Application of Learning Fuzzy Inference Systems in Electricity Load Forecast

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Abstract. This paper highlights the results and applied techniques for the electricity load forecast competition organised by the European Network on Intelligent Technologies for Smart Adaptive Systems (www.eunite.org). The electricity load forecast problem is tackled in two different stages by creating two different models. The first model will predict the temperature and the second model uses the predicted temperature to forecast the maximum electricity load. For both model, learning fuzzy inference systems are applied. Initial fuzzy rules are generated and then the numerical data provided by Eastern Slovakian Electricity Corporation are used to learn the parameters of the learning fuzzy inference systems. The learning technique is applied for both temperature and load forecast.

1 Introduction

This paper present the results and techniques applied for solving the electricity load forecast competition organised by the European Network on Intelligent Technologies for Smart Adaptive Systems (EUNITE). The electricity load forecast is a challenging problem introduced by the Eastern Slovakian Electricity Corporation, which can bring a very significant financial profit using more accurate prediction technology. The problem is to forecast maximum daily electricity load based on previous data available for electricity load and average daily temperature [1]. The average daily temperature and every half an hour load for the time period January 1997 until December 1998 are given. List of public holidays for the same period of time are also provided. The actual task is to supply the prediction of maximum daily values of electrical loads for January 1999.
The electricity load consumption (L_i, $i = 1, 2, \ldots, 365$) is mainly influenced by the following factors:

- Average daily temperature (T_i)
- Day of the week (D_i)
- Public holidays (H_i)
- Time of the Day (t_i)

[1] http://neuron-ai.tuke.sk/competition

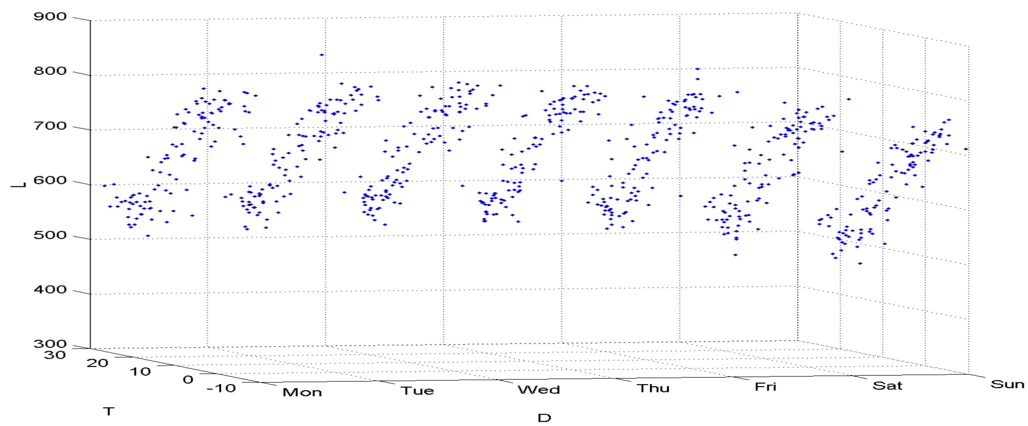

Fig. 1. Maximum load (L_i) in 97 and 98 as a function of average daily temperature (T_i) and day of the week (D_i).

There are numerous things that can compose the electricity load which are very difficult to be modelled. For instance during Christmas period shops are open very late which will increase the load regardless of the average temperature and in summer time more people intend to go on holiday and naturally the electricity consumption will be reduced. Even the consumer's characteristics of electricity usage would not be similar in different countries. As part of this competition we intend to create a simple model based on available measurement data. Figure (1) illustrates the maximum load in 97 and 98 as a function of average daily temperature and day of the week.

The methodology used in this study is the learning fuzzy inference systems modelling for temperature and load forecast. Electricity load forecast is mainly tackled in two different stages. The first model will predict the temperature and the second model uses the predicted temperature to forecast the maximum electricity load. For both model, learning fuzzy inference systems are applied. More details on learning fuzzy inference systems and their training algorithm can be found in [1],[2],[3],[4].

2 Temperature Forecast

The average daily temperature in 95, 96, 87 and 98 are given and the average daily temperature in 99 must be predicted before we can forcast the load. The average temperature is represented by the variable T_i where $i = 1, 2, \ldots, 365$. The only exception is for the year 1996 with 366 days (leap year). For ease of calculation and modelling it was decided to remove information about an extra day in 96. Comparing the correlation coefficients of data for all years show that removing the data for February 29 would be the best with the maximum correlation coefficients. The correlation coefficients are given below.

$$\begin{bmatrix} 1.0000 & 0.8351 & 0.8180 & 0.8556 \\ 0.8351 & 1.0000 & 0.8309 & 0.8397 \\ 0.8180 & 0.8309 & 1.0000 & 0.8073 \\ 0.8556 & 0.8397 & 0.8073 & 1.0000 \end{bmatrix}$$

A model was built that predict $\hat{T}_{i+365}$ from the current and past values of the average temperature, that is, T_i, and T_{i-365}. A fuzzy rule of the following form will be used as the model for temperature forecast.

