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SHORT TERM POWER LOAD FORECASTING USING A MODIFIED GENERALIZED REGRESSION NEURAL NETWORK

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ABSTRACT
Short Term Load Forecasting is very important from the power systems grid operation point of view. The short term time frame may consist of half hourly prediction up to monthly prediction. Accurate forecasting would benefit the utility in terms of reliability and stability of the grid ensuring adequate supply is present to meet with the load demand. Apart from that it would also affect the financial performance of the utility company. An accurate forecast would result in better savings while maintaining the security of the grid. This paper outlines the short term load forecasting using a Modified Generalized Regression Neural Network (MGRNN). The experiments are based on the power load data from Jan 1997 to Jan 1999 of East Slovakian Electricity Corporation. Simulation results show that MGRNN has comparable prediction accuracy compared to benchmark result archived by Support Vector Regression.

KEY WORDS
ε-Insensitive Loss Function, Generalized Regression Neural Network, Load Forecasting, Time Series Prediction

1. Introduction

Time series prediction using artificial neural networks is one of the main interests of data regression research. Unlike other type of regression, time series prediction use historical outputs of a problem as the training inputs to the neural network. A time series problem with one output and *M* inputs can be modeled as shown in the following equation.

$$x_k = f(x_{k-1}, x_{k-2}, \ldots, x_{k-M+1}, x_{k-M}), \qquad (1)$$

where function *f(.)* is the model of the problem and x_k is the output at time-*k*. Generally, solving time series prediction problem using neural network would have the same solution approach for other type of regression problem with the exception that the inputs and output for the neural network would consist of historical data.

One of the most basic approaches to forecasting would utilize the time series model. A time series model would require an extrapolation of future load based upon historical load information. This method does not take into account external factors such as weather and significant events. The disadvantage of this method is that error in the forecasted values will occur if there are future events that are available in the historical data. In order to improve the accuracy of this model, more data is required which makes the prediction process to be complicated. A solution to this problem would involve implementing different approaches e.g. Multiple Linear Regression, Auto Regressive Moving Average (ARMA) [1] and various type of Neural network especially Multilayer Perceptron (MLP) [2]. Comparing these methods with Neural Network based model, the Neural Network based model has the advantage of black box capabilities which means that the user would not be required to be an 'expert'. There have been several efforts in implementing Neural Network in the load forecasting algorithm, e.g. Support Vector Machine (SVM) [3], and Back Propagation Neural Network [4]. The result of these efforts opened up several avenues in improving the load forecasting results.

This paper is organized as follows. Section 2 introduces Slovakia power load data. Section 3 describes the learning algorithm and architecture of a modified generalized regression neural network (MGRNN) and Section 4 presents a series of experiments and results. Section 5 presents a summary of this paper, with suggestions for further work.

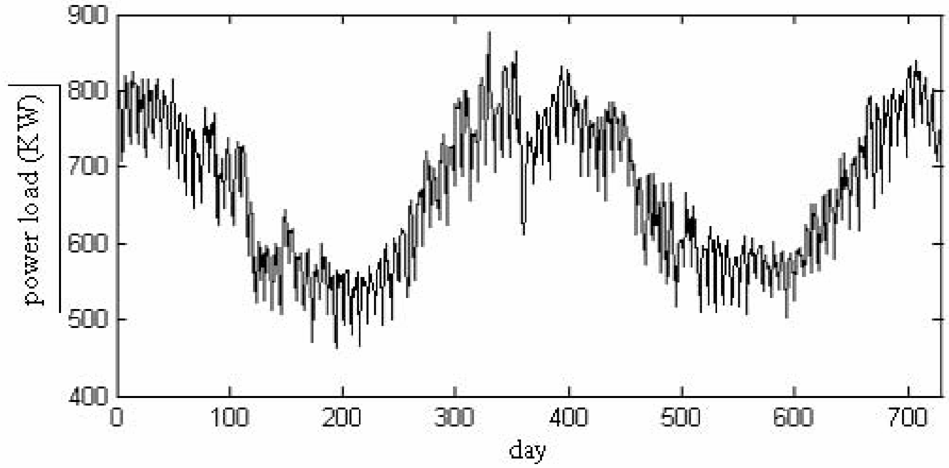

Figure 1. Maximum daily load for years 1997-1998 of East Slovakian

2. Data Description

In year 2001, the EUNITE (*EUropean Network on Intelligent TEchnologies for Smart Adaptive Systems*) [5] has published a power load dataset from East-Slovakia for a competition (EUNITE2001) purpose. The data provided are

- Half an hour of power load from Jan 1997 to Jan 1999 (hence, 730 maximum daily loads can be obtained from here);
- Average daily temperature from 1995 to 1998;
- Dates of publications for years 1997 to 1999.

