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Artificial Neural Network based Short Term Load Forecasting

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Abstract

Accurate Short Term Load Forecasting (STLF) is essential to the operating and planning for electricity supply industry. For increase accuracy of the STLF, we analyzed load patterns which are categorized by the weather-load relationship and the time-load relationship. The time-load relationship has typical patterns which show the concentrated load consumption shape under the specific time period. The weather-load relationship is identified by correlation between weather factors and load demand and used to adjust the weather weight for the load forecasting accuracy. This paper describes the analyzing of the relationships which are concern with load demand and proposed the improved an Artificial Neural Network (ANN) based non-linear model for 24-hour-ahead load forecasting.

Keywords: *neural network, short term load forecasting, temperature sensitivity*

1. Introduction

Load forecasting is classified into three categories which are long-term load forecasting (LTLF) for longer than year, mid-term load forecasting (MTLF) for a week to a year and short-term load forecasting (STLF) for one hour to one week. STLF is an essential component for electric supply decision involving of optimizing power control to serve the reliable power grid and reduce equipment failures in terms of load flow [1, 2]. Accurate load forecasting ensures that prevents a waste of electricity and system failures. Therefore, accurate load forecasting lead to save operating cost of the power supplier [3].

In this paper, weather-load and time-load relationships are analyzed for the load demand prediction. Weather-load relation is specified by correlation analysis between weather factors and load data. The specified meaningful weather factors are selected for input parameters of the neural network. Especially, temperature is the most correlated factor [4]. Temperature factor is used to make the temperature sensitive value for adjusting the weather weight. Time-load relation is analyzed by shape of the time-load relationship which has a particular pattern due to consumer's life style. In the weekdays, Load demand concentrated in particular time period such as working time. The time of the load concentrated period is directly affected by weather factor. In order to improve the accuracy of the load forecasting, weather weight is differently applied in particular time periods which are divided into concentrated load demand time period and non-concentrated load demand time period.

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2. Load Pattern Analysis

Load consumption is closely related to the electricity consumer's life pattern such as working and activity time cycle [5, 6]. According to analyze the load consumption pattern in summer, the load concentrated pattern is appeared between 9am to 10pm and can be quantified by peak load rate (Figure 1). Equation (1) below has been used to measure the rate of the load demand in a day.

$$PeakLoadRate = \frac{Load}{Max(Load)} \times 100 \qquad (1)$$

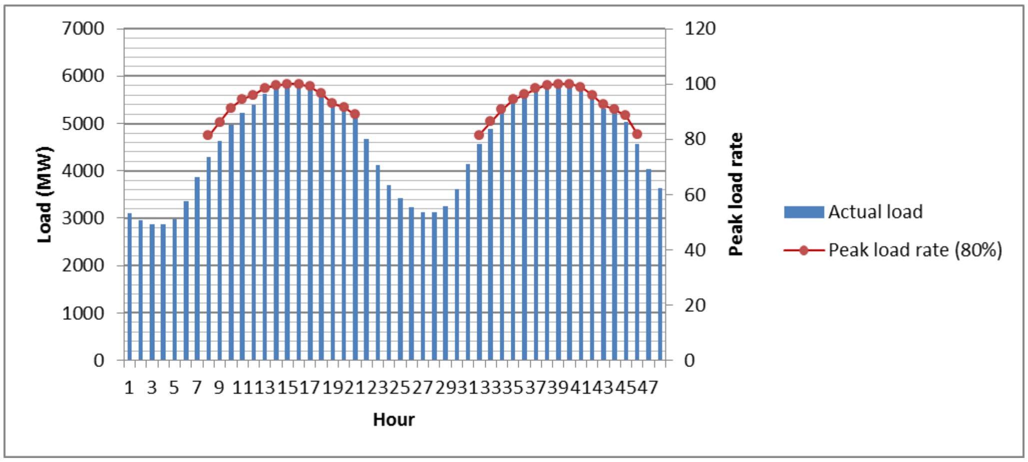

Figure 1. The Relation between Actual Load and Peak Load Rates above 80% (July 6th-7th, 2011)

Figure 1 presents that above 80% of the peak load rate occupies about 70% of the total load rate in summer. Also, the peak load range of the above 80% is very sensitive under temperature change. In order to improve the accuracy of the load demand forecast, the suggested model uses the temperature sensitive variable at particular time period. Temperature sensitive variable is used differently in two parts which are the sensitive range of the temperature and insensitive range of the temperature. Above 80% of the peak rate is the sensitive range of the temperature and under 80% of the peak rate is the insensitive range of the temperature.

