The Study on Cooling Load Forecast of an Unit Building using Neural Networks

Kwan-Woo Shin†, Youn-Seop Lee

Department of Electrical Engineering, Kongju National University, Chungnam 314-710, Korea

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ABSTRACT: The electric power load during the summer peak time is strongly affected by cooling load, which decreases the preparation ratio of electricity and brings about the failure in the supply of electricity in the electric power system. The ice storage system and heat pump system etc. are used to settle this problem.

In this study, the method of estimating temperature and humidity to forecast the cooling load of ice storage system is suggested. The method of forecasting the cooling load using neural network is also suggested.

The daily cooling load is mainly dependent on actual temperature and humidity of the day. The simulation is started with forecasting the temperature and humidity of the following day from the past data. The cooling load is then simulated by using the forecasted temperature and humidity data obtained from the simulation. It was observed that the forecasted data were closely approached to the actual data.

Nomenclature

e : water vapor partial pressure [kgf/cm^2]

E : water vapor partial pressure of saturated vapor [kgf/cm^2]

O_{pi} : activation at node i

RH : relative humidity [%]

T : normalized daily temperature data

t : temperature

T_d : outdoor temperature [℃]

$T_f(t_i)$: forecasted temperature at t_i [℃]

$T_{f,\max}$: max. forecast temperature for the following day [℃]

$T_{f,\min}$: min. forecast temperature for the following day [℃]

TH : temperature × humidity at t_i

TH_{aver} : daily average for temperature × humidity

THM : temperature × humidity

t_i : sampling time

TM : daily temperature model

tn : forecast temperature

t_{pj} : actual operation data

W_{ji} : weight between node i and j

Greek symbols

α : momentum factor

β : forgetting factor($\beta<1$)

η : learning rate

θ_j : threshold at node j

Subscripts

$aver$: daily average

N : model after renewal

O : model before renewal

† Corresponding author

Tel.: +82-41-850-8610; fax: +82-41-857-8411

E-mail address: skw@kongju.ac.kr

1. Introduction

The electric power load during the peak time in summer is strongly affected by its cooling load, which decreases the preparation ratio of electricity and brings about the failure in the supply of electricity in the electric power system. Heat-exchange system, such as an ice storage system, can mitigate this problem by storing cooling load at night time and supplying it at day time. Heat-exchange system can both efficiently and economically operate an electric facilities as well as electrical systems.[1 2]

The stored energy at night time can be utilized by ice storage system users at day time so as to increase the efficiency of ice storage system. On the other hand, if the ratio of unused stored energy keeps increasing, the efficiency of the ice cooling system becomes in vain.

From this perspective, we need to consider economical aspects such as deciding ice storage by forecasting the cooling load of the following day. Cooling load is dependent on the weather characteristics such as temperature and humidity of that time, so the method to forecast the weather needs to be proposed in order to forecast the cooling load.

This study proposes the method to forecast the temperature and humidity of the following day to forecast the cooling load, and the cooling load forecast algorithm based on the forecasted data by using neural networks.

2. The method of cooling load forecast

Since the cooling load of an unit building is mainly dependent on weather condition such as temperature and humidity, forecasting the precise weather condition is very important.

Accordingly, the temperature and humidity of the following day need to be forecasted first, and then by using the forecasted data, the neural network is used to forecast cooling load of the following day.

2.1 Temperature forecast

Forecasting the temperature can be done as following steps.

(Step 1) Measure outdoor weather data, such as temperature and humidity, of the building and smooth the measured data. Since the outdoor temperature is not changed abruptly, the Eq. (1) is used to smooth and minimize the errors caused by sensors and noises, and to get smooth weather curve as in Fig. 1.

$$T_i = \frac{1}{2m+1} \sum_{k=i-m}^{i+m} T(t_k) \tag{1}$$

(Step 2) Normalization of the measured data. Since daily temperature data shows certain regularity, the minimum temperature between 3 AM and 7 AM is set to 0, and the maximum tem-

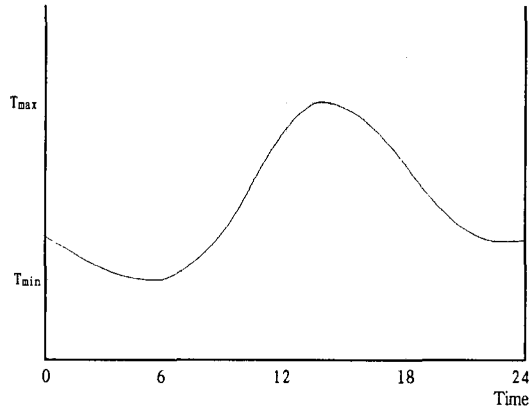

Fig. 1 Smoothed data after measurement.

