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Short term peak load forecast using detrended partitioned data training of a neuro-fuzzy regression machine

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Load forecasting using neural networks can suffer from poor quality of data, non-stationary load patterns and poor forecasting accuracy. To address some of these problems, a neuro-fuzzy based forecasting model trained with detrended data is proposed. Feature extraction methods to provide better data partitioning, capture important correlations, and detrend non-stationary data are developed. As a result, forecasting accuracy and robustness are enhanced.

Keywords: load forecasting, neuro-fuzzy regression machine, detrended partitioned data

1. INTRODUCTION

Electric load forecasting is the art of predicting power system energy demand over a specified period of time. It is an essential tool for power system control centers and Energy Management Systems (EMS). Load forecasting is also used in state estimation and security analysis [1–5]. Many major load forecasters are either using or experimenting with the neural networks (NN's) as a viable forecasting tool. Prediction accuracy is the main reason for the popularity of the NN approach.

Unfortunately, the NN, like other forecasting techniques trained from historical data typically deals with non-stationary load pattern in the training data. This paper addresses this problem through data massaging prior to training. The data is first detrended. A neuro fuzzy based forecasting model is developed to reduce the effect of data uncertainty, and errors in weather conditions. Feature extraction methods are applied to provide better data partitioning, and to capture important feature correlations. All these measures enhance the accuracy and the robustness of the forecasting results.

2 NEURO-FUZZY FORECASTING MODEL

Energy customers buy comfort and utility rather than electric power directly. Comfort parameters are typically described as fuzzy linguistic variables, e.g. "The room is a little too warm" or "The humidity in this office is much too high." Fuzzy logic allows linguistic descriptions to be quantified. Similar linguistic descriptors in control led to control by fuzzy inference – to date the most commercially successful application of fuzzy logic. These linguistic similarity gives rise to our motivation for using fuzzy logic for electric load forecasting.

Figure 1 shows a general procedure to develop a neuro-fuzzy forecast model. In the first step, the input data are processed and the features are extracted. These features are fuzzified and then used for NN training. The output of the NN is a fuzzy load forecast which is converted into a crisp value by defuzzification.

2.1 Fuzzification

The fuzzification of a variable is determined by its linguistic membership functions. Fuzzification transforms a single numerical value into a membership value vector. The size of the vector is dependent on the number of membership functions.

The fuzzification of the maximum temperature is shown in Figure 2. The temperature variable has three membership functions, S1 (less than normal), S2 (normal) and S3

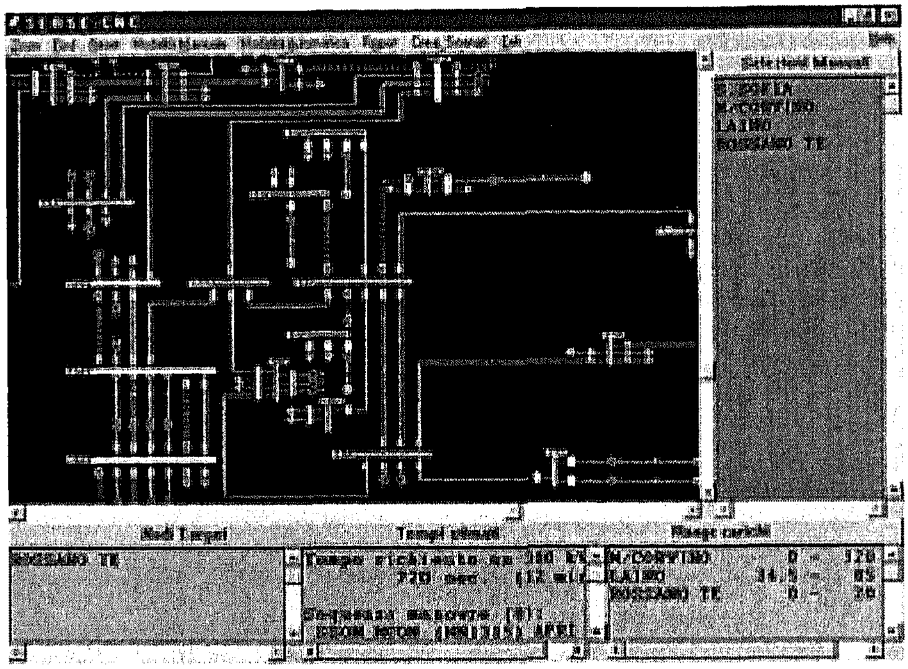

Figure 4 The winning solution is presented to the operator. It can be identified as it is drawn in white

