논문 00-02-06

Industrial load forecasting using the fuzzy clustering and wavelet transform analysis

In-keun Yu*
(劉 仁 根*)

Abstract

This paper presents fuzzy clustering and wavelet transform analysis based technique for the industrial hourly load forecasting for the purpose of peak demand control. Firstly, one year of historical load data were sorted and clustered into several groups using fuzzy clustering and then wavelet transform is adopted using the Biorthogonal mother wavelet in order to forecast the peak load of one hour ahead. The 5-level decomposition of the daily industrial load curve is implemented to consider the weather sensitive component of loads effectively. The wavelet coefficients associated with certain frequency and time localization is adjusted using the conventional multiple regression method and the components are reconstructed to predict the final loads through a five-scale synthesis technique. The outcome of the study clearly indicates that the proposed composite model of fuzzy clustering and wavelet transform approach can be used as an attractive and effective means for the industrial hourly peak load forecasting.

I. Introduction

Industrial hourly peak load forecasting is an essential function in the electric load management field, especially, for the peak demand control of the big companies. The authors presented a novel industrial load forecasting approach based on wavelet transform, which was aimed at the analysis of weather sensitive components of the loads [1]. The results of the wavelet transform based industrial load forecasting has proven that the approach is relatively a good challenge, however, there are still some problems unsolved because of the historical data were classified mainly depending on the only calendar date. As a matter of fact, the characteristics of daily loads for each time interval, even in the same weekday, are represented differently due to the unique characteristics of industrial company loads and the vacation or special days, etc. That's the main reason why the fuzzy clustering[2-4] is used for the clustering of the industrial load in this paper, and combined with the wavelet transform for the purpose of establishing an effective composite forecasting model. The fuzzy clustering is implemented to classify and cluster the historical industrial load data into several groups so that the accuracy of forecasting is much improved. In this paper, the 1998 and 1999's industrial load data of a Korean steel company are used for numerical case study.

The outcome of the study clearly indicates that the composite model of the fuzzy clustering and wavelet

* 昌原大學校 工科大學 電氣工學科
(Department of Electrical Engineering Changwon National University)

接受日: 2000年 7月8日, 修正完了日: 2000年 11月30日

transform approach can be used as an attractive and effective means of the industrial hourly peak load forecasting.

Ⅱ. Fuzzy clustering

2.1 Cluster analysis

Theory of fuzzy sets was first applied to cluster analysis by E. Ruspini. More recently, J. Dunn and J. Bezdek have made a number of important contributions to this subject and have described effective algorithms for deriving optimal fuzzy partitions of a given set of sample points. The Dunn and Bezdek fuzzy ISODATA algorithm stated as follows.

Let $\mu_1, \ldots, \mu_k$ denote the membership functions of $F_1, \ldots, F_k$. Where the $F_i, i=1, \ldots, k$ are fuzzy subsets(clusters) of a finite subset, X, of points in U. The fuzzy clusters $F_1, \ldots, F_k$ from a fuzzy k-partition of X if and only if

$$\mu_1(x) + \ldots + \mu_k(x) = 1, \quad x \in X \tag{1}$$

The goodness of a fuzzy partition is assumed to be assessed by a criterion functional

$$J(\mu) = \min_{v} \sum_{i=1}^{k} \sum_{x \in X} (\mu_i(x))^2 \| x - v_i \|^2 \tag{2}$$

Where

$$\mu \triangleq (\mu_1, \ldots, \mu_k), \quad v = (v_1, \ldots, v_k), \quad v_i \in L,$$

and $L \triangleq$ vector space with inner product induced norm $\| \ \|$. Intuitively, the v_i represent the "centers" of $F_1, \ldots, F_k$ and $J(\mu)$ provides a measure of the weighted dispersion of points in X in the relation to the optimal locations of the centers $v = v_1, \ldots, v_k$.

