Fault detection and diagnosis system for air-conditioning units using recurrent type neural network

Herath K.U.Samarasinghe (Waseda University) Shuji Hashimoto (Waseda University)

Abstract: **The air-conditioning systems of buildings have been diversified in recent years, and the complexity of the system has been increased. At the same time, stability in the system and the low-running cost are demanded. To solve these problems, various researches have been done. The development of the energy load prediction systems and the faults detection and diagnosis systems have received greater attention. In this paper, we propose a real time fault diagnosis system for air conditioning units (the heating unit, the cooling unit, the air intake unit, and the air-recycling unit) using a recurrent type neural network.**

Index terms: Air-conditioning system, simulation, recurrent type neural network fault detection and diagnosis.

I. Introduction

The knowledge base systems, variety of qualitative models, physical models, ARMAX models, fuzzy models, and neural network models were proposed so far in the fault diagnosis and detection of the air-conditioning system. However, the sufficient fault detection method was proposed and established in the past.

Observing the state variables, the volume of the air flow, and the volumes of the chilled water and the hot water in each part of the air-conditioning system, is the most effective method of detecting a fault in air-conditioning units. But as a matter of fact, this method is difficult to apply because some data cannot be observed in the ordinary air-conditioning system. Therefore, the fault diagnosis system using only the state variables that can be easily observed is demanded. The temperature and the relative humidity are the state variables most acceptable to observation. On the other hand, the quick diagnosis system is indispensable to save energy and to keep the user's amenity safe and operational. Therefore, it is necessary to develop a simple and real-time fault diagnosis system.

In this research, we propose a real time fault diagnosis system for air-conditioning units by introducing the Recurrent type Neural Network (RNN).

II. Outline of the system

The observation parameters in the air-conditioning system were restricted to the temperatures and the relative humidities. It is necessary to perform the accurate fault diagnosis using this small number of state variables. We tried to apply the RNN for this task. The non-recurrent type neural network is also examined in the same task for the comparison. To apply the RNN for the fault diagnosis, the fault case database in the air-conditioning system is required. Our research strategy is illustrated in Fig.1.

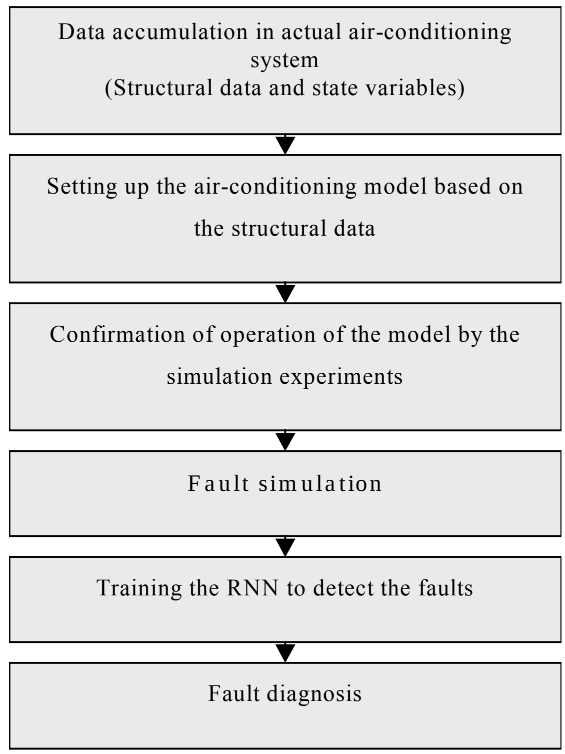


Fig.1 Research Strategy

III. Air-conditioning system

The composition of the air-conditioning system under consideration is shown in Fig.2. The system is a fixed air volume air-conditioning system of the specific building, run by using chilled water and hot water. The air-conditioning system is mainly composed of a cooling dehumidification unit, a heating unit and a humidifying unit. The air is chilled and dehumidified in the dehumidification unit. The temperature of the air is raised again in the heating unit. The steam is added to the air in the humidifying unit. The temperature and humidity of the air are controlled with these three units.

Herath K.U. Samarasinghe is with the Department of Applied Physics, Waseda University, 3-4-1 Okubo, Shinjuku-ku, Tokyo 169-8555, Japan.

