal and predicted temperature.

Both models are recurrent; for each predicted value was created appropriate ANN particularly initialized and training. The prediction of results was done always with ANN and its appropriate architecture, which reached best results during experiences. The training array are whole both year.

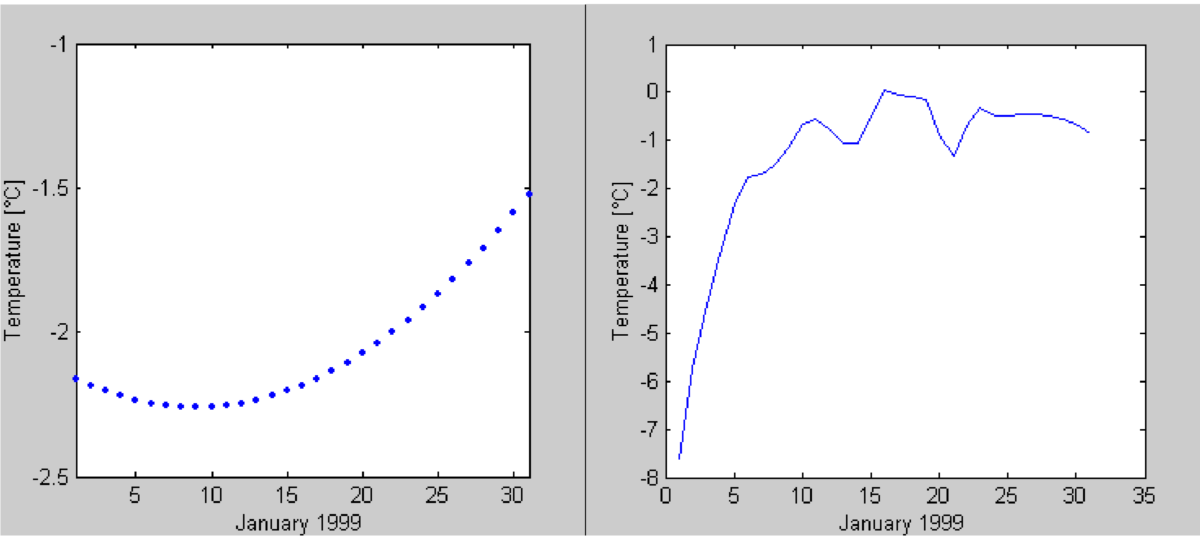

Fig. 5 a) Temperature normal January **b) Predicted temperature for January 1999**

