Comparative Study of Short-term Electric Load Forecasting

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Abstract—**In this paper, we performed short-term electric load forecasting using three methods and compared each results. We classified before making a forecasting model using K-means and k-NN to eliminate error from calendar based classification. Classified load data used as inputs of forecasting model. We compared three methods such as ANN, SES, GMDH. We carried out 1-day ahead prediction for two weeks, January 10 to 16, March 14 to 20, 2011 using hourly Korean electric load data. The results of forecasting, all methods were mostly good in general without applying meteorological data. Most of them, GMDH expressed the most performance in MAPE except for Saturday.**

Keywords-component; formatting;Short-term electric load foreacasting, ARIMA, k-NN, Artificial Neural Network, Simple Exponential Smoothing, GMDH

I. INTRODUCTION

As the capacity of power system has been expending, grid has become more complicated and needed to more effort to safe operation in a secure manner. In addition, if power system is in the situation that isolated and hasn't sufficient spinning reserve, the importance of accurate electric load forecasting become increase. There are many economical and technical problems in grid operation, it can be one of solution that electric load forecasting using advanced techniques. Normally, it can provide standard for bidding generation pool, generator maintenance scheduling, unit commitment and also as inputs to load flow study or contingency analysis.[1]-[2]

Electric load forecasting classified to short-term, long-term forecasting. Short-term electric load forecasting usually meaning next day forecasting, it divided into their day-type such as weekdays(Tuesday through Friday), Monday, Saturday, Sunday, holiday forecasting. As see the Fig.1, each day-type has their unique characteristic, forecasting models have to be established reflecting their inherent patterns. weekdays model normally has high accuracy results from their definite time series characteristic. However, Monday, Saturday, Sunday relatively lower accuracy than weekdays comes from their lack of data causing lower continuity than weekdays. For this reason, exponential smoothing is frequently chosen as method of weekdays forecasting and

auto regression and fuzzy linear regression, neural network, experts system are frequently adopted to express their pattern.
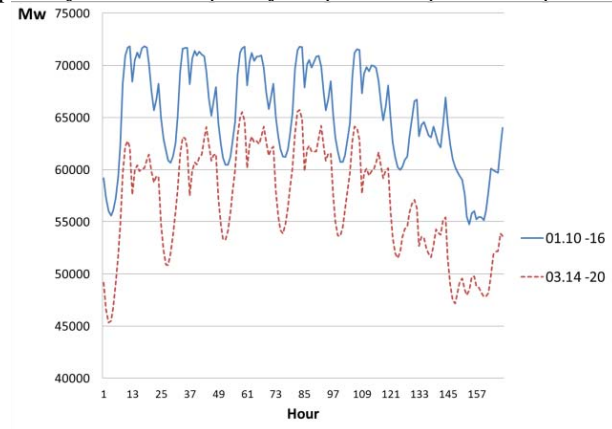

Figure 1. Weekly electic load pattern(Mon.-Sun.)

Electric load pattern includes implicit factors. It normally follows their previous load pattern, however, it will lead to wrong prediction between successive days if the date-type is different compare to previous day. In addition, seasonal variation and social effectiveness, meteorological such as air-temperature and weather are also considered. Consequently, load classification by their inherent characteristics is inevitable procedure.

Classical linear methods have been used to electric load forecasting include moving average and exponential smoothing, linear regression[3]-[7]. However, nowadays, data mining methods such as Artificial Neural Network[8]-[11] and SVM(Support Vector Machine) are showing satisfactory results. So, this paper compare to results of some methods applying load classification.

II. LOAD CLASSIFICATION

A. Load Preparing

Electric loads is expressed in total generated power(hourly). These data are sorted by calendar based and it probably not proper. Generally, they can reflect their day-

type faithfully. For example, Comparing weekday loads with Saturday loads, the level of Saturday loads is relatively low during p.m.. The level of Monday loads during a.m. relatively low to weekdays affected by Sunday break. However, sometimes some of data show different characteristic other same day-type data. This can possibly exist that a data present Monday pattern that lower load during a.m. compare to weekdays actually Wednesday in calendar. For this reason, this paper suggests load classification before establishing forecasting model. It divided into seasonal and day-type classification. K-mean and k-NN algorithm are used to Seasonal and day-type classification respectively.