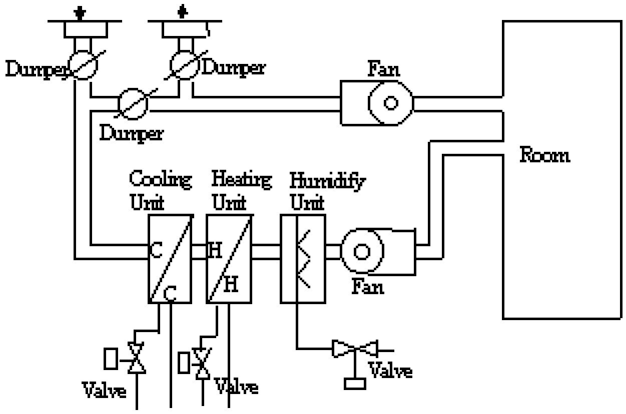


Fig. 2 Composition of the air-conditioning system

The opening states of the cooling unit valve and the heating unit valve are 100% controllable from full-closed to full-open. The temperature of the chilled water is 7°C and the temperature of the hot water is 50°C. The humidifying unit can be adjusted by on-off control.

The heat flows through the wall, the glass and the heat in the draft are considered to be the intruding heat loads from the out side. The heat from the office automation apparatus and the illuminations are considered to be the intruding heat load in the indoor area. The releasing heat load from the human body is assumed to be constant. The heat penetrating with the steam can be disregarded. In addition we assume the following points.

1. The temperature on the surface of the outside wall does not depend on the position and the direction.
2. The temperature on the surface of the inner wall and the ceiling does not depend on the surrounding situation.
3. The temperature and the humidity of the indoor air do not depend on the place.
4. There is no dynamic characteristic in all heat coefficients.

These assumptions are usually introduced in the theoretical treatment of the air-conditioning systems. The air-conditioning is done by the PI control. The gain of P is 0.6 and gain of I is 0.7 in the target system.

Eq.1 shows the relation between the temperature T and the absolute saturation humidity $M_{(T,S)}$ of the damp air.

$$\begin{aligned} M_{(T,S)} &= 2.406163\times10^{-9}\times T^{4} \div 1.404653\times10^{-6}\times T^{3} \\ &\quad -2.874345\times10^{-4}\times T^{2} \div 0.0778877\times T \\ &\quad -5.58008-4.87304\times10^{-3}\times\left|T\right| \end{aligned} \qquad \text{.......... (1)}$$

IV. Simulating experiments

The objected period of the experiment is summer of year 1992, 1993 and 1994 (July, August and September). Two hundred seventy days in total. The time zone of the operation is assumed to be ten hours from 8 a.m. to 6 p.m. We made a simulation software of the air-conditioning system to calculate the system dynamics described above applying the observed outdoor temperature and humidity for the objected period. The calculation cycle in the model is 30 seconds. The calculation frequency becomes 1200 times a day within ten hours. The validity of the model was confirmed by the simulation experiments. The experimental result is evaluated by Eq. 2. The obtained results are shown

$$Y_t = \frac{\sum_{d=1}^{D}\left|P_{S,d,t}-P_{A,d,t}\right|}{D} \qquad \text{......(2)}$$

in Fig.3 and Fig.4.

$P_{S,d,t}$: Calculated state variable in indoor air at time t of the day d.

$P_{A,d,t}$: Observed actual state variable in indoor air at time t of the day d.

D : Number of days (=270).

t : the time from 8a.m. to 6p.m.

Y_t : Evaluation value. Y_t in Fig.3 and Fig.4 is concerning the indoor temperature and the indoor absolute humidity, respectively.

Although the error at the worming-up time is caused by the difference of the starting time between the model and the actual system. We can see that the error is fairly small. Therefore, we can consider that this model is enough to obtain the fault data by the simulation.