Step 1 : choose a fuzzy partition $F_1, \ldots, F_k$ characterized by k nonempty membership functions $\mu = (\mu_1, \ldots, \mu_k)$, with $2 \le k \le n$.

Step 2 : compute the k weighted means(centers)

$$v_i = \sum_{x \in X} (\mu_i(x))^2 x \ / \sum_{x \in X} (\mu_i(x))^2, \quad 1 \le i \le k \tag{3}$$

Step 3 : construct a new partition, $F_1, \ldots, F_k$, characterized by $\hat{\mu} = (\hat{\mu}_1, \ldots, \hat{\mu}_k)$, according to the following rule.

Let $I(x) \triangleq (1 \le i \le k \mid v_i = x)$. If $I(x)$ is not empty let $\hat{i}$ be the least integer $I(x)$ and put

$$\begin{aligned} \hat{\mu}_i(x) &= 1 \quad \text{if } i = \hat{i} \\ &= 0 \quad \text{if } i \neq \hat{i} \end{aligned} \tag{4}$$

For $1 \le i \le k$. Otherwise, if $I(x)$ is empty, set

$$\hat{\mu}_i(x) = \frac{1}{\| x - v_i \|^2} \Big/ \sum_{j=1}^{k} \left(\frac{1}{\| x - v_j \|^2} \right) \tag{5}$$

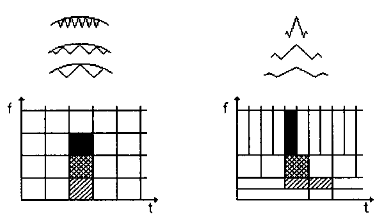
Step 4 : compute some convenient measure, δ, of the defect between μ and $\hat{\mu}$, If $\delta \le \varepsilon \triangleq$ a specified threshold, then stop. Otherwise return to Step 2.

2.2 Fuzzy c-means clustering

Clustering of numerical data forms the basis of many classification and system modeling algorithms. The purpose of clustering is to identify natural groupings of load data from a large load data set to produce a concise representation of a systems behavior. Fuzzy c-means(FCM) is data clustering technique wherein each load data point belongs to a cluster to some degree that is specified by a membership grade. It provides a method of how to group data points that populate some multidimensional space into a specific number of different clusters. FCM starts with an initial guess for the cluster centers, which is intended to mark the mean location of each cluster. The initial guess for these cluster centers is most likely incorrect. Additionally, FCM assigns every data point a membership grades for each cluster. By iteratively updating the cluster centers and membership grades for each data point, FCM iteratively moves the cluster centers to the right location within a data set. This iteration is based on minimizing an objective function that represents the distance from any given data point to a cluster center weighted by that data points membership grade. The clustering process stops when the maximum number of iteration is reached, or when the objective function improvement between two consecutive iteration is less than the minimum amount of improvement specified.

Ⅲ. WAVELET TRANSFORM

Wavelet theory provides a unified framework for a number of techniques which had been developed independently for various signal processing applications [5-7]. In particular, the wavelet transform is of interest for the analysis of non-stationary signals, because it provides an alternative to the classical Short-Time Fourier Transform (STFT) or Gabor transform. The basic differences in contrast to the STFT, which uses a single analysis window, is the wavelet transform uses short windows at high frequencies and long windows at low frequencies and is also related to time-frequency analysis. Thus the windowing of wavelet transforms is adjusted automatically for low or high frequencies and each frequency component gets treated in the same manner without any reinterpretation of the results. This difference is that wavelet transform provides an alternative way of breaking a signal down into its constituent parts. The basic functions in wavelet transform employ time compression or dilation rather than a variation in frequency of the modulated signal. Figure 1(a) shows an example of the time-frequency plane tiling for the STFT. The shaded squares in the figure correspond to waveforms, which are localized in the same time interval and in three adjacent frequency levels. On the other hand, wavelets offer, as is shown in Figure 1(b), a different compromise, the frequency localization is logarithmic, that is, proportional to the frequency level. As a consequence time localization gets finer in the highest frequencies.