B. K-mean algorithm

K-mean algorithm was proposed by Cox (1957) and Fisher (1958) and developed by Hartigan (1975) and MacQueen (1967). However, this algorithm assign k as an input, and split the data set into several clusters now. The data which was gathered to same cluster have strongly similar characteristic. However, data similarity among the intercluster is relatively low compare to similarity among the intracluster data. The similarity can be measured by cluster's centroid or center of gravity. This can be established by following procedure. [12].

Input :
- k: the number of cluster
- D: a data set containing n objects.

Output: A set of k clusters.

Method
(1) arbitrarily choose k objects from D as the initial cluster centers
(2) repeat
(3) (re)assign each object to the cluster to which the object is the most similar, based on the mean value of the objects in the cluster
(4) update the cluster means, i.e., calculate the mean value of the objects for each cluster
(5) It the square-error criterion converges, stop.

$$E = \sum_{i=1}^{k} \sum | p - m_i |^2 \qquad (1)$$

where,

E: the sum of the square error for all objects in the data set
P: the point in space representing a given object
m_i: the mean of cluster C_i

C. k-Nearest Neighbor algorithm

K-Nearest Neighbor method was first described in the early 1950s. This algorithm wasn't popular before supported by computing technology. This method is one of famous technique in the pattern recognition. In basically, this algorithm giving a tag to certain data that we want to classify. That is, training sets are described by n attributes. Each set represents a point in an n-dimensional space. In this way, all the training data are stored in an n-dimensional space. When

given an unknown datum, k-NN model finds k data among trained data by order of the shortest distance.
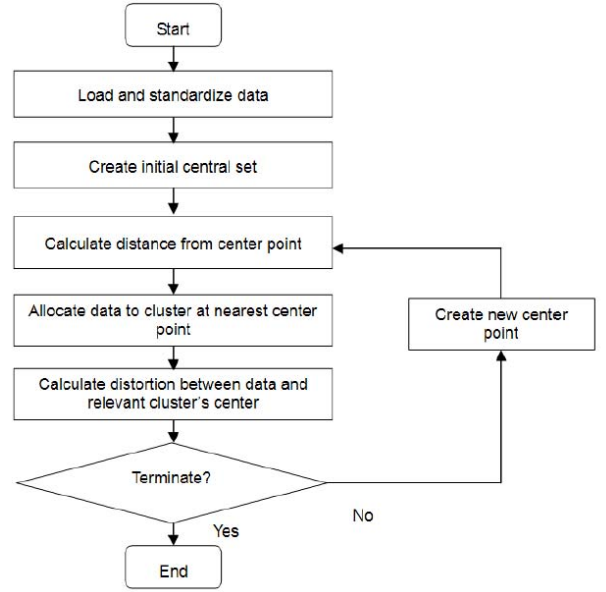

Figure 2. K-mean clustering procedure

Distance is defined in terms of a distance metric. In this paper, we used the Euclidean distance between two points,

$$X_1 = (x_{11}, x_{12},...,x_{1n})$$

$$X_2 = (x_{21}, x_{22},...,x_{2n})$$

$$\mathrm{dis}(X_1, X_2) = \sqrt{\sum_{i=1}^{k}(X_{1i} - X_{2i})^2} \qquad (2)$$

For determine optimal k, we selected certain odd k starting from 1 and tested comparing the error rate of classifier. Repeating this experiment, we choose the best k which is the lowest error rate.

III. LOAD FORECASTING

A. GMDH(Group Method of Data handling)

GMDH has been developed by A.G.Ivaknenko[13]. After initial development, its advanced models also have developed to express multi-variable, non-linear system[14]. The GMDH is one of inductive self-organization data driven approach, it is only small data samples. Its basic equation is called Kolmogrov-Gabor polynomial, expressed by (3) which is discrete form of Volterra series.

$$\phi = a_0 + \sum_{i}^{N} a_i x_i + \sum_{i}^{N}\sum_{j}^{N} a_{ij} x_i x_j + \sum_{i}^{N}\sum_{j}^{N}\sum_{k}^{N} a_{ijk} x_i x_j x_k + ... \quad (3)$$

where, x_i(i=1,2,···,N) and Φ represent input and output variable respectively. Relationship between two variables can express $\Phi = f(x_1, x_2, ···, x_N)$ and