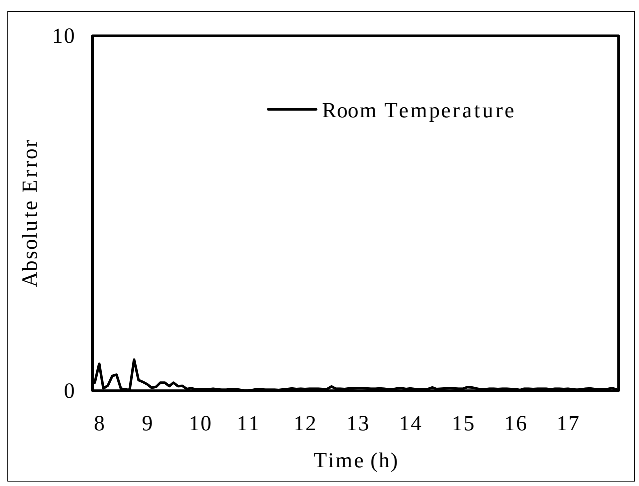


Fig. 3 Comparison of the room temperature

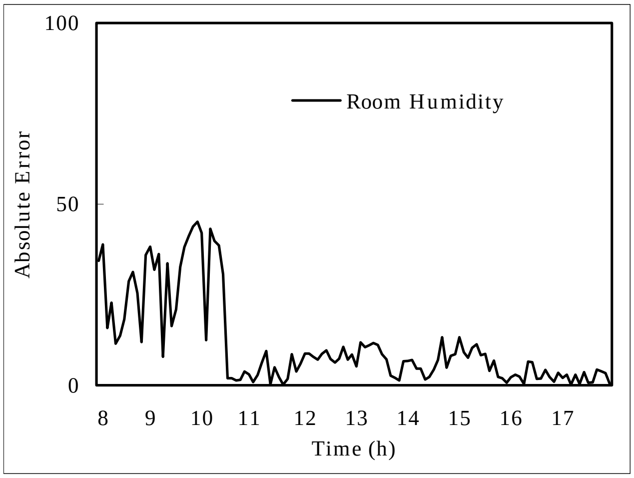


Fig. 4 Comparison of room relative humidity

We considered the following four types of system faults and made the fault simulations for each case.

1. The faults of the outdoor air intake volume control valve.
2. The faults of the recycling air volume control valve.
3. The faults of the chilling water flow control valve in the cooling unit.
4. The faults of the hot water flow control valve in the heating unit.

The PI controller operates the cooling unit valve and the heating unit valve. The air intake valve and the air-recycling valve are taken at a constant opening degree. The opening degree of the valve of the cooling unit or heating unit is fixed when the fault occurred; out of control. If the fault is caused in one of these two units at time *t*, the opening degree of the valve after time *t* is fixed to that of the time *t*. When the fault cause in air intake unit or air-recycling unit, the open degree of the valve is changed and fixed. The valves of other units except the fault unit are operated without fault.

We obtained the data in following two cases using this model.

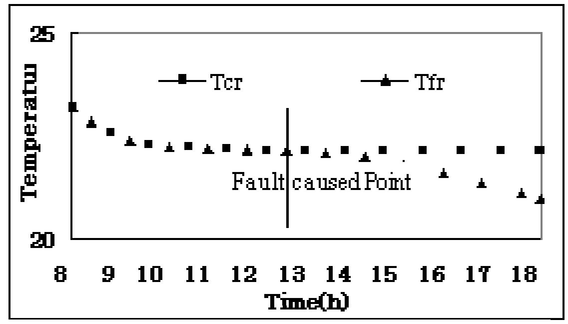
1. Correct case data

When the system is running without fault as the correct data.

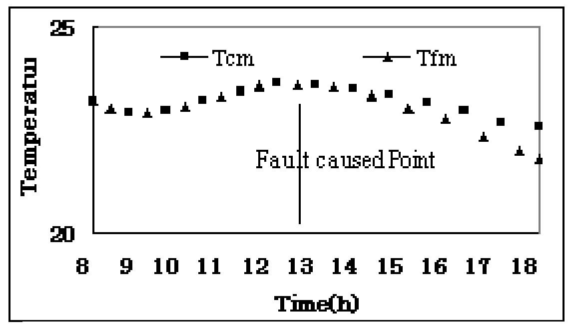
2. Fault case data

When the system is running with a fault as fault data.