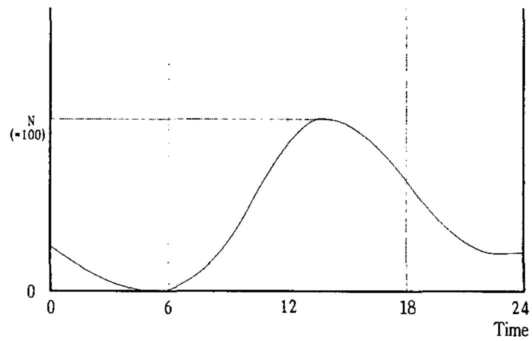

Fig. 2 The normalized temperature graph.

perature between 12 PM and 5 PM is set to 100. From the measured data, we normalized daily temperature data as in Fig. 2.

(Step 3) Figure out daily temperature characteristics model. Daily temperature characteristics model can be derived using the Eq. (2) with new daily temperature data under the condition of $\beta<1$.

$$TM_N(t_i)=(1-\beta)\cdot T(t_i)+\beta\cdot TM_O(t_i) \quad (2)$$

(Step 4) Forecast the temperature of the following day. In forecasting daily temperature, daily temperature characteristics model and forecast data from meteorological observatory were used to forecast the temperature as in the Eq. (3).

$$T_f(t_i)=(T_{f,\max}-T_{f,\min})\frac{TM(t_i)}{100}+T_{f,\min} \quad (3)$$

(Step 5) The method to compensate the offset in order to forecast today's temperature: To minimize the forecast error between the actual temperature data from present to past and daily temperature characteristics model, we move daily forecast temperature vertically down or up to the actual temperature. The difference between daily forecast temperature and actual temperature can be calculated by the Eq. (4).

Error:

$$e=\sum_{current}^{past\ n}[\{T_M(i)+a\}-T(i)]^2 \quad (4)$$

To minimize the error:

$$\frac{de}{da}=0 \quad (5)$$

Difference of temperature characteristics model:

$$a=\frac{1}{n}\sum_{current}^{past\ n}[T_M(i)-T(i)] \quad (6)$$

2.2 Humidity forecast

2.2.1 Characteristics of product of temperature and relative humidity

Relative humidity is defined in the Eq. (7).[7]

$$RH=\frac{e}{E}\times 100\,(\%) \quad (7)$$

Saturated vapor in air can be defined in many ways. It is found that saturated vapor in an air and temperature have characteristics as in the Eq. (8).[7]

$$E(t)=6.1078\cdot\exp\left(\frac{17.08085\cdot t}{234.175+t}\right) \quad (8)$$

Outdoor temperature (T_d), with daily temperature characteristics, rises at day time due to increased water vapor, and falls at night time with decreased water vapor. The temperature range for cooling in summer is between 25℃ and 40℃, and the change of outdoor temperature is as the Eq. (9).[7]

$$T_d(t)=0.1\cdot\left(t-\frac{40+25}{2}\right)+25 \quad (9)$$

To study the relation between relative humidity and temperature, we multiplied temperature data and relative humidity data as in the Eq. (10).

$$RH\cdot t=\frac{e}{E}\cdot t=\frac{E(T_d)}{E(t)}\cdot t =\frac{6.1078\cdot\exp\left(\frac{17.08085\cdot T_d}{234.175+T_d}\right)}{6.1078\cdot\exp\left(\frac{17.08085\cdot t}{234.175+t}\right)}\cdot t \quad (10)$$

The result data from the Eq. (10) was shown as in Fig. 3.

The graph used a percentile to show the characteristics of temperature and relative humidity.

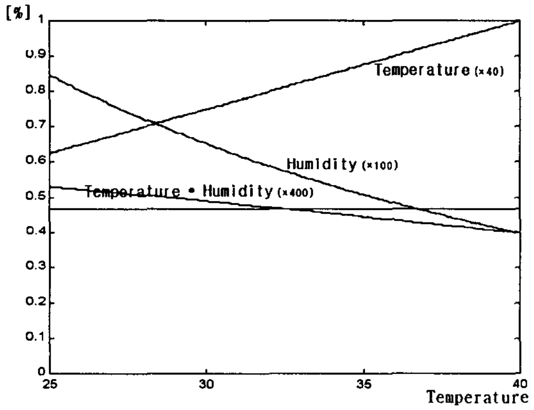

Fig. 3 The graph of product of temperature and relative humidity.