3. Input Parameters

The selection of the input variables is a very important phase for ANN based STLF modeling. The performance of the load forecast is highly affected by selecting the input variables [4, 7]. In this our model, we determined the appropriate input variables through the statistical correlation which are derived from historical load and weather data. Figure 2 shows the Autocorrelation (ACF) patterns in summer and winter which are derived from the actual data of the historical load. Roughly, correlation of the historical load has a cycle of each week on same day.

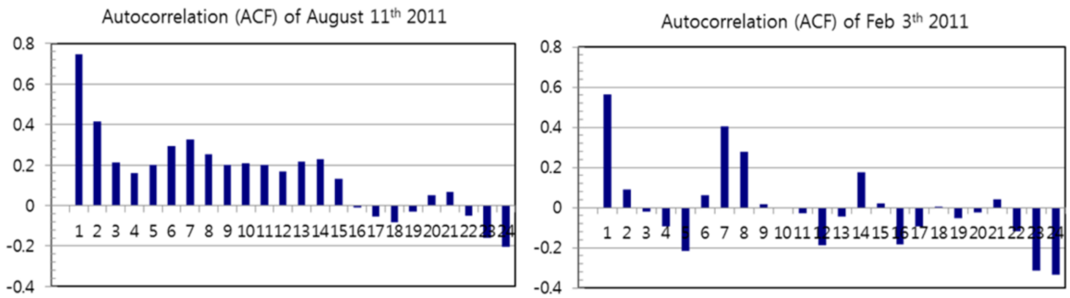

Figure 2. Autocorrelation (ACF) of the Historical Load in Summer and Winter Pattern

Table 1 and Table 2 show the correlation coefficients between historical load demand and each weather factors. The correlation between temperature and historical load for the summer season has value 0.8313 and the next largest value is the dew point which has value 0.5566. Also, in the winter season, the correlation between temperature and historical load is -0.7683 as the most correlated parameter and as the second, dew point is 0.6308. Other weather factors are negligible on the load demand because it has meaningless correlation coefficient.

Table 1. Correlation Coefficients between Weather Factors and Load Demand in Summer 2011

Correlation coefficient in summer season 2011						
	Load	Temp	Dew	Hum	Hpa	Win
Load	1					
Temp	0.8313	1				
Dew	0.5566	0.6254	1			
Hum	-0.1543	-0.1864	0.6027	1		
Hpa	-0.1884	-0.2670	-0.3512	-0.24855	1	
Win	-0.0032	0.0381	0.0489	0.01389	-0.3335	1

Table 2. Correlation Coefficients between Weather Factors and Load Demand in Winter 2011

Correlation coefficient in winter season 2011						
	Load	Temp	Dew	Hum	Hpa	Win
Load	1					
Temp	-0.7683	1				
Dew	-0.6308	0.7765	1			
Hum	-0.0197	0.0049	0.6067	1		
Hpa	0.3619	-0.4624	-0.5989	-0.4090	1	
Win	-0.0634	0.1015	-0.2152	-0.4362	-0.0683	1

According to the analysis of the autocorrelation and correlation coefficient during summer and winter season, we identify the input parameters which are categorized by weather factors and timer factor. Time factors consist of four elements which are previous one, two day, one week and two weeks ago historical load data. Weather factor consist of two elements which are temperature and dew point data as in Equation (2).

$$Load_{input} = \text{L1(d-1,t), L2(d-2,t), L(d-7,t), L(d-14,t)} \quad (2)$$

$$Weather_{input} = \text{Temperature, Dew point}$$

4. Experiments and Results

The proposed model used the actual hourly load and weather data of the U.S. State of Connecticut during the years 2009-2011 and it is tested on the summer and winter season 2011. Figure 3 shows the results of 24 hours ahead load prediction which are 7days simulation in summer (July 1th - 7th, 2011) and winter (Jan 1th - 7th, 2011).