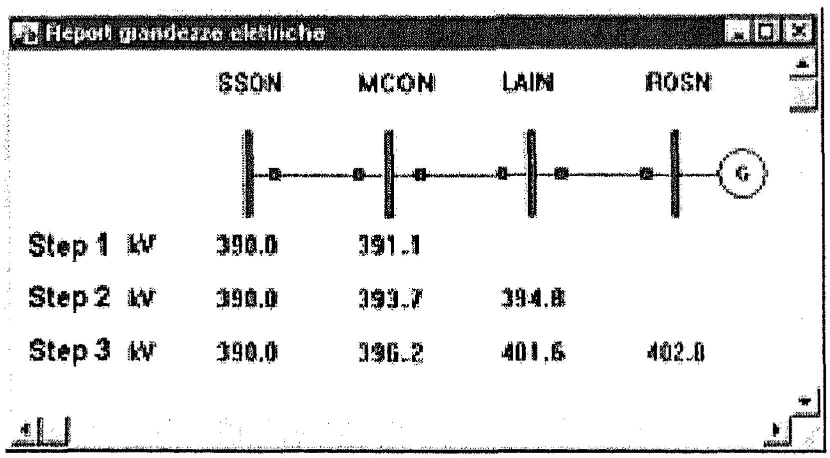

Figure 5 The table assuming that the lower bound of the load is supplied in each substation

SERSE, as shown in Figure 4. In an additional window, SERSE can show the expected voltages in each substation after each step of the creation of the path, namely after that each substation is energized. Figure 5 shows the table assuming that the lower bound of the load is supplied in each substation.

After that all substations in the path have been energized, the voltage in ROSN is 402.8 kV which is still within the accepted operating limits.

7. CONCLUSION

In this paper we have presented SERSE, a software system currently under development at ENEL for supporting the dispatcher during the restoration task. The paper has focussed on the description of the module that is executed in the case of a partial blackout, for delivering cranking power from the nodes of the still energized network to the non-black-start units. The transmission paths thus computed, are then compared with the pre-defined paths starting from black-start units for choosing the best.

Current work concerns the improvement of the Time Estimation Module for taking into account all the allowed configurations of the high voltage substations. Further work is required to include in the goals of the system the possibility to energize important loads as well as non-black-start units, when possible.

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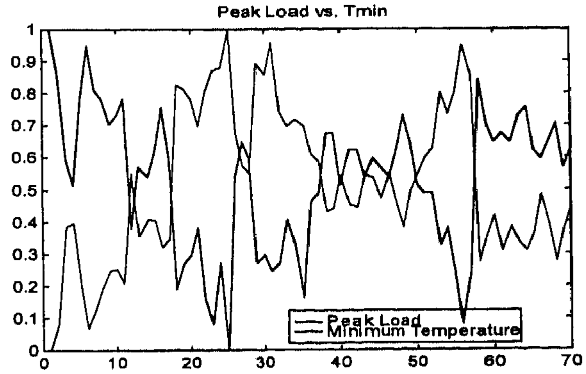

Figure 3 Daily peak load and minimum temperature

$$r_k = \sum_{i=1}^{N-k} \frac{x_i y_{i-k}}{\sigma_x \sigma_y} \tag{6}$$

where k represents the time lag, and σ_x and σ_y are the sample variances

$$\sigma_x^2 \triangleq \frac{1}{N-1} \sum_{i=1}^{N} x_i^2, \quad \sigma_y^2 \triangleq \frac{1}{N-1} \sum_{i+1}^{N} y_i^2 \tag{7}$$

Figure 4 shows the autocorrelation of the electric load of *Puget Sound Energy f*or one normal week. In the figure, a peak occurs every 24 hours. The peak of the previous day is highly correlated with the current day's load. and the load of the previous day has the greatest impact on the current day's load.

One can therefore conclude that the previous day's load and temperature have the greatest impact on the next day's load. When such features are selected, the correlation factor can be used as a forecasting input We form the composite correlation factor:

corr = (previous day's load correlation factor
+ forecasted temperature correlation factor)/2

where the previous day's load can be either the daily peak load or total load, and the forecasted temperature can be either the daily maximum, minimum or average temperature.