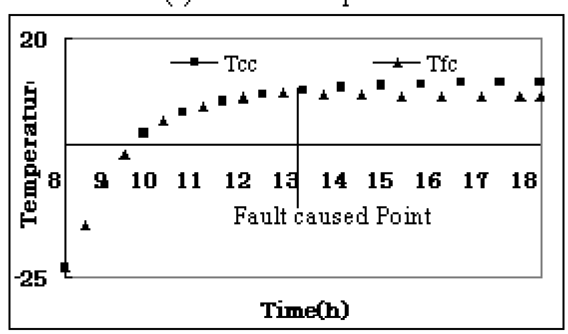
We put the first 100 minutes as the worming period and faults were caused during 100 minutes to 550 minutes at the step of 50 minutes. The relative humidity setting in the room is set to be 50% constant. The temperature setting changed from 17°C to 23°C at the step of 1°C. The obtained data are the temperatures and the relative humidities at the out of door, at the cooling unit entrance (the outdoor air and the recycling air mixing part), the cooling unit exit, the heating unit exit and in the room. These data were collected from 8a.m. to 6p.m. every 30 seconds. As an example, figure 4 shows the temperature at the above- mentioned four locations in the fault case and the correct case. In this example, the setting temperature in the room was 22°C. The fault took place at 13:00.



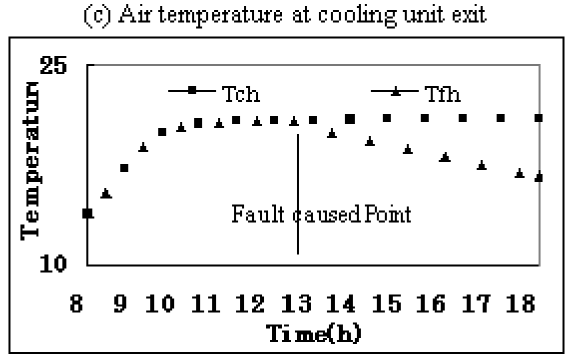
(a) Room temperature



(b) Mixed air temperature



(c) Air temperature at cooling unit exit



(d) Air temperature at heating unit exit

Fig. 5 Example of fault pattern with correct pattern

Tc: Correct case temperature

Tf: Fault case temperature

r, m, c and h mean the room, the air mixing part, the cooling unit and the heating unit respectively.

V. Fault diagnosis method

Fig.6 shows the structure of the RNN used in our experiment. The number of layers is three (the input layer, the hidden layer and the output layer). The number of units in the input layer depends on the number of input data. The number of units in the output layer is the same as the number of the fault classes. The number of units in the hidden layer has to be decided by considering the number of units in the input and the output layers. The generalization ability of the network is the most important to decide the number of the units in the hidden layer.

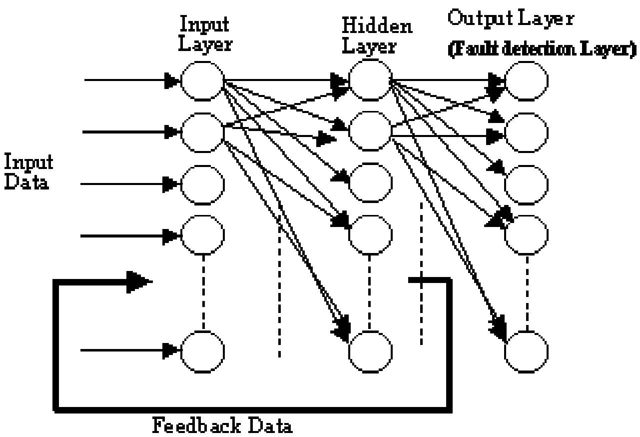


Fig.6 Structure of the RNN

We used the Back Propagation (BP) learning algorithm for training the RNN. BP process is shown as follows.

O_k^l : Output of unit *k* in layer *l*.

$w_{ik}^{l-1,l}$: Weight between unit *k* in layer *l* and unit *i* in layer *l*-1.

O_i^{l-1} : Output of unit *i* in layer *l*-1.

n: Number of units in layer *l*-1.

E: Error of the unit output unit.

t_k^{ol} : Teaching signal of the unit *k* in output layer.

O_k^{ol} : Output of the unit *k* in output layer.