By using these data given, the task is to forecast the maximum daily loads of the days from 1st Jan to 31st of Jan 1999. Note that all the forecast must be done in the condition that the actual maximum loads for any days of Jan 1999 is unknown, such as forecasting is conducted on 31st of December 1998, where the predicted value is used to predict the next value. The performance of forecasting is evaluated by a mean of percentage absolute error (MAPE)

$$MAPE = 100\frac{\sum_{i=1}^{31}\left|\frac{y_i - \bar{y}_i}{y_i}\right|}{n}, \qquad (2)$$

where y_i and $\bar{y}_i$ are the real and predicted maximum daily load of i^{th} day of Jan 1999 respectively. The goal of forecasting is to achieve the smallest value of MAPE. Note that all load data has been normalized into the range of (0, 1). Fig. 1 shows the normalized power load data for 1997 and 1998.

During the training, out of two years daily maximum loads (730 data), 723 pairs of training samples are created. The j^{th} training pair (j=1, 2…,723) is presented in the form of {$\mathbf{A}_j$, B_j} where $\mathbf{A}_j$ is a nine dimension features vector as {seven historical data, type of day, public holiday}. Where

- "seven historical data" – maximum power load for the last seven days before the targeted day (j^{th} day), such as {B_{j-7}, B_{j-6},…, B_{j-1}},
- type of day" - a numerical number representation j^{th} day, such as 0 for Monday,
- 0.16667 for Tuesday,…, 0.8333 for Saturday and 1.0 for Sunday. Note that in [3], a seven bit of binary string strategy is used to represent type of day,
- "public holiday" – 0 for normal day and 1 for public holidays of j^{th} day,
- "B_j" – the maximum power load of j^{th} day.

Note that accordance to [3], temperature information did not help for the forecasting hence it is not used.

3. Modified Generalized Regression Neural Network (MGRNN)

The Generalized Regression Neural Network (GRNN) is a memory based supervised learning neural network that was first proposed by Specht [6]. It provides an estimate of continuous variables and converges to the underlying linear and nonlinear regression surface. Apart from that it has the ability to perform online learning with a parallel architecture. The MGRNN learning process is instantaneous as it is able to do one pass learning with all knowledge distributed and stored in a parallel architecture. If there is any new knowledge that needs to be learned, the MGRNN will create another neuron to memorize the new information. All neurons in the GRNN are treated equally as kernels and are utilized to compute the independent gaussian probability density function (PDF), respectively to the new input sample. Generalization can be achieved by using an estimator that comprises of combinatory PDFs, as proposed by Parzen [7].

Consider a training set {($\mathbf{A}_1$, B_1), ($\mathbf{A}_2$, B_2), …, ($\mathbf{A}_j$, B_j)…, ($\mathbf{A}_N$, B_N)}, where $\mathbf{A}_j \in \mathbf{R}^{\mathbf{M}}$ and $B_j \in \mathbf{R}^1$ are the input vector and kernel label of j^{th} training sample, respectively, are presented to GRNN. Hence, the prediction of an unknown vector **x** can be done by

$$f(\mathbf{x}) = \frac{\sum_{j=1}^{N} B_j K(\mathbf{A}_j, \mathbf{x}; \sigma)}{\sum_{j=1}^{N} K(\mathbf{A}_j, \mathbf{x}; \sigma)}, \tag{3}$$

where σ > 0 is a user defined standard deviation and $K(.)$ is the gaussian kernel function

$$K(\mathbf{A}_j, \mathbf{x}; \sigma) = \exp\left(-\frac{1}{2} \sum_{i=1}^{M} \left(\frac{A_{ji} - x_i}{\sigma} \right)^2 \right). \tag{4}$$

Note that Eq (3) is a standard GRNN with quadratic loss function (QLF). In research of Support Vector Machine, a better loss function has been used to improve the result of regression. Vapnik and Chu [8, 9] proposed a ε-insensitive loss function (ε-ILF) in order to handle data consists of small noise. In contrast to QLF, the formulas of ε-ILF are

$$K(\mathbf{A}_j, \mathbf{x}; \sigma, \varepsilon) = \exp\left(-\frac{1}{2} \lambda(\delta_j) \right), \tag{5}$$

$$\lambda(\delta_j) = \begin{cases} 0 & \delta_j \le \varepsilon \\ \delta_j - \varepsilon & otherwise \end{cases}, \tag{6}$$

$$\delta_j = \sum_{i=1}^{M} \left(\frac{x_i - \mathbf{A}_{ji}}{\sigma} \right)^2 . \tag{7}$$

The architecture of MGRNN is shown in the following Fig. 2.