(a) STFT (b) wavelet transform

Figure 1 Basis function and corresponding tiling of the frequency plane

The wavelet analysis procedure is to adopt a wavelet prototype function (mother wavelet). Temporal analysis is performed with a contracted, high-frequency version of prototype wavelet, while frequency analysis is performed with a dilated, low-frequency version of the prototype wavelet. Because the original signal or function can be represented in terms of a wavelet expansion using coefficients in a linear combination of the wavelet functions, data operations can be performed using just the corresponding wavelet coefficients. There are several types of wavelet transforms. Depending on the applications, one may be preferred to the others. For a continuous input signal, the time and scale parameters can be continuous, leading the continuous wavelet transform, On the other hand, the discrete wavelet transform can be also defined for discrete time signals. In the case of wavelet transforms, the original domain is the time domain. The transformation process from time domain to time scale domain is a wavelet transform, technically known as signal decomposition because a given signal is decomposed into several other signals with different levels of resolution. From these decomposed signals, it is possible to recover the original time domain signal without losing any information. This reverse process is called the inverse wavelet transform or signal reconstruction.

Ⅳ. PROPOSED FORECASTING APPROACH

The process of the industrial hourly peak load forecasting using the fuzzy clustering and the wavelet transform is shown in the Figure 2.

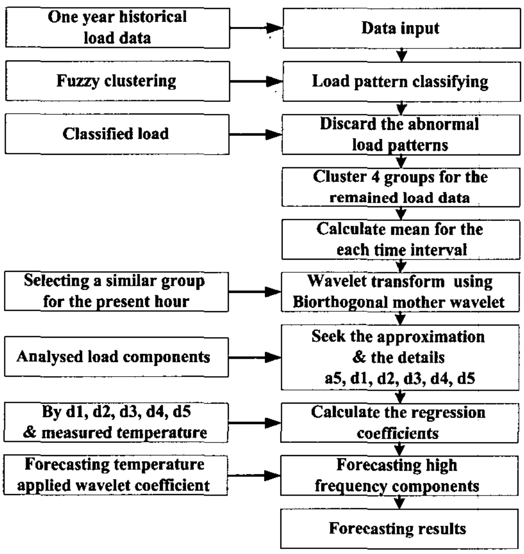


Figure 2 Flow of the proposed industrial load forecasting method

Input load data consist of one-hour interval, and load pattern classified by FCM. Wavelet transform is performed using the classified load, and used to obtain the approximation and details.

The regression coefficients are calculated using the high frequency components(the details) d1, d2, d3, d4 and d5. The next hours temperature applied wavelet coefficients is predicted. For this purpose, the conventional second order regression polynomial is used to describe the relationship between the temperatures and the loads.

$$L_F = a_0 + a_1 T^1 + a_2 T^2 \tag{6}$$

Where L_F represents forecasted load, a_0, a_1 and a_2 are the coefficients and T is the measured temperature. For convenience, the coefficients a_0, a_1 and a_2 are included in A. Matrix algebra, for the load forecasting, can be used as follows.

$$L_F = TA + e \tag{7}$$

Where L_F is a $n\times 1$, T is a $n\times k$, A is a $k\times 1$ e(error) is a $k\times 1$ matrix, respectively. In order to obtain the values of A, the sum of squared deviations must be minimized.

$$\sum e_i^2 = e'e = (L_F - TA)'(L_F - TA) \tag{8}$$

Where $e', (L_F - TA)'$ is the transpose of e. Thus the coefficients are finally calculated as

$$A = (T'T)^{-1} T' L_F \tag{9}$$

Where $(T'T)^{-1}$ is the inverse of $(T'T)$.

The detailed procedure for the industrial load forecasting using the fuzzy clustering and the wavelet transform consists of the following steps.

Step 1 : load patterns are classified into two, effective and abnormal, groups.