The output of the unit in the hidden or output layer is shown in Eq. 5.1.

$$O_k^l = f\sum_{i=1}^{n} w_{ik}^{l-1,l} O_i^{l-1} \quad ....(5.1)$$

Function *f* in the above equation is a sigmoid function as,

$$f(x) = \frac{1}{(1+\exp^{-x})} \quad ....(5.2)$$

Eq. 5.3 shows the error between the output and the teaching signal.

$$E = \frac{1}{2}(t_k^{ol} - O_k^{ol}) \quad ....(5.3)$$

The weights are corrected according to the inclination of the error shown in Eq. 5.4.

$$\Delta w_{ik}\alpha - \frac{\partial E}{\partial w_{ik}} = -\frac{\partial E}{\partial O_k}\frac{\partial O_k}{\partial w_{ik}} \quad ....(5.4)$$

The error signal can be defined by Eq. 5.5 and Eq. 5.4 can be written like Eq. 5.6.

$$\delta_k = -\frac{\partial E}{\partial O_k} \quad ....(5.5)$$

$$\Delta w_{ik} = \eta\delta_k O_k \quad ....(5.6)$$

The error correction at the learning step *n*+1 can be shown in Eq. 5.7.

$$\Delta w_{ik}(n+1) = \alpha\Delta w_{ik}(n) + \eta\delta_k O_k \quad ....(5.7)$$

η : Learning rate, α : Interior constant

The value of η and α is assumed to be 0.9 and 0.25, respectively.

The fault detection and diagnosis using the above RNN are examined by using the observed correct data and fault data. We observed the temperature and humidity at five points in the air-conditioning system (shown in Fig.7) as the input data for the RNN.

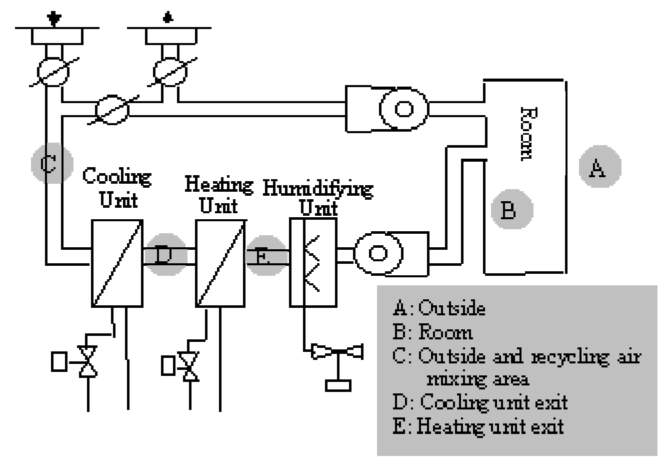


Fig.7 Five points of the observing data

We added five feedback data from the middle layer to the above observed ten data as the input data. Therefore, the number of units in the input layer is fifteen. The number of units in the output layer is four, which correspond to the faults of the cooling unit valve, the heating unit valve, the air intake unit valve and the air recycling unit valve. The number of units in the middle layer is set at fifteen. The training and testing processes are shown in Fig.8.

The correct and fault training data sequences are fed to the input layer randomly after all the weights and the thresholds are initialized with random numbers. The desired output is 1 for the fault case and 0 for the correct case. The unlearned data are used for the testing after training the network.

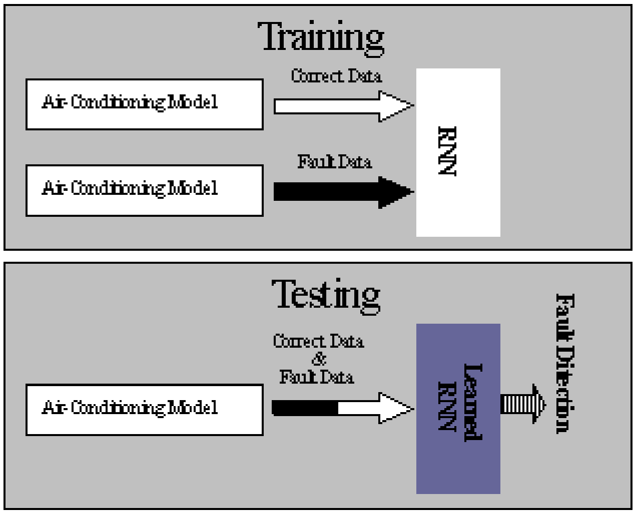
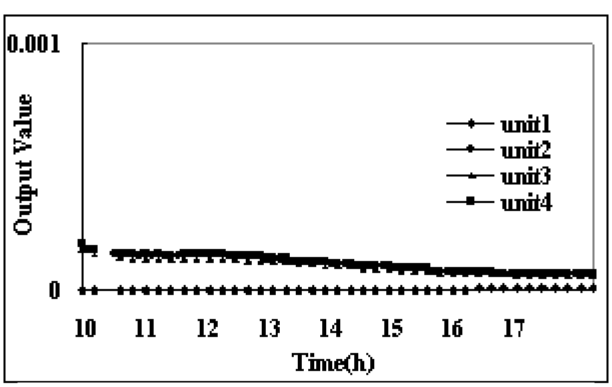