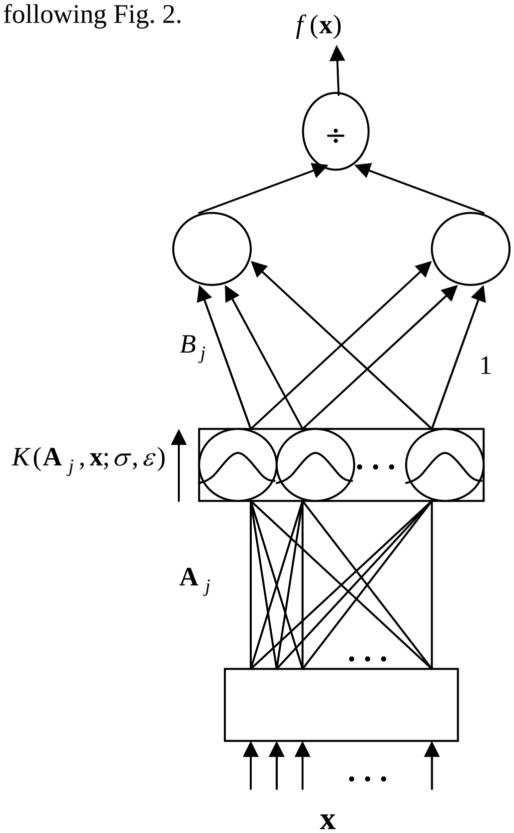

Figure 2. Architecture of the proposed MGRNN

4. Experiments and Results

4.1 Forecast based on seven historical data

In this experiment, only seven historical data is used to predict the maximum daily load of Jan 1999. It is expected the results are not very accurate because of unable to identify weekends and public holidays that used to have a lower power load demand. After several trials with different values of σ and ε, 0.006 and 3.5, are selected as parameter of this experiment. The forecasted results and actual maximum daily load value of Jan 1999 are shown in Fig. 3. Note that the forecasted error of 6th Jan 1999 is rather big because MGRNN unable to foresee that this day is a public holiday. However the forecast results still able to show that it has four cycles which indicated it has made the forecasting for four weeks.

4.2 Forecast based on seven historical data and type of day

In this experiment, seven historical data and type of day is used to predict the maximum daily load of Jan 1999. After several trials with different values of σ and ε, 0.1 and 5.5 are selected. The forecasted results and actual maximum daily load value for Jan 1999 is shown in Fig. 4. Note that as shown, the results are expected to be better than Experiment A, because it has learned the information of type of day hence forecasting of the weekends should be good. However, forecasting of the public holidays such as 6th Jan 1999 are still not accurate.

4.3 Forecast based on seven historical data, type of day and public holiday

In this experiment, seven historical data, type of day and information of public holiday are used to predict the maximum daily load of Jan 1999. After several trials with different values of σ and ε, 0.15 and 2.0 are selected. The forecasted results and actual maximum daily load value for Jan 1999 is shown in Fig. 5. Note that the results are expected to be better than Experiment A and Experiment B because it has learned the information of type of day and public holidays, hence forecasting of the weekends should be better. Forecast result of 6th Jan 1999 is much better than before.

4.4 Comparisons with winner of EUNITE2001 – SVM

Fig. 6 shows the comparison result in between winner of EUNITE2007 (SVM) [3, 5] and MGRNN. Both are having almost the same results. SVM has better forecast accuracy for 1st Jan while MGRNN has better result for 6th Jan 1999. However, MGRNN performs better, achieving MAPE of 1.94 which is 0.04 lower than MAPE of SVM.