Step 2 : the effective group will then be reclassified into four particular classes.

Step 3 : evaluate the mean value of each hour of the clustered groups.

Step 4 : select a group which has the nearest mean to present hour load.

Step 5 : perform the wavelet transform for the 20 load patterns ahead from the present hour of the selected group.

Step 6 : the regression coefficients are calculated using the high frequency components(the details), d1, d2, d3, d4, d5, and the temperature data.

Step 7 : predict the high frequency components of the next hour.

Step 8 : calculate the low frequency component of the next hour using the mean value of the applied low frequencies.

Step 9 : the hourly peak load forecasting is then finally implemented using the calculated low frequency and the forecasted high frequency components.

The accuracy of the forecasted results is estimated by the following percentage error calculation.

$$Error(\%) = \frac{|\,actual\ load - forecasted\ load\,|}{actual\ load} \times 100 \tag{10}$$

Ⅴ. Numerical results

Figure 3 illustrates the basic concept of the peak demand control of industrial field for the purpose of load management.

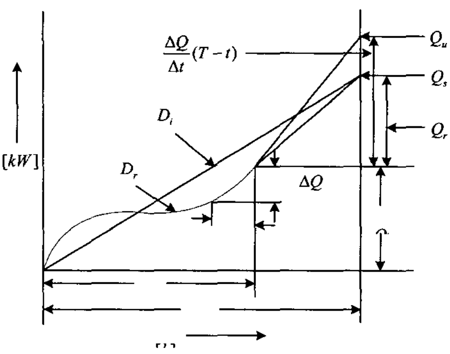


Figure 3 Basic concept of peak demand control

In the Figure 3, Q_u, Q_s, Q_r, Q_t denote forecasted, target, remained and present demand, respectively. D_i, D_r illustrate ideal trend of demand and actual load curve, and T, t denote control time interval and elapsed time from the previous stage, respectively. Once the hourly peak load of the system is forecasted, it will be the target value Q_s of that interval. Within the interval, a new forecasted value of load will be calculated using the slope of actual load curve D_r and the time difference (T-t) as shown in Figure 3.

In general, the peak demand control of an industrial company is implemented in order to save the extra cost of electric energy that is imposed by the supply contract of the peak between the consumer and the supplier. As can be seen in Figure 3, if the forecasted demand would likely be exceeded the target value, then some amount of load shedding will be needed following the schedule order in order to maintain the peak within the contract level. In this paper, a steel company is selected as a study case, the load characteristics of the company is briefly given in Table 1.

Table 1 The load characteristics of a steel company

Total	Electric furnaces	Cooling system	Others
182 [MW]	130 [MW]	20 [MW]	32 [MW]

About 24(%) of the total daily load patterns were discarded at the first clustering using the FCM and Figure 4 shows the first discarded load patterns. The main purpose of the clustering is to sort the load data into several groups so that it may possible to use those groups as forecasting references for the hourly peak load prediction.

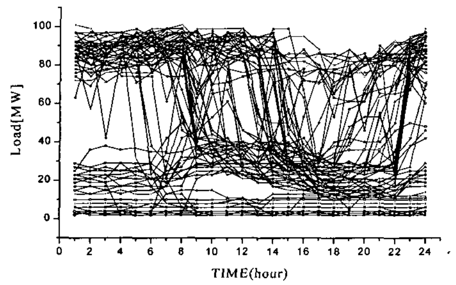


Figure 4 The discarded load patterns by the first clustering - 88days

Since the main goal of the industrial load forecasting in this study is to the peak demand control, it is obvious that the major concerns should be given to the demand saving of peak time rather than the off peak hours. That's why a couple of clustering were carried out for the purpose of discarding the abnormal load patterns in advance, judging from the simulation results, 40(%) of the annual load patterns were discarded, that is, 60(%) of the daily load patterns were remained and then clustered into four other effective groups again.