Figure 5 shows an example of the composite correlation factor. The electric load and temperature data are for a normal weekdays of the 1985–86 winter seasons. The correlation factor can also be used in a simple regression and time series load forecast model

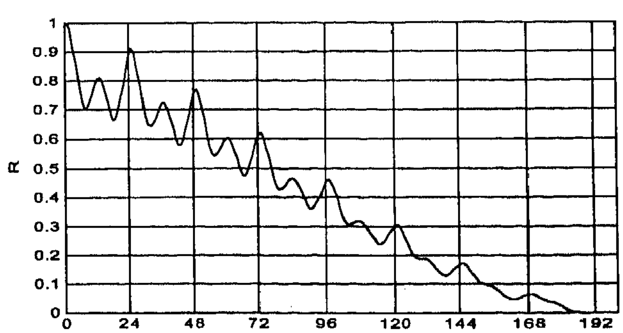

Figure 4 Autocorrelation of one week's eletric load

3.3 Trend Analysis

Electric load variation contains trend components such as growth and seasonal oscillations. Although electric load forecasting, in general, is modeled as a stationary process, trending adds a non-stationary component. This reduces the accuracy of load forecasting over extended periods. It is therefore desirable to identify trend components and adjust the historical data accordingly. The trend components can be modeled separately by data partitioning. The trend can be later added to the forecasting model. The two major trend components are:

- Seasonal, monthly and/or weekly trends
- Load growth trend

Generally, electric loads are classified into two categories: base load and weather dependent load. The trend simply reflects the long-term movement of the electric load from year to year, or from season to season. Figure 6 shows winter daily peak load from 1985 to 1990 in the Puget Sound area.

The electric load grows at a certain rate every year. The base load trend can be modeled by various functions, such as linear or exponential growth. Herein a simple linear model is used. The coefficients are estimated by the least squares method. Figure 7 shows the base load growth trend of the winter daily peak load from 1985 to 1990.

After the base load growth is removed from the data, only the weather dependent load component remains. This is shown in Figure 8.

3.4 Day Type Partitioning

Similar load patterns among subsets of days in a week allows splitting of the week into several components. A different model forecasts each component. This partitioning scheme makes the forecast model simpler and easier to develop. Figure 9 shows a normal week load profile of *Puget Sound Energy*. From this figure, Tuesday through Thursday have similar load patterns and Friday through Sunday are similar. The load pattern of Monday is different than any oth-

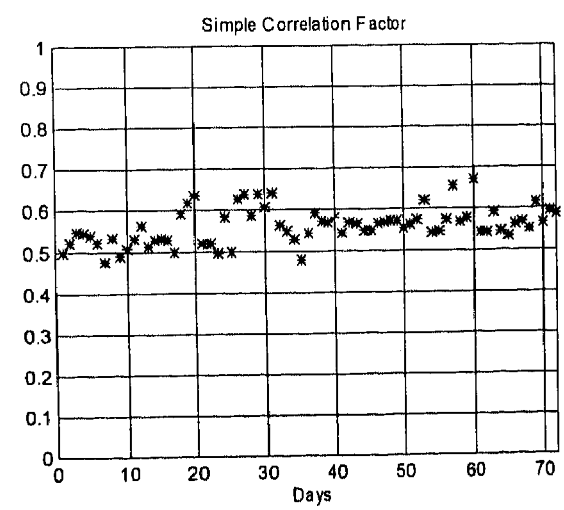

Figure 5 Correlation factor of load and temperature

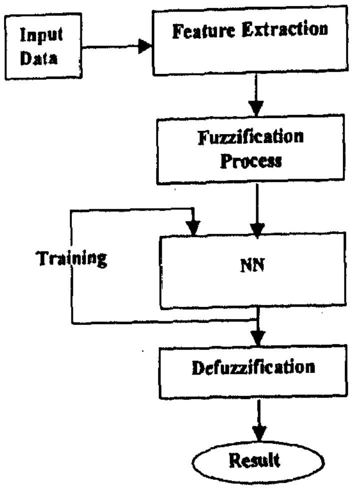

Figure 1 A neuro-fuzzy forecasting model

(larger than normal). Suppose the normalized value of the maximum temperature is 0.2, then the membership value vector is [0.6 0.4 0.0] which is used in training the NN instead of crisp value of 0.2.