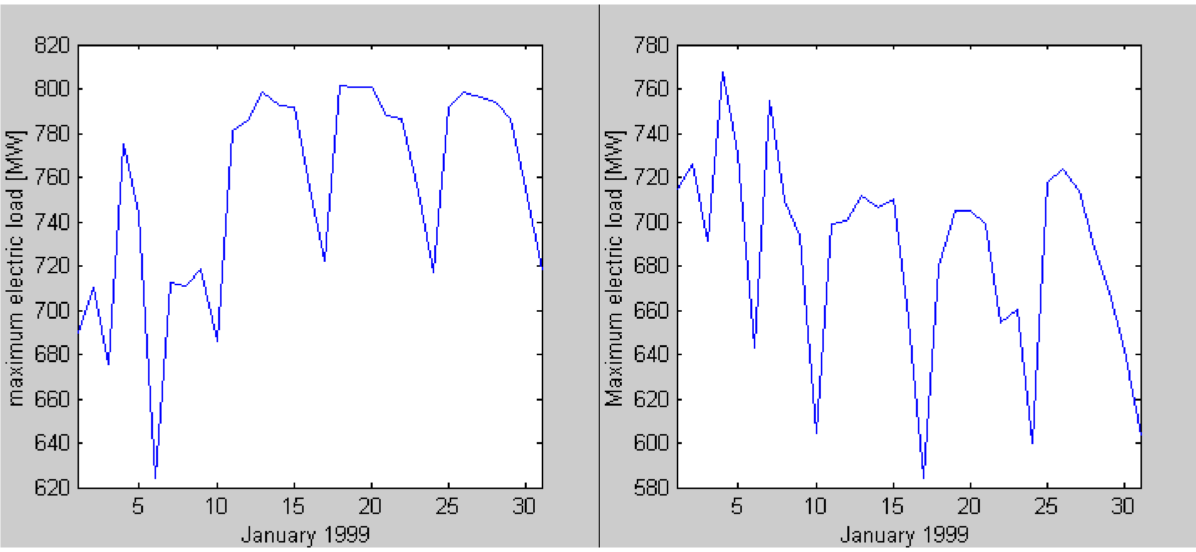

Fig. 6 a) Input without predicted temperature for January **b) Input with predicted temperature for January**

Analyzing these result, behavior of predicted temperature and own experiences. The result will consist of predicted value of both models. The prediction of maximum electric load about first 7 days (base on experience, the 8^{th} value have both the same) is from Model 1 (input consist of predicted temperature for January 1999) and all other are taken from Model 2 (except predicted temperature).

The result is shown on Fig. 7. How we can see the resulting curve copy the Model 2 till 7^{th} (8^{th}) value and than copy the Model 1. The next possible improvements are count for next 5 or 7 days the resulting values as average of both models. But to this is needed some more experiences and bigger training array. In Tab. 1 are resulting value of predicted electric load.

3 Conclusion

Main problems occurred during solving proposed problem was with small input set and long time interval. To improve and make more reliable prediction is important except notted ideas also consulting with experts at operating control.

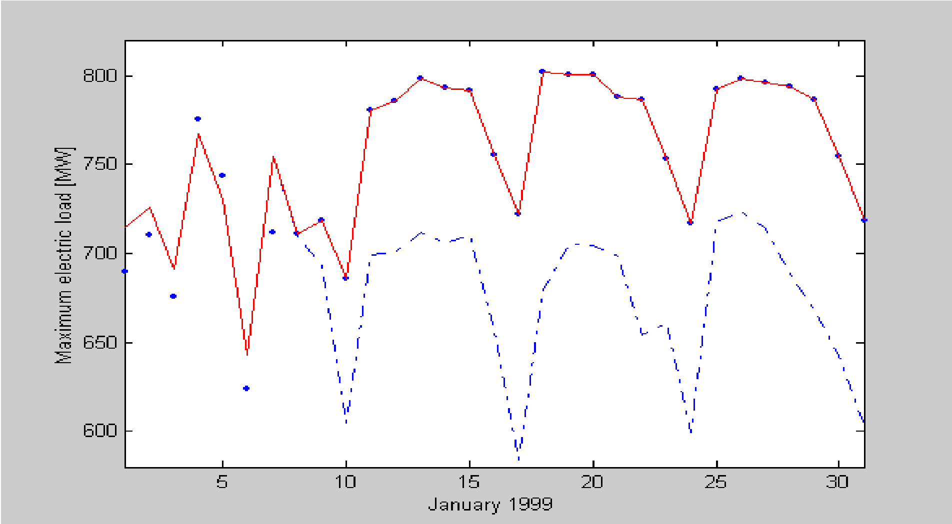

Fig. 7 Predicted maximum electric load, both model (Model 1- dotted, Model 1-dashdot) and resulting curve (line)

Day	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*	*15*
El. Load [MW]	714.7	726	691.4	767.3	730.6	643.2	754.9	711	718.7	686.2	780.8	785.9	798.1	792.8	791.4
16	*17*	*18*	*19*	*20*	*21*	*22*	*23*	*24*	*25*	*26*	*27*	*28*	*29*	*30*	*31*
722.4	755.2	801.8	800.8	800.4	788.1	786.3	753.4	716.7	792	798.2	796.1	793.8	786.5	754.7	718.1

Tab. 1 The resulting value of electric load

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