From Figure 5 to Figure 8 illustrate the four groups of the 60(%) of annual load patterns, some of the interesting observations which can be made from those Figures are that the relatively normal or general load patterns those can be utilized as reference data for the

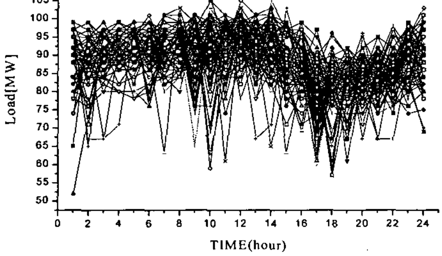


Figure 5 The clustered group - 1(104days)

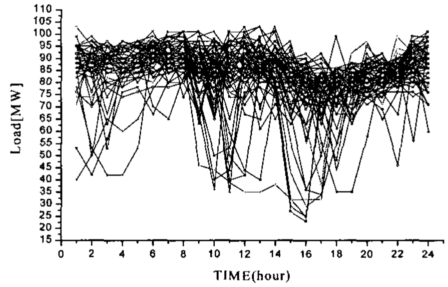


Figure 6 The clustered group - 2(72days)

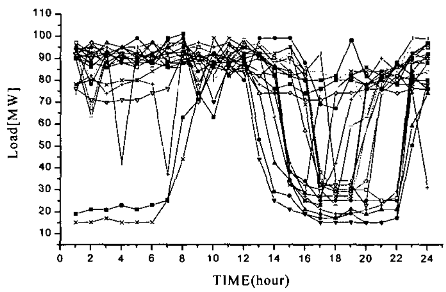


Figure 7 The clustered group - 3(22days)

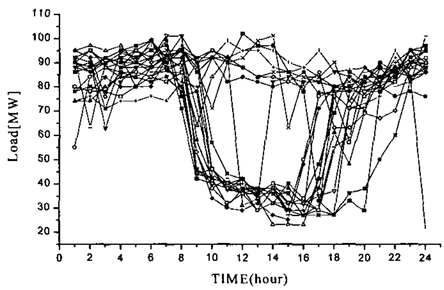


Figure 8 The clustered group - 4(21days)

peak load forecasting were obtained. Using those grouping information, the hourly peak load forecasting was performed following the steps described in the previous section.

In order to verify the effectiveness of the proposed forecasting approach, four seasons (Jan., Apr., Jul., and

Oct.) load forecasting of 1998 and 3-hours load prediction of randomly chosen date (7-days, 1999) and an hourly peak load forecasting for one day were also performed.

Table 2 shows the forecasting error summaries of four seasons load forecasting of 1998. The peak load forecasting of every three hours interval was performed since the only three hours interval temperature data are available from the historical weather information in Korea.

Table 4 Groups used for Table 3

Date \ Hour	10 am	15 pm	21 pm
13, May	2	2	1
8, Jun.	1	1	1
14, Jul.	1	1	2
19, Aug.	1	4	4
17, Sept.	2	1	4
9, Oct	1	1	1
13, Nov.	3	1	2

Table 2 Forecasting error summaries for four seasons prediction (%)

Month \ Hour	3am	6am	9am	12am	15pm	18pm	21pm	24pm	Mean
Jan.	1.77	2.25	3.97	2.77	3.43	3.61	2.74	3.28	2.97
Apr.	3.04	2.50	4.99	2.97	2.98	2.79	2.31	2.43	3.00
Jul.	4.40	3.25	3.31	3.06	2.88	2.42	1.81	3.95	3.13
Oct.	2.36	2.45	2.52	3.43	2.06	4.94	2.82	2.70	2.91
Mean	2.89	2.61	3.69	3.05	2.83	3.44	2.42	3.09	3.00

Table 3 shows the forecasting error summaries of 3-hours load prediction of randomly chosen date (7-days, 1999). The groups selected in the study are summarized in Table 4.