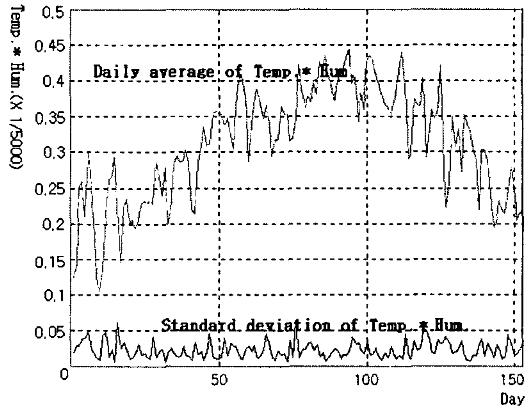

Fig. 4 The daily average and standard deviation of product of temperature and humidity of Gangneung in 1997.

We could find two factors by analyzing Fig. 3 as followings.

(1) We tried to convert and express the difference between temperature and relative humidity with percentile and product of temperature and relative humidity. The difference between temperature and relative humidity gets relatively larger when it is expressed with percentile.

(2) We can find that the difference of temperature and relative humidity becomes relatively small at day time and becomes large at night time. The multiplication of temperature by relative humidity gets small at day time due to higher temperature, and vice versa. To find yearly distribution of multiplying the temperature by humidity, we used the temperature data for 153 days of Gangneung from May to September 1997 and daily temperature change at this period is drawn in Fig. 4.

2.2.2 Relative humidity forecast

Humidity forecasting by using the characteristics of product of temperature and humidity can be done as the following steps.

(Step 1) Measure daily temperature and humidity and store daily average of product of temperature data and humidity data.

(Step 2) Forecast daily average of product of temperature and humidity.

(Step 3) Product of daily temperature and humidity has certain characteristics. However, it has small difference as shown in Fig. 4, so daily humidity model needs to use the Eq. (11) in order to compensate the small differences.

$$THM(t_{i+1}) = \frac{(1-\beta)\cdot TH(t_i)}{TH_{aver}(t_i)} + \beta \cdot THM(t_i) \tag{11}$$

(Step 4) By using daily average of product of temperature, humidity and daily humidity model, hourly value of product of temperature and humidity of the day can be forecasted.

(Step 5) Hourly humidity can be forecasted by dividing daily forecast of product of temperature and humidity with forecasted temperature.

2.3 Cooling load forecast

Neural network has a structure with 8 input nodes, 16 hidden nodes and 1 output node as in Fig. 5.

Once input data is received at each node, the learning of neural network transmits the activation by forward propagation. In order to

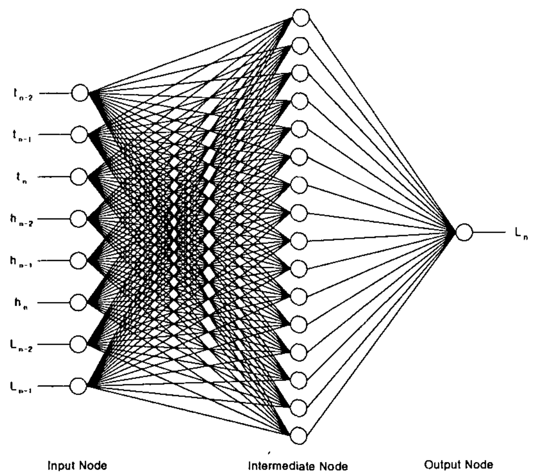

Fig. 5 The structure of neural networks for the fixed period.

match the output value with the desired value, weight and threshold are first modified and then learn neural networks accordingly.

The learning is dynamically decided by the factors such as the differential of the Eq. (12), non-decreased activation. The range here is the range of output value.

$$f\{N_{pj}(n+1)\} = O_{pj}(n+1) = 2 \cdot Range \cdot \left[\frac{1}{1+\exp\{-N_{pj}(n+1)\}} - \frac{1}{2}\right] \tag{12}$$

$$N_{pj}(n+1) = \sum_i W_{ji}(n+1) \cdot O_{pj}(n+1) + \theta_j(n+1) \tag{13}$$

The learning error rate which is the difference between output value of neural network and actual operation data can be derived from the Eqs. (14) and (15).