2.2 Defuzzification

Defuzzification transforms a fuzzy membership vector into a crisp value. The commonly used centroid method [13], defuzzifies in accordance to the formula

$$y + \frac{\sum_{i=1}^{L} output\_mem(i) * A_i * I_i}{\sum_{i=1}^{L} output\_mem(i) * A_i * I_i}, \tag{1}$$

where y denotes the final forecast result, $output\_mem(i)$ is the grade of the ith membership function, A_i is the area under the ith membership function, I_i is the centroid of inertia of A_i, and L is the number of membership functions.

3. FEATURE EXTRACTION FOR LOAD FORECASTING

The accuracy of load forecasting depends on the selection of the essential variables that strongly correlate with the electric load. These forecast features can be obtained heuristicically or through numerical analysis. Importable features include regional features dependent on the characteristics of the providing utility. Some forecast features, such as calendar variation and climate factors, are portable from one forecasting model to another.

The feature extraction in this paper is performed using four techniques: data preprocessing, data partitioning, linear correlation, and trend analysis.

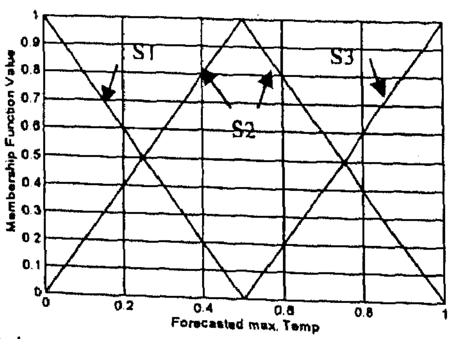

Figure 2 An example of fuzzification

3.1 Data Preprocessing

Data preprocessing can remove detracting artifacts and redundant information from raw data. Regression machines generally train more accurately using the refined data.

The original temperature and electric load are often transformed by operations such as *max(.)*, *min(.)*, *average(.)*, *sum(.)*, *difference(.)* and *delay(.)* operators, *e.g.* last week's averaged temperature/electric load and the minimum and maximum values of yesterday's electric load. A general method to normalize a data is:

$$\bar{x}_i = K\frac{x_i - x_{min}}{x_{max} - x_{min}}, \quad K = 0.8, 1.0 \tag{2}$$

where $\bar{x}_i$ is the normalized data, x_{min} is the minimum and x_{max} is the maximum of the data set, subscript i is the index of the data, and k is a constant normalization factor. The benefit of using the factor $k = 0.8$ is to keep the normalized data away from the saturation region of the NN sigmoid. If a NN is saturated, it loses its sensitivity to variations in the input.

Singleton calendar features such as the day of week and the day of year can be transforming to a cyclic doublet as follows [5]:

$$week\_day = \{\sin(2\pi d/7), \cos(2\pi d/7)\}, d = [1,...,7] \tag{4}$$

$$day\_of\_year = \{\sin(2n\pi d/365), \cos(2n\pi d/365)\}, \quad i = [1,...,365] \tag{5}$$

Doing so enforces data continuity.

3.2 Linear Correlation

Some forecasting features exhibit strong correlation with electric loads. These features prove to be the most important for forecasting. An example is given in Figure 3 where the relation between the peak load and the minimum temperature for winter in the northwestern United States is shown. One would expect these variables to be positively correlated and therefore rise and fall with each other. Clearly, from Figure 3, this is not the case. Other features such as the maximum and the average temperature have a similar relation with peak loads. Such features are weighted heavily in the forecasting model. To evaluate the correlation between two variables, the correlation is computed by first subtracted the average value.

$$x_i = x_i - \bar{x}$$

The correlation index follows as:

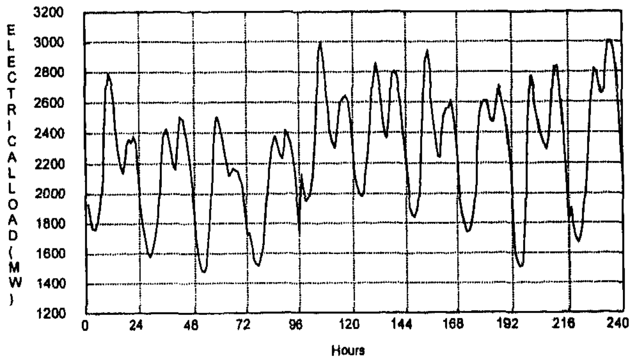

Figure 10 Christmas and New Year (1985–90, weekdays only)