> *If T_i (average temperature this year on Day i) is cold and T_{i-365} (average temperature last year on the same day) was very cold, ... then $\hat{T}_{i+365}$ (average temperature next year on the same day) will be cold.*

Fuzzy if-then rules of the following configuration can be employed for the modelling of linguistic information.

R_k: If T_i is $\tilde{A}_k^1$ and ... $T_{i-j*365}$ is $\tilde{A}_k^j$ ... and $T_{i-p*365}$ is $\tilde{A}_k^p$ then $\hat{T}_{i+365}$ is B_k

where R_k is the label of kth rule, $T_{i-j*365}: \; j = 0, 1, \ldots, p$ is the jth input, $\hat{T}_{i+365}$ is the output, $\tilde{A}_k^j$ ($k = 1, 2, \ldots, n$ and $j = 0, 1, \ldots, p$) is a fuzzy label, and B_k is either a real number or a linear combination of inputs $B_k = q_{0i} + q_{1k} * T_i + \ldots + q_{pk} * T_{i-p*365}$. The decision, $\hat{T}_{i+365}$, for the ith day, as a function of inputs $T_{i-j*365}: \; j = 0, 1, \ldots, p$, is given in the following equation:

$$\hat{T}_{i+365} = \frac{\sum_{i=1}^{n} w_k B_k}{\sum_{i=1}^{n} w_k}$$

where B_k is the consequent parameters and w_k is the rule firing strength given by:

$$w_k = \prod_{j=0}^{p} \mu_{\tilde{A}_k^j}(T_{i-j*365}) \quad i = 1, 2, \ldots, n$$

where $\mu_{\tilde{A}_k^j}$ is the membership function (MF) of the fuzzy value $\tilde{A}_k^j$. Some commonly used MF shapes are Gaussian, triangular and trapezoidal. Regardless of the shape of MFs, they can be adjusted.

Since the data provided is very limited and only four sets of training data is available, it is decided only the current year average temperature and a year earlier information to be used to forecast next year's average temperature.

$$\hat{T}_{i+365} = f(T_i, T_{i-365})$$

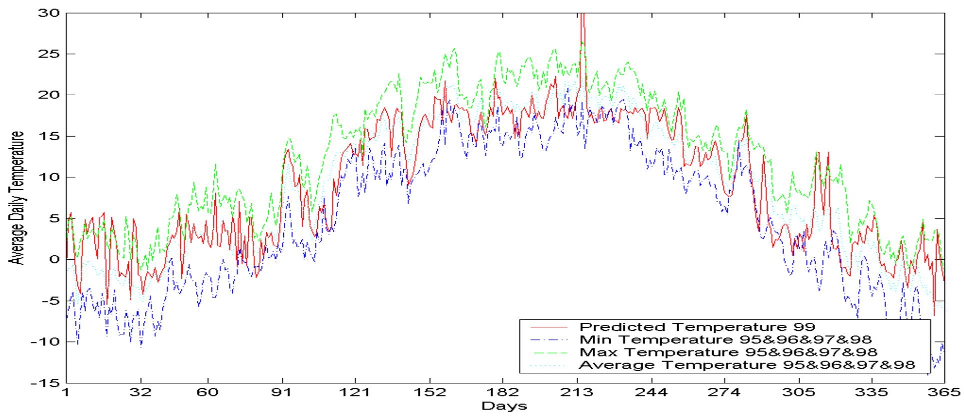

Fig. 2. Predicted Temperature $\hat{T}_i$ in 99.

A Fuzzy rule-based model with two inputs and one output was generated. For both inputs 4 membership functions in the universe of $[-15° \; 30°]$ are defined. The initial grade of membership functions are shown in Figure (3-a). The parameters of the membership functions were learned using the numerical data provided. The average daily temperature in $[95, 96]$ and $[96, 97]$ as the inputs and the average daily temperature in [97] and [98] as the output are applied for training of the learning fuzzy inference system. Figure (2) shows the predicated average temperature in 99 along with the minimum, maximum and average temperature for four years in 95,96,97 and 98.

3 Maximum Electricity Load Forecast

To model the maximum energy consumption L_i, $i = 1, 2, \ldots, 365$, we consider that the maximum load is only function of the average temperature T_i, day of the week D_i and wether that day is a public holiday or not represented by H_i. D_i is a number between 1 to 7 representing Monday to Sunday respectively. H_i is 1 if the i^{th} day of the year is a public holiday. The above expression can be formulated as follows:

$$L_i = g(T_i, D_i, H_i) \qquad i = 1, 2, \ldots, 365$$

Since the average temperature information is not available and it should be predicted, the actual modelling of the load forecast can be formulated as follows:

$$\hat{L}_i = g(\hat{T}_i, D_i, H_i) \qquad i = 1, 2, \ldots, 365$$

A learning fuzzy inference system was again employed to predict the load. A fuzzy rule of the following form will be used to model the electricity load.