Figure 9 depicts the comparison of the actual and the forecasted load for 1-day, the mean percentage error

Table 3 Forecasting error summaries for randomly chosen date (%)

Date \ Hour	10 am	15 pm	21 pm	Mean
13, May	2.6	1.8	3.1	2.5
8, Jun.	4.4	0.3	3.2	2.6
14, Jul.	3.6	2.6	1.2	2.5
19, Aug.	1.7	7.5	2.3	3.8
17, Sept.	3.2	2.5	0.5	2.1
9, Oct.	3.0	0.2	4.4	2.5
13, Nov.	4.7	3.8	2.6	3.7
Mean	3.3	2.7	2.5	2.8

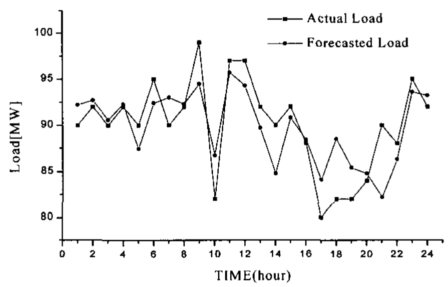


Figure 9 Comparison of the actual and the forecasted load for 1-day (Oct. 28, 1999)

of 2.9(%) is given. The hourly temperature was calculated using the linear interpolation method in this case.

VI. Conclusions

This paper presents fuzzy clustering and wavelet transform based technique for industrial hourly peak load forecasting for the purpose of peak demand control. Firstly, one year of historical load data were sorted and clustered into several groups using fuzzy clustering and then wavelet transforms are adopted using the Biorthogonal mother wavelet in order to forecast the peak load of one hour ahead. The 5-level decomposition of the daily industrial load curve is implemented to consider the weather sensitive component of loads effectively.

The numerical results shows the reasonable forecasting error of 3.0(%) for four seasons prediction, 2.8(%) for the randomly chosen date and 2.9% for a daily load forecasting, respectively. It can be concluded that the outcome of the study clearly indicates that the proposed composite model of fuzzy clustering and wavelet transform approach can be used as an attractive and effective means for the industrial hourly peak load forecasting. The forecasting results of every 15 or 30 minutes is necessary for the real time implementation of peak demand control, this will be the final goal of the study that is being under researching by the authors.

VII. Acknowledgements

The author would like to acknowledge the financial support for this paper provided by KEMCO(Korea Energy Management Co-operation), and in part by the Korea Science and Engineering Foundation(KOSEF) through the Machine Tool Research Centre at Changwon National University.

References

[1] B.T. Kim, C.I. Kim, W.H. Kim and I.K. Yu, Industrial load forecasting using wavelet transform, KIEE Proceeding of Kyungnam regional conference, pp. 25-27, 1999

[2] J. C. Dunn., Indicise of partition fuzziness and the detection of clusters in large data sets, Fuzzy automata and decision process, Elsevier New York, 1977

[3] Leon Bobrowski and James C. Bezdek., C-means clustering with the l_1 and l_∞ norms, IEEE Trans. on Power Systems, MAN and CYBERNETICS, Vol. 21, No. 3, pp. 1342-1350, 1991

[4] Y. Fukuyama, M. Sugeno., A new method of choosing the number of clusters for fuzzy c-means method, 5th Fuzzy system symposium, pp. 247-252, 1989

[5] O.Rioul and M.Vetterli., Wavelets and signal processing, IEEE SP magazine, Oct 1991

[6] Charles K. Chui., An introduction to wavelets, Academic Press, Inc., 1992

[7] I.K. Yu and Y H Song., Wavelet Analysis and Neural Network based Adaptive Single-pole Autoreclosure Scheme for EHV Transmission Systems, Electric Power and Energy Systems, Vol. 20, No. 7, 1998

저 자 소 개

劉仁根 (正會員)
第4券 第1號 論文00-01-02 參照.
現在 昌原大學校 電氣工學科 敎授