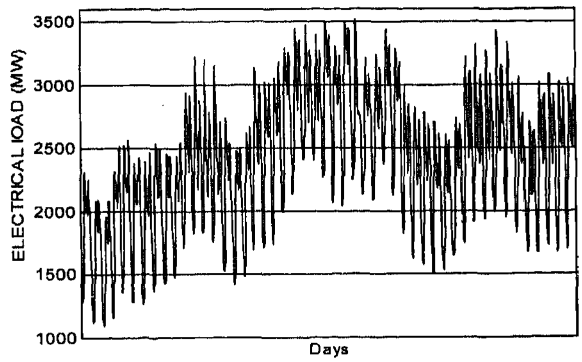

Figure 11 Load patterns of a normal winter season

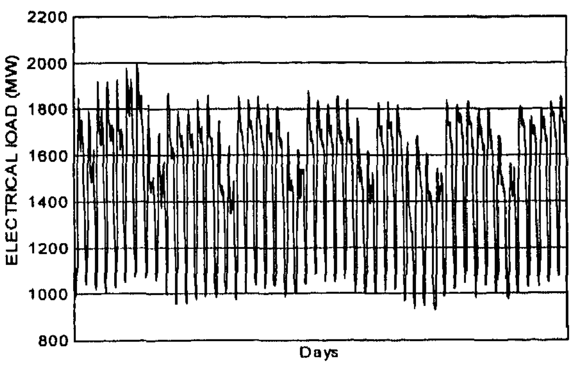

Figure 12 Load patterns of a normal summer season

- Maximum Temperature of day k
- Minimum Temperature of day k
- Average Temperature of previous two days
- Detrended peak load of the previous day
- Day of year
- Day of week

NN Output:

- Detrended peak load at day k

The index k represents the forecast day. In the fuzzificaiton process, each input temperature is represented by three membership functions: high, low, and medium. The forecast of the detrend peak load has five membership functions, which are for positive large (PL), positive small (PS), zero (ZE), negative small (NS), and negative large (NL) and shown in Figure 13.

Table 1 Test data sets

sets	Test data from
Set 1	10/01/89 - 10/31/89
Set 2	11/01/89 - 11/30/89
Set 3	12/01/89 - 12/31/89
Set 4	01/01/90 - 01/31/90
Set 5	02/01/90 - 02/28/90
Set 6	03/01/90 - 03/31/90

4.2 Test Results

Figure 14 shows the forecast and the actual peak load of each day. Figure 15 shows the MAPE of each day in the test sets. The MAPE for all six sets is 1.32%.

The neuro-fuzzy forecasting is also compared with other forecast models – a hybrid model of regression and time series, and multi-layer perceptron models. The test results are shown in Table 2. Intially, all NNs are trained using the same structure and number of epochs. The training is refined to ensure that each NN has the best structure and is trained without memorization or saturation problems. The regression technique is also developed using various models.

The table shows the best among all these variations. As seen in the table, the neuro-fuzzy model can achieve more accurate forecast than the other models, especially with noisy forecasted temperature data. The noisy temperature