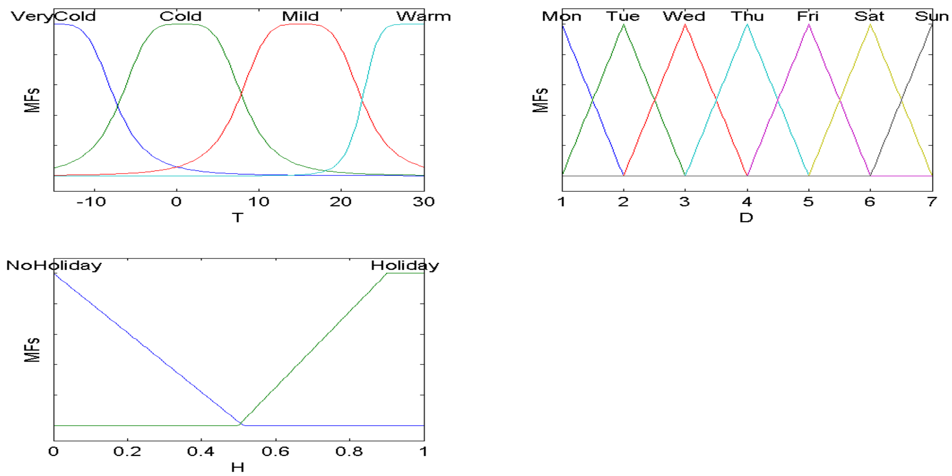

Fig. 3. Membership Functions of Temperature T_i, Day of the week D_i, and Public holiday H_i.

> *If T_i (average temperature this year on Day i) is cold and D_i (Day of the week) is Thursday and H_i (that day is a public holiday) is true, then $\hat{L}_i$ (Maximum load on the same day) will be Low.*

A fuzzy inference system with 3 inputs and 1 output is built. The fuzzy values for all three inputs of the fuzzy inference system are given below.

$\tilde{A}_1^1$: Very Cold	$\tilde{A}_1^2$: Monday (1)	$\tilde{A}_1^3$: No Holiday (0)
$\tilde{A}_2^1$: Cold	$\tilde{A}_1^2$: Tuesday (2)	$\tilde{A}_2^3$: Public holiday (1)
$\tilde{A}_3^1$: Mild	$\tilde{A}_1^2$: Wednesday (3)	
$\tilde{A}_4^1$: Warm	$\tilde{A}_1^2$: Thursday (4)	
	$\tilde{A}_1^2$: Friday (5)	
	$\tilde{A}_1^2$: Saturday (6)	
	$\tilde{A}_1^2$: Sunday (7)	

The membership functions of the above fuzzy values are illustrated in Figure (3).

4 results

To give an indication of the success of the proposed method to forecast the maximum electrical load, this section presents brief results. The average temperature in 95, 96, 97 and 98 are used for training the first model. The learning method was used for 500 epochs. Using the learned model and average temperature in 97 and 98 as the inputs, the forecast for average temperature in 99 calculated. Figure (2) shows the predicated average temperature in 99.

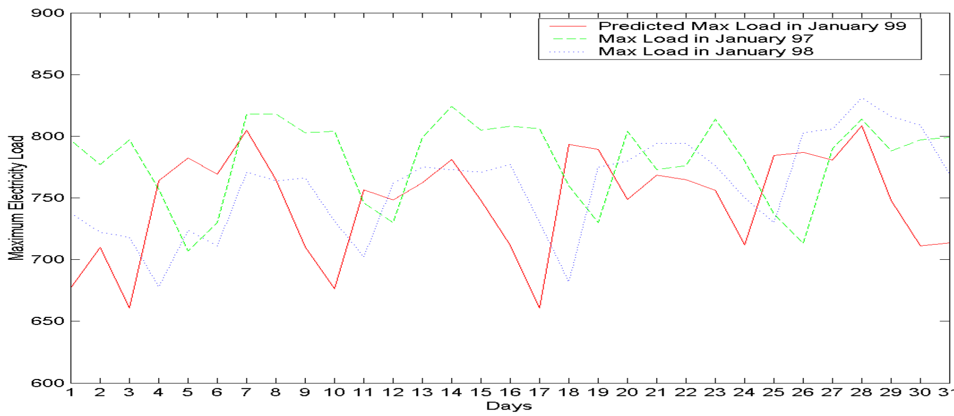

Fig. 4. Predicted Maximum Electricity Load $\hat{L}_i$ in 99.

The second model to forecast the maximum load was created by the information provided. For this model the fuzzy inference system with $4*7*2 = 56$ rules were used. The information in 97 was used for training and then the data in 98 was employed for testing the algorithm. Employing the achieved results for the temperature in 99, the second model is used to forecast the maximum electricity load in 99. The training algorithm was sloped after 200 epochs. Figure (4) shows the maximum predicted load in January 99 along with the minimum and maximum load for the same period in 97 and 98.

5 Conclusions

The temperature forecast is relatively more difficult than load forecast. For temperature forecast a long history of data would make the forecast more accurate. If there are some errors in load prediction, it could be caused mainly from the temperature forecast.

References

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