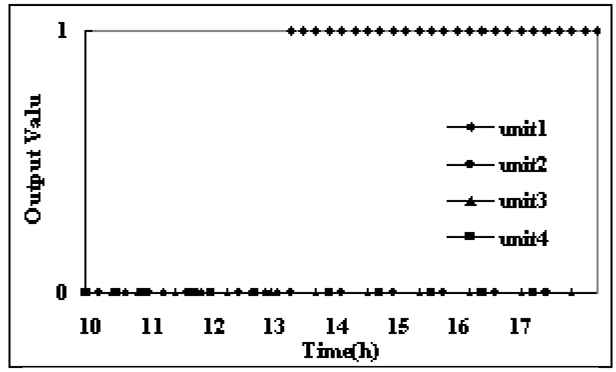
Fig. 8 Training and testing process

VI. DIAGNOSIS RESULTS

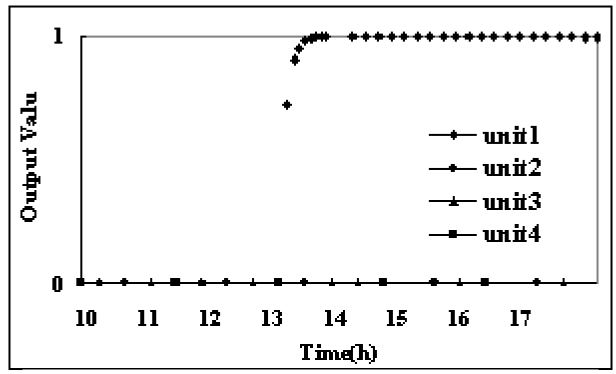
In total 15120 cases of the fault data (4 kids of faults×7 setting temperatures×9 faults occurrence times×60 days) and 420 cases of the correct data (7 setting temperature×60 days) were collected in a period of 60 days from beginning of July to end of August, 1992. The data from 10 days are used for the training and the data from 50 days were used for the testing. Four RNN were used according to 4 kinds of faults. Fig.9 shows the fault diagnosis result for the cooling unit valve fault case as an example. The spindle is the output of the 4 units in the output layer. Unit1 is set as the fault-recognizing unit. The desired output of the 4 units is 0 for the correct data. Therefore, 1 is the desired output of the unit1 and 0 is the other three units in this case. The fault caused time for the fault case is 13.00. The result for the correct data is shown in Fig.9 (a) and the results for the fault data are shown in Fig.9 (b) and (c). (b) is a result for the case when the fault was recognized quickly, while (c) is for the case when the recognition was delayed.



(a) Result for correct case



(b) Result for fault case (quickly fault



(c) Result for fault case (delayed fault

Fig 9. Example of fault diagnosis result

The output values of 4 units for the correct data are almost 0 in (a), meaning that the air-conditioning system is running without fault. On the other hand, the output value of the unit1 in Fig.9 (b) and (c) is almost 1 after 13:00 and the output value of the other three units stays at almost 0, meaning that the air-conditioning system is running with a fault and the fault location is the cooling unit valve.

We tested the same task by using three-layered neural network (10 input units, 15 hidden units and 4 output units) without feedback for comparison. The diagnosis result for the fault cases is shown in figure 10.