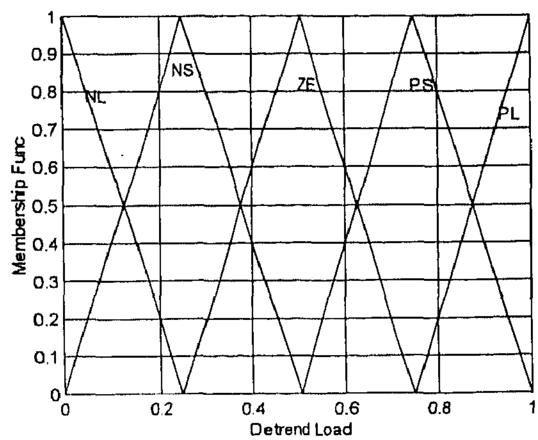

Figure 13 Membership functions of detrend load varaible

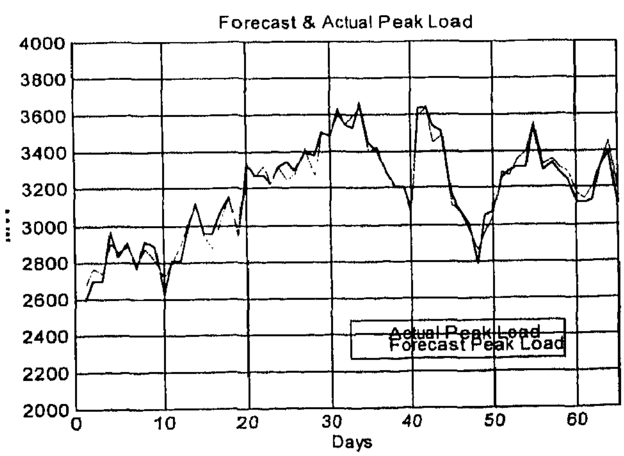

Figure 14 Actual and forecast peak load

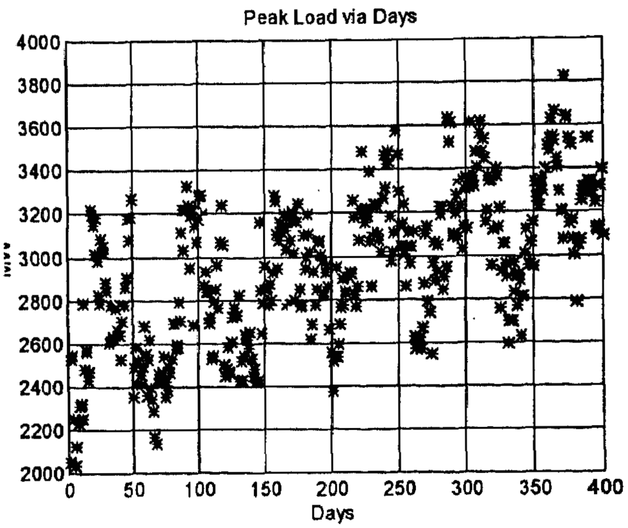

Figure 6 Winter daily peak load of PSE (1985–90)

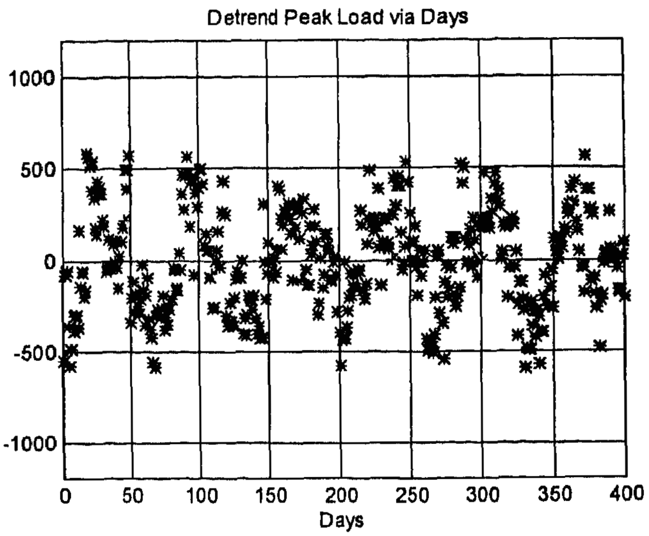

Figure 8 Detrended winter daily peak load (1985–90)