If the structure of model is unknown and input parameter N=4, parameters to estimation are 70. It also considers tremendous structures. Due to avoid this complexity, this paper used 1 parameters and 1st-order self-organized model as seen below

$$y_k = a_0 + \sum_i^N a_i x_i \dots \qquad (4)$$

B. SES(Simple Exponential Smoothing)

The simple exponential smoothing model is a moving average method that places a greater weight on the recent demand when calculating the average.

$$F_{t+1} = F_t + \alpha(Z_t - F_t) \qquad (5)$$
$$F_t = \alpha Z_{t-1} + (1-\alpha)F_{t-1} \qquad (6)$$

Where,

F_{t+1}: predicted value at time point t+1
Z_t: observed value at time point t

$Z - F$: error

α: smoothing constant

Larger the smoothing constant α value (0−1), the greater the weight given to the recent data. For data with a particular pattern, more weight should be given to recent data, and for data without a particular pattern or with severe variation, more past data should be included. In addition, α should minimize error..

The advantage of this technique is that it needs only three data (the prediction value just obtained, the observed value, and smoothing constants) whereas the weighted moving average method requires the previously observed value and the weight.

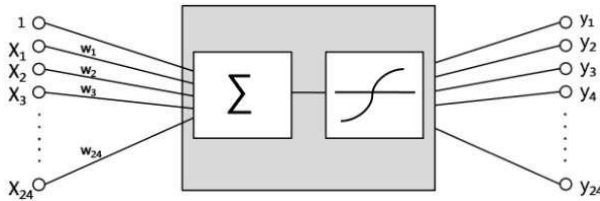### C. ANN(Artificial Neural Network)
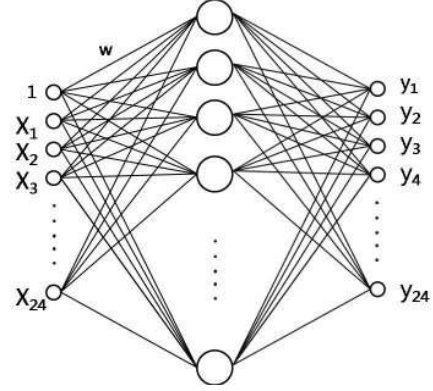

Figure 3. An artificial neuron

Figure 4. A two-layer feed-forward neural network

Neural networks are mathematical tools originally inspired by the way the human brain processes information. Their basic unit is the artificial neuron, schematically represented in Fig.3. The neuron receives (numerical) information through a number of input nodes, processes it internally, and puts out a response. The processing is usually done in two stages: first, the input values are linearly combined, then the result is used as the argument of a non-linear activation function. The combination uses the weights w_i attributed to each connection. The activation function must be a non-decreasing and differentiable [10].

The neurons are organized in a way that defines the network architecture. The one we shall be most concerned with in this paper is the multilayer perceptron (MLP) type, in which neurons are organized in layers. The neurons in each layer may share the same inputs, but are not connected to each other. If the architecture is feed-forward, the outputs of one layer are used as the inputs to the following layer.

The layers between the input nodes and the output layer are called the hidden layers. Fig.4 shows an example of a network with 28 input nodes, 2 layers (one of which is hidden), and 24 output neurons.

IV. CASE STUDY

In this paper, we carried out for one-day-ahead prediction of hourly electric load using electric load data of Korea. The electric load data were used except for special holidays. (Thanks giving day, New year's day etc.) After that, electric load data were classified by K-mean and k-NN algorithm and normalize by (7)

$$\frac{|L^i_{forecasted} - L^i_{actual}|}{L^i_{actual}} \times 100 \qquad (7)$$

where, L_{normal} is normalized load. L_{max} and L_{min} represent maximum and minimum load among the classified load.

Test results were evaluated by MAPE(Mean Absolute Percentage Error). MAPE can be expressed following equation.

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$$\text{MAPE} = \frac{1}{24} \sum_{i}^{24} \frac{|L^i_{forecasted} - L^i_{actual}|}{L^i_{actual}} \times 100 \qquad (8)$$

where, $L^i_{forecasted}$ and L^i_{actual} represent forecasted load and actual load respectively.

