Partial Fault Detection of an Air-conditioning System by using a Moving Average Neural Network

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ABSTRACT: The fault detection and diagnosis technology may be applied in order to decrease the energy consumption and the maintenance cost of the air-conditioning system. In this paper, two fault detection methods were considered. One is a generic neural network, and the other is an moving average neural network. In order to compare the performance of fault detection results from these methods, two different types of faults in an air-conditioning system were applied. These are the condenser 30% fouling and the evaporator fan 25% slowdown. Test results showed that the moving average neural network was more effective for the detection of partial faults in the air-conditioning system.

Nomenclature

b : bias
P_h : compressor outlet pressure [kg/cm^2]
P_l : compressor inlet pressure [kg/cm^2]
T_c : condenser temperature [℃]
T_e : evaporator temperature [℃]
T_h : compressor outlet temperature [℃]
T_{in} : indoor air temperature [℃]
T_{out} : outdoor air temperature [℃]
W : synaptic weights
X : input value
Y : output value

Greek symbols

δ : error

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1. Introduction

Total portion of the national energy consumption by the air-conditioning system is rapidly increasing. Considerable researches for the development of energy saving technologies have been performed in recent years. Among them, application of the fault detection and diagnosis (FDD) technology to the air-conditioning system shows good opportunities to save energy consumption.

In general, system faults may be detected after complete breakdowns. Therefore, the unnecessary energy consumption by partial faults is prevailed. Intelligent fault detection and diagnosis schemes are necessary for the early detection of partial faults.

To develop the FDD system, the use of low-cost sensors is recommended. Temperature and pressure sensors may be generally used for economic reasons.

In recent years, Braun et al.[1,2] studied the effects of various parameters for partial faults of an air-conditioning unit, and analyzed cost saving possibilities by the early detection of partial faults. McIntosh et al.[3] applied mathematical models for the partial fault detection, and Frank[4] suggested the use of the neural network because of its self-learning and pattern recognition capabilities. Ch'ng et al.[5] also utilized a neural network algorithm (NNA) to detect defected products in the manufacturing process.

In order to develop FDD algorithms for a multi-type air-conditioning system, the fault simulation system was developed. Neural network algorithms were developed and tested by using this system.[6]

2. Fault simulation system

A 5 RT multi-type air-conditioning system was designed and modified to simulate various faults for the system. This fault simulation system was installed in environmental chambers. Chambers consisted of one outdoor chamber and four indoor chambers. Desired environmental conditions for these chambers were controlled by a chamber control system, and test data were obtained by a data acquisition system.

Fig. 1 shows the schematic diagram of a multi-type air-conditioning system used for the fault simulation. As shown in this figure, the fault simulation system was composed of two major parts. An outdoor unit consisted of a compressor, an oil separator, a condensing unit, a condensing fan, a receiver tank, and an accumulator. Four indoor units consisted of electronic expansion valves, evaporator units, and evaporator fans.

For this study, two types of faults at an air-conditioning system were considered. These faults are the condenser fouling and the evaporator fan slowdown.

The condenser fouling represents the condenser surface pollution by various polluting materials, and results in the net loss of the surface area and the air flow rate at the condensing coil. This fault was simulated by blocking the condenser surface area. The level of the fouling was simulated by the level of the condenser frontal area blockage.

The evaporator fan slowdown represents the decrease of air flow rates at evaporator coils by damaged fan motors. This fault was simulated by equally reducing the speed of four variable-speed fans. The level of a fan slowdown was simulated by the reduction of airflow rate against the nominal airflow rate.

The location of the temperature and the pressure sensors is also shown in Fig. 1. Data from these sensors were obtained through the data acquisition system. T-type thermocouples

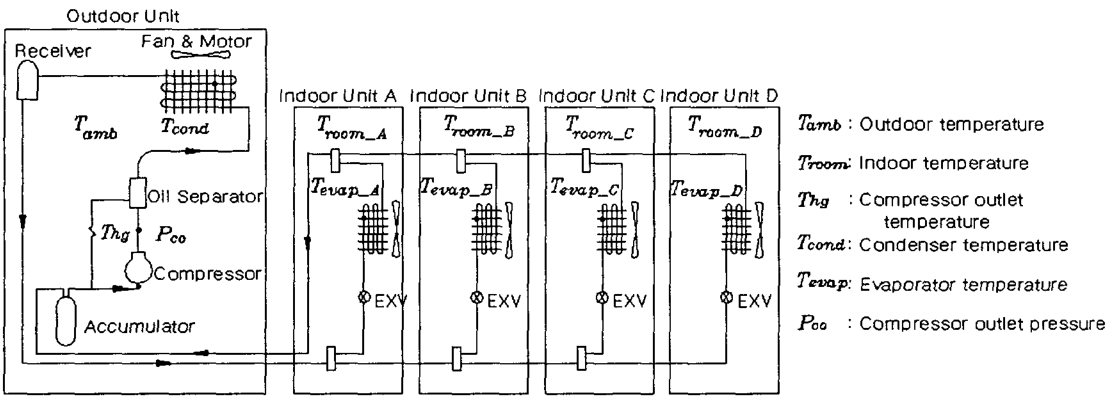

Fig. 1 Fault simulation system.

were used to measure temperatures, and pressure transducers were used to measure pressures.

3. FDD system

The model based method using NNA was selected for the fault detection of the air-conditioning system. Fig. 2 shows the fault detection scheme, which is composed of inputs, a data preprocessor, NNA, and outputs. Compared with a generic neural network, the data preprocessor was added. Five temperature and two pressure informations were used as inputs, and outputs were classified as the normal operation (no fault), the condenser fouling, and the evaporator fan slowdown.

3.1 Data preprocessor

The data preprocessor plays an important role for reducing the noise effects from on-line input data.[7] The moving average method was used for this study. At every 5-second time internal, new data were obtained and recently obtained