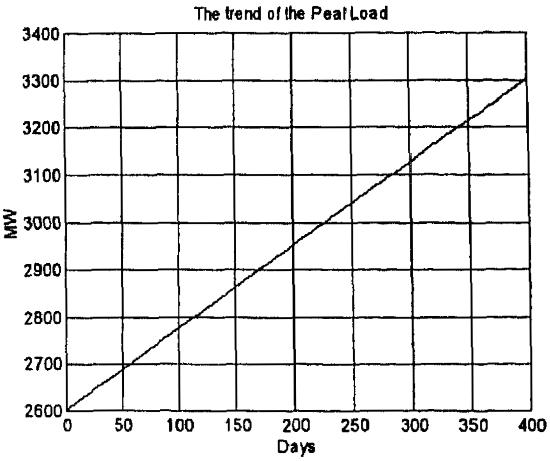

Figure 7 Trend of base load growth of PSE

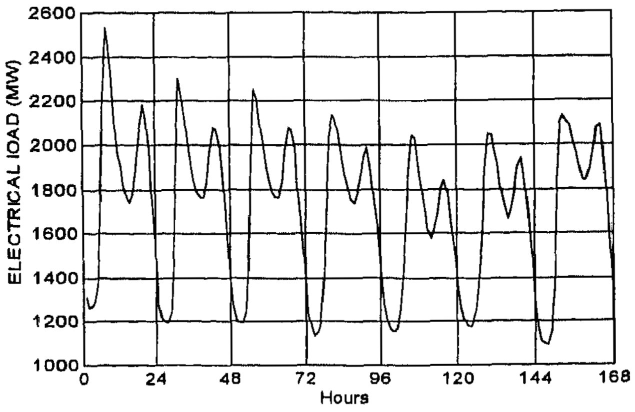

Figure 9 Weekly load patterns of PSE, weekdays only

er day. Therefore, one week can be divided into three groups: 1) Monday, 2) Tuesday through Thursday, and 3) Friday through Sunday. Figure 10 shows Puget Sound Energy load patterns of Christmas and New Year's. Clearly, specialized models need to be developed to forecast these unique loads.

3.5 Season Type Partitioning

The load pattern changes with the season. In the northwest of the United States, the electric load is used primarily for cooling in the summer and heating in winter. Figure 11 shows the load patters of a normal summer season of *Puget Sound Energy*, and Figure 12 shows the pattern of a normal winter season. In this paper, a year is divided into three groups: 1) winter, 2) summer, and 3) transition.

4. TEST RESULTS

The performance of the proposed neuro-fuzzy forecast model is evaluated using the hourly temperature and load data for Seattle/Tacoma area for Jan. 1, 1985 through Mar. 31, 1990. The *Puget Sound Energy Company* collected the data. The focus of this forecast is on a normal weekday in the winter season. Table 1 shows six data sets used for the test. Each set contains a month of normal weekday data (Tuesday through Thursday). The test data is not used in the training process of the forecast model. The neuro-fuzzy regression machine was trained to forecast the next day's peak load. The accuracy of the neuro-fuzzy model is evaluated by the mean absolute percentage error (MAPE), as defined by:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y'_i - Y_i}{Y_i}\right| \qquad (8)$$

where y'_i is the output of the forecast model and y_i is the actual load, and N is the total number of the testing data.

4.1 Structure of the Neuro-Fuzzy Forecast Model

The topology of the neuro-fuzzy forecast model is described as follows:

NN Input:

- Average Temperature of day k

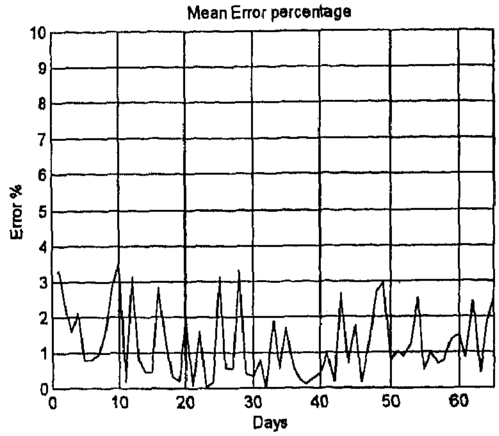

Figure 15 MAPE of peak load forcasting

Table 2 Error (%) of peak load forecast

	Regression	ANN	Fuzzified ANN	ANN with Noise	FANN with Noise
Set 1	1.56	2.55	2.08	2.46	2.23
Set 2	3.82	1.48	1.26	1.91	1.32
Set 3	2.08	1.3	1.1	1.53	1.15
Set 4	1.06	0.84	0.75	1.46	0.76
Set 5	2.62	1.83	1.5	1.77	1.59
Set 6	2.13	1.4	1.24	1.71	1.3
Avg	2.21	1.56	1.32	1.81	1.39

data represents the forecast of the temperature.

5. CONCLUSIONS

In this paper, we have presented the neuro-fuzzy model for load forecast with feature extraction techniques. The forecast accuracy can be greatly improved when forecast feature extraction techniques and data detrending procedures are used.

The neuro-fuzzy forecast model produces more accurate forecast results than tested traditional forecasting techniques. Also, the neuro-fuzzy model is more robust and more tolerant to noisy data.

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