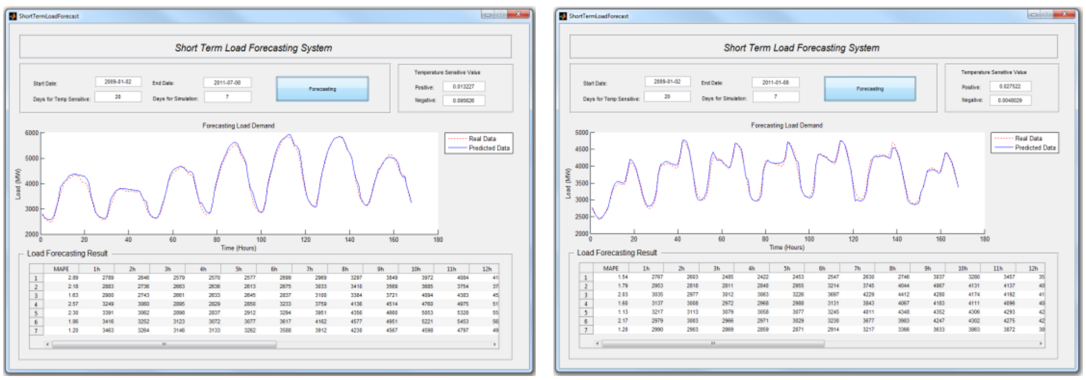

Figure 3. Result of the 7days Load Forecasting in Summer (July 1th - 7th, 2011) and Winter (Jan 1th - 7th, 2011)

Table 3. The Result of the MAPE with Temperature Weight

	Summer		Winter		Improvement (%)	
Days	Excluding	Including	Excluding	Including	Summer	Winter
1	7.8169	2.8912	14.5288	1.5429	63.0135	89.3804
2	8.6404	2.1764	4.5624	1.7874	74.8114	60.8233
3	6.5511	1.6321	12.8802	2.0256	75.0866	84.2735
4	6.8939	2.5685	4.1125	1.5992	62.7424	61.1137
5	9.9781	2.2979	3.9278	1.1267	76.9706	71.3147
6	2.9578	1.0566	4.2662	2.1659	64.2775	49.2312
7	2.9359	1.1954	5.3955	1.1997	59.2834	77.7648
Average	6.5392	1.974	7.0962	1.6353	68.0265	70.5574

In order to evaluate the performance of the load forecasting model, the mean absolute percentage error (MAPE) is considered to measure the accuracy of the load forecasting performance between the actual load data and the forecasted load data [8, 9]. The MAPE is defined as shown in Equation (3):

$$\text{MAPE} = \frac{1}{N}\sum_{n=1}^{n}\left|\frac{Y_i - X_i}{Y_i}\right| \times 100 \quad (3)$$

Y_i is the actual load data, and X_i is the forecasted load data.

Table 3 presents the 7days of MAPE during the summer and winter 2011, using the temperature sensitive weight brings out more accuracy of the load forecasting. In the summer season, the average of the 7days MAPE is 1.974%, and winter season, the average of the 7days MAPE is 1.6353%.

5. Conclusions

Electric load demand is closely related with consumer's life pattern and temperature. Therefore, we analyzed relationships not only the consumer's life pattern and load demand, but also temperature and load demand. As a result of the relationships analyzing, we identified the categories which are temperature sensitive range and temperature insensitive range. In order to improve the accuracy of the load forecasting, the temperature sensitive value is differently applied in the temperature sensitive range and temperature insensitive range. The result of the experiment with the actual load demand has shown the reducing of the load forecasting error in both summer and winter using the temperature sensitive value differently.

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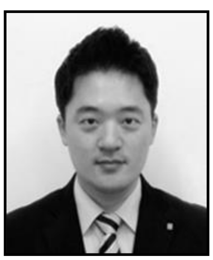

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