Output node:

$$\delta_{pj}(n) = f'\{N_{pj}(n)\} \cdot \{t_{pj}(n) - O_{pj}(n)\} \tag{14}$$

Hidden node:

$$\delta_{pj}(n) = 2 \cdot Range \cdot \left[\frac{1}{4} - \left\{\frac{O_{pj}(n)}{2 \cdot Range}\right\}^2\right] \cdot \{t_{pj}(n) - O_{pj}(n)\} \tag{15}$$

The weight and threshold are renewed as backward propagation with the Eqs. (16) and (17). α has the range of $0 < \alpha < 1$, and this value is critical to decide the performance of learning.

Weight renewal:

$$\begin{aligned} W_{ji}(n+1) &= W_{ji}(n) + \Delta W_{ji}(n+1) \\ \Delta W_{ji}(n+1) &= \eta \cdot \delta_{pj}(n) \cdot O_{pj}(n) \\ &\quad + \alpha \cdot W_{ji}(n) \end{aligned} \tag{16}$$

Threshold renewal:

$$\begin{aligned} \theta_j(n+1) &= \theta_j(n) + \Delta\theta_j(n+1) \\ \Delta\theta_j(n+1) &= \eta \cdot \delta_{pj}(n) + \alpha \cdot \theta_j(n) \end{aligned} \tag{17}$$

The cooling load is set to forecast every 30 minutes and 48 neural networks are used to forecast it. 48 neural networks assign one neural network for every hour. 48 neural networks are used since the size of neural network gets much bigger and takes longer time to learn it with one neural network. With 48 neural networks, the learning is scheduled to perform at midnight so as not to impact the performance of computers during the operating hours of ice storage system by learning the neural networks.

The cooling load forecasting by using neural networks is done as the following steps.

(Step 1) The learning of neural networks uses temperature, humidity and cooling load operation data (0 to 4 data) for maximum two hours. In order to learn the n^{th} neural network by using the previously learned data, temperature (t_{n-3}, t_{n-2}, t_{n-1}), humidity (h_{n-3}, h_{n-2}, h_{n-1}) and cooling load (L_{n-3}, L_{n-2}, L_{n-1}) are used as the past operating data. As the background data for forecasting data, forecast temperature (t_n) and forecast humidity (h_n) are used and output data by the neural networks (L_n) learns the neural networks. The input data of load forecast (L_n) is temperature data (t_{n-2}, t_{n-1}, t_n), humidity data (h_{n-2}, h_{n-1}, h_n) and load data (L_{n-2}, L_{n-1}).

(Step 2) Learn the step 1 from the first to the 48^{th} of neural network. To learn the first neural network, use the data up to yesterday.

(Step 3) The learning method from step 1 to step 2, which learns by using the today's data collected previously, is repeated for total days (from T to T-4).

(Step 4) Repeat the learning from step 1 to step 3 for 300 times as a default.

3. Test result and findings

The simulation was conducted in order to verify the accuracy of cooling load forecast algorithm. The simulation used temperature and humidity data of Gangneung collected by meteorological observatory in 1997. KEPCO Sokcho training center is selected as a simulation site. We first conducted the simulation in order to achieve target cooling load of the building with indoor temperature of 26℃ and humidity of less than 50% with assumption of no heat loss from the floor. Then, we conducted the simulation in order to achieve the total cooling load of the building based on the forecasted temperature and humidity data.

In the field test, temperature, humidity and cooling load data from the ice storage system were transmitted to the computers with real-time, and tried to forecast the temperature, humidity, and cooling load for the following day.

Table 1 Forecast error of simulation

Day	Temp. error %	Humidity error %	Cooling error %	Remark
7.20	4.62	18.93	9.75	
7.21	5.44	14.11	6.59	rain
7.22	4.96	19.46	4.64	
7.23	1.97	1.41	4.13	
7.24	3.98	10.83	1.32	rain
7.25	3.80	12.61	0.98	
7.26	5.82	3.61	11.04	
7.27	1.38	7.57	9.14	rain
7.28	3.50	7.38	4.11	
7.29	1.07	13.44	1.94	
7.30	3.37	1.98	2.72	
7.31	2.11	2.82	3.71	
8. 1	3.11	4.84	1.10	
8. 2	7.54	13.79	8.30	heavy rain
8. 3	14.94	24.66	28.17	heavy rain
8. 4	2.41	16.58	5.16	
8. 5	9.04	31.86	12.81	
8. 6	1.19	10.55	5.86	
8. 7	5.65	15.10	3.46	
8. 8	1.15	7.87	2.26	
8. 9	7.23	7.19	8.99	
8.10	1.07	9.74	2.02	
aver	4.33	11.65	6.28	

3.1 Simulation

According to the simulation results, the cooling load is relatively large at 9 AM to 5 PM from July 20 to August 10 and the error rate at that time period is shown in Table 1. The simulation result for July 20 is shown in Fig. 6.