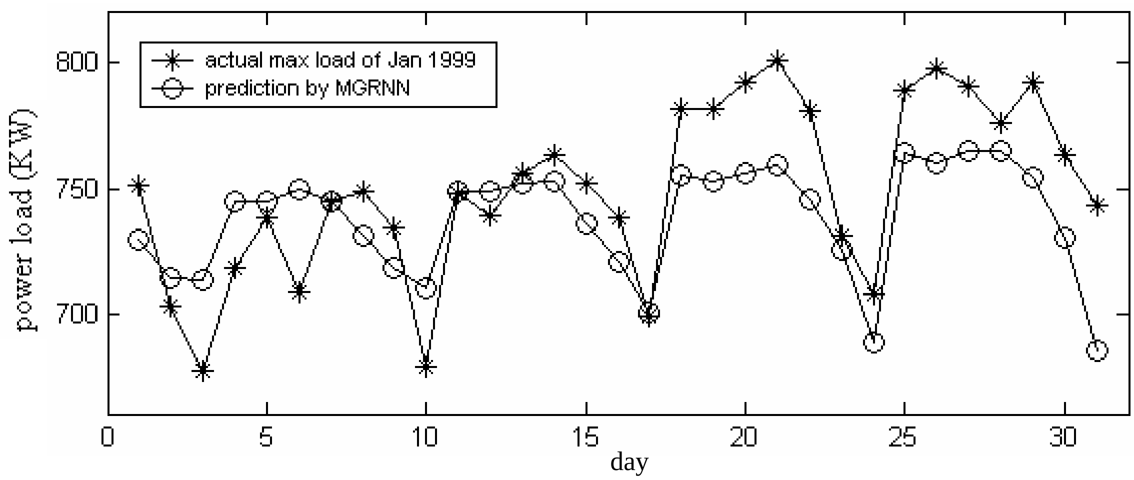

Figure 3. Forecast results of the daily maximum load for Jan 1999 by seven historical data. (σ = 0.06, ε = 3.5 and MAPE = 2.96)

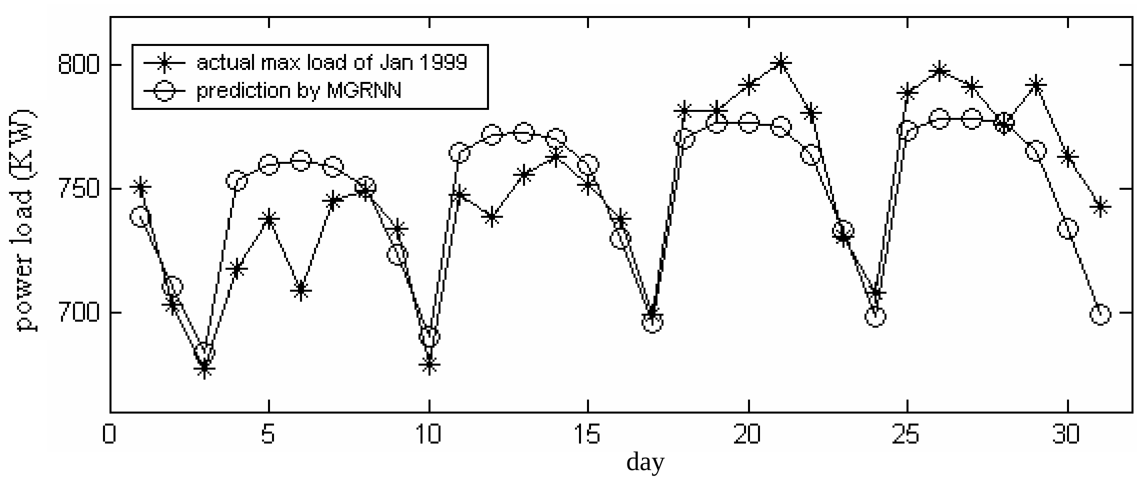

Figure 4. Forecast results of the daily maximum load for Jan 1999 by seven historical data and type of day. (σ = 0.1, ε = 5.5 and MAPE = 2.16)