Case studies from the proposed algorithm were carried out for two weeks, January 10 to 16, March 14 to 20, 2011. We experimented three methods as previously have been introduced to predict. All methods used classified data as an input. From Fig.5 to Fig.7 show forecasted load patterns compare to actual load. Table Ⅰ shows the summary of prediction results.

For ANN, we chose a multilayer perceptron with 28 inputs, 1 hidden layer, 24 outputs. Smoothing constant α of SES, we selected 0.75 to minimize prediction errors.

The accuracies of three models are slightly different. SES is mostly low accuracy for all day- type and max error compare to the other methods. It had also quite large difference between min and max error rage. However, GMDH shows 1.055% in MAPE, which is the best performance among all day-type and methods despite of excluding weather data. ANN showed middle performance between other two methods.
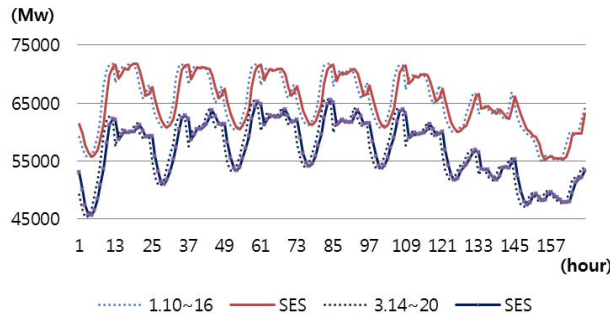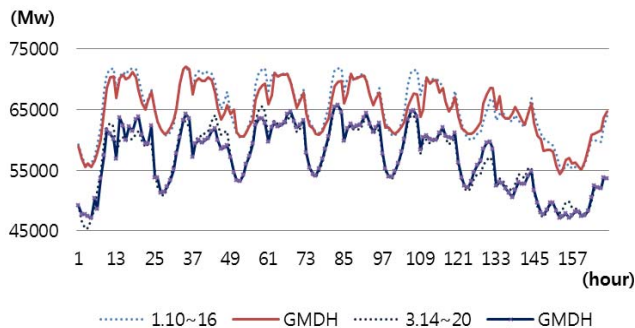

Figure 5.   Prediction result of SES

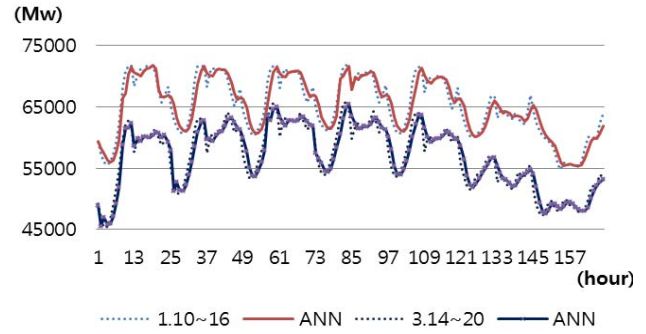
Figure 6.   Prediction result of GMDH

Figure 7.   Prediction result of ANN

TABLE I.   MAPE OF PREDICTION ERRORS

Methods		MAPE					
		Week days	Mon	Sat	Sun	Min	Max
S E S	1.10 - 16	2.239	2.477	1.872	1.650	0.005	7.616
	3.14 - 20	2.503	2.776	2.257	2.099	0.007	10.06
G M D H	1.10 - 16	1.486	1.192	1.876	1.749	0.003	6.293
	3.14 - 20	1.055	1.926	2.121	1.150	0.006	6.212
A N N	1.10 - 16	1.701	1.833	1.598	1.504	0.004	5.352
	3.14 - 20	1.949	2.069	1.821	1.758	0.017	6.609

V.   CONCLUSION

In this paper, we carried electric load classification and short-term electric load forecasting using ANN, SES, GMDH. Compare to other two methods, GMDH was the best performance. However, it have to be improved that the type of load for weekend and Monday are forecasted relatively higher MAPE than weekdays and large value of maximum MAPE. These can help to improve study that using additional meteorological data or constructing more sophisticated classification model using data mining techniques.

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