●Recurrent: Fault diagnosis result by using RNN

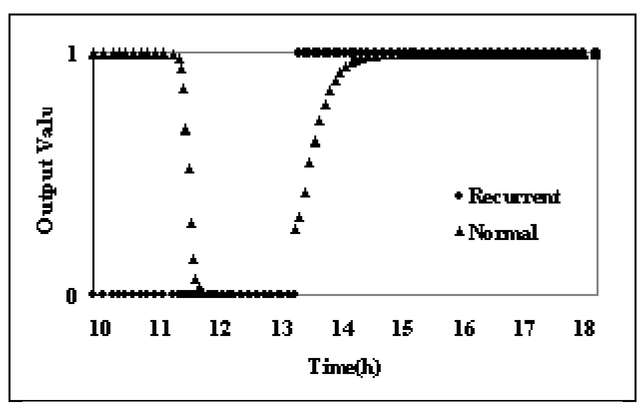


Fig. 10 Comparison result

▲Normal: Fault diagnosis result by using non-feedback neural network

You can see the mis-recognizing from the time zone 10 to 11:30 by the non-feedback neural network, even when the system is running without fault

The ignition unit in the output layer is shown in Table1 for each fault position. The diagnosis result as tested 50 days in RNN is shown in Table2 and 3. Table2 is the result for the correct data while Table3 is for the fault data. The minimum value, maximum value and the average value of the 4 output units in 4 cases of faults are calculated.

Table1. Allocation of the ignition unit in each fault

Fault position	RNN number	Ignition unit
Cooling unit	1	1
Heating unit	2	2
Air recycling unit	3	3
Air intake unit	4	4

Table2. Diagnosis result for correct data

For correct data		Unit1	Unit2	Unit3	Unit4
Cooling Unit	Maximum Value	0.53873	0.00032	0.00042	0.0004
	Minimum Value	0.00004	0.00005	0.00004	4E-05
	Average Value	0.04745	0.00005	0.00004	0.0005
Heating Unit	Maximum Value	0.00089	0.29145	0.00097	0.001
	Minimum Value	0.00021	0	0.00019	0.0002
	Average Value	0.00024	0.00089	0.00022	0.0003
Air recycling Unit	Maximum Value	0.00083	0.00081	0.50518	0.0008
	Minimum Value	0.00025	0.00026	0	0.0003
	Average Value	0.00028	0.00029	0.00151	0.0003
Air Intake Unit	Maximum Value	0.00039	0.00021	0.00024	0.4275
	Minimum Value	0.00004	0.00003	0.00006	1E-05
	Average Value	0.00043	0.00004	0.00017	0.0534

Table3. Diagnosis result for fault data

For fault data		Unit1	Unit2	Unit3	Unit4
Cooling Unit	Maximum Value	1	0.00032	0.00043	0.0004
	Minimum Value	0.81467	0	0	0
	Average Value	0.99964	0.00002	0.00002	2E-05
Heating Unit	Maximum Value	0.00045	1	0.00046	0.0005
	Minimum Value	0	0.80532	0	0
	Average Value	0.00001	0.98464	0.00001	1E-05
Air recycling Unit	Maximum Value	0.00084	0.00083	1	0.0008
	Minimum Value	0	0	0.78699	0
	Average Value	0.00011	0.00013	0.97773	0.0001
Air Intake Unit	Maximum Value	0.00088	0.00083	0.00094	1
	Minimum Value	0	0	0	0.8535
	Average Value	0.00012	0.00012	0.00013	0.9877

The maximum output value for the correct data is smaller than 0.55 and the minimum output value for the fault data is larger than 0.75. This means the above-mentioned faults can be diagnosed by the proposed system.

VII. CONCLUSIONS

The faults of the valve in four air-conditioning units are considered in this study and we propose a fault diagnosis system using a recurrent type neural network. In the current experiments the recognition rate obtained was over 96%. The recognition rate using the non-feedback neural network was less than 60%. Therefore, it can be said that the proposed system is effective for the fault diagnosis. In addition, this system has the following advantages. It can diagnose the faults in real time. Input data required are only the temperature and the relative humidity, which can be easily observed and the training time of the RNN can be shortened.

It this research, we allocated one individual RNN for each kinds of fault. We are examining the optimization of the input data set and the configuration of RNN for more effective trend diagnosis of the air-conditioning system.

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