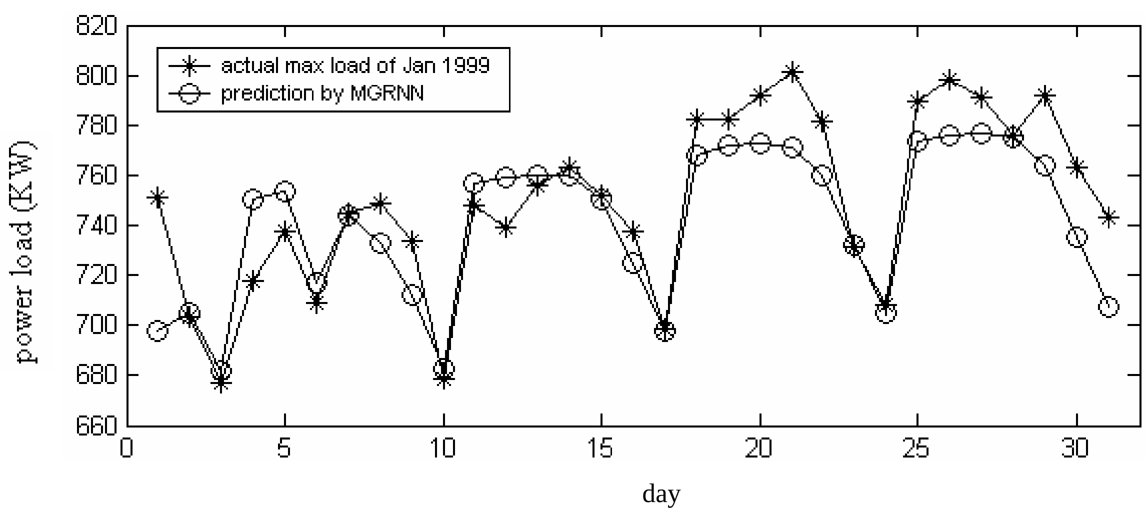

Figure 5. Forecast results of the daily maximum load for Jan 1999 by seven historical data, type of day and public holiday. (σ = 0.15, ε = 2.0 and MAPE = 1.94)

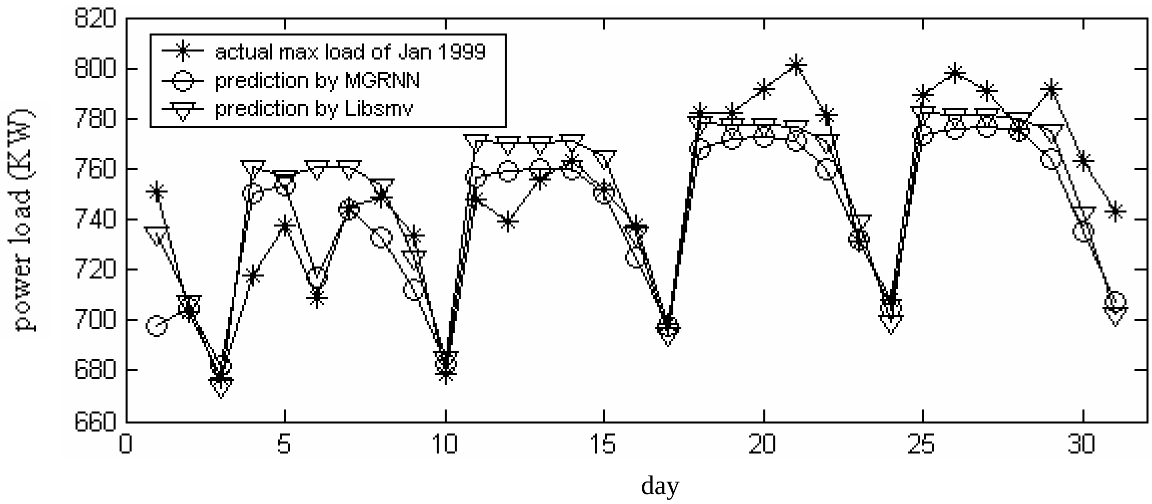

Figure 6. Comparison of Forecast results by Libsvm and MGRNN. Note that the MAPE of SVM is 1.98 while MAPE for MGRNN is 1.94.

5. Conclusion

This paper introduced results of power load forecast by a class of memory neural network, namely MGRNN with modification by ε-ILF which can performance better than original GRNN in a noisy environment because it used a ε-ILF. A series of experiments based on a benchmark Slovakia power load dataset from EUNITE2007 has been conducted. It shows that results MGRNN are comparable to the SVM, the winner of EUNITE2007.

One of the potential improvements of MGRNN is to use a non-quadratic loss function, such as one norm of ε-ILF [9]. This could be used not just to prevent noise data problem but as well as outlier problem. Other potential developments are study the load forecast includes with temperature information as well as middle and long terms forecast.

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