3.1.1 Simulation result for temperature forecast

The temperature forecast test was performed every 30 minute using the Gangneung data collected by meteorological observatory in 1997. The test result showed that the average error rate from July 20 to August 10 was 4.33%, and the forecasted temperature was very close to the actual temperature.

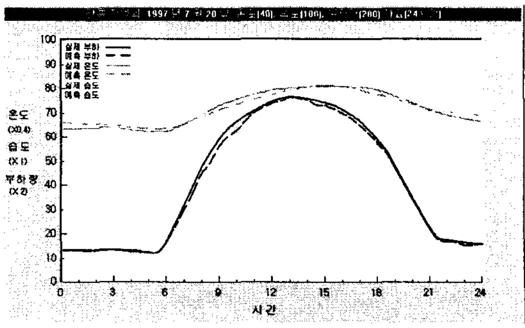

Fig. 6 Result of simulation.

3.1.2 Simulation result for humidity forecast

The humidity forecast test was performed with the same manner as in the temperature. The average error rate was 11.65%. However, the error rate tends to be relative large since it was more difficult to forecast the humidity in rainy days. Heavy rainfall on August 2 and 3 caused large error rate in the test. Humidity forecast is largely affected by sudden weather change so it was very difficult to forecast as precise as the temperature.

3.1.3 Simulation result for cooling load forecast

The simulation for cooling load forecast modeled KEPCO training center located in Sokcho.

The forecast error rate is shown in Table 2 and the following results are derived by analyzing data obtained.

(1) Simulation result showed that the average error rate was closely forecasted as 6.28% between 9 AM to 5 PM from July 20 to August 10.

(2) Heavy rainfall on August 2 and 3 caused relatively larger error rate at that time period. The error rate tends to be increased due to the sudden weather change, but we could get satisfied test simulation results of 6.28%.

3.2 Field test

Field test was performed at "A" golf course club house located in Ansung where an ice storage system was built and operating. The temperature, humidity, and cooling load of the following day is forecasted at midnight by using the input data from the ice storage system. For the realtime data from the ice storage system, we tried to compensate the offset every 30 minute to decrease the error rate so as to increase the accuracy the learning of neural networks for forecasting the following day at midnight.

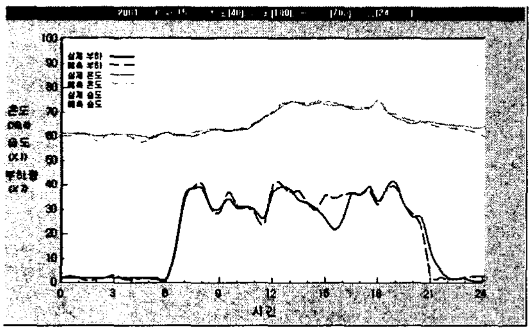

Fig. 7 Result of field test.

3.2.1 Field test result

The result of field test is shown in Fig. 7. The forecast of temperature and humidity was very accurate as in simulation test except rainy days. The cooling load was not proportional to outdoor temperature and humidity. The difference between the forecasted and actual cooling load is mainly caused by operators who manually turned on and off the HVAC systems.

4. Conclusion

In this study, the neural network is used to forecast the cooling load of the building unit in summer by forecasting temperature and humidity, and suggest the forecast method based on forecasted data. Especially, this study proposed how to forecast the weather by simply measuring the temperature and humidity of the building with limited facilities.

The simulation result showed the error rate of 4.33%, 6.28%, and 11.65% for temperature forecast, cooling load forecast, and humidity forecast respectively. The field test had some restrictions since the test was performed at a real site. But we obtained the satisfied results for both tests as in Fig. 6 and Fig. 7.

The load data used in this study were acquired by real weather, so those could be sensitive to abrupt weather change. But the actual cooling load in unit buildings is not dominant as temperature changes day by day. Once operating the cooling load system based on the forecasted cooling load of the following day, it was observed that the system used ice storage more efficient compared to that of legacy cooling system. Moreover, it was possible to operate an ice storage alone at power peak load time (12 PM to 4 PM) without operating cooler to save peak electricity in summer time. If ice storage systems and HVAC systems are integrated and automated together. in near future, the cooling load will show more regular pattern, and the accuracy of cooling load forecast will be significantly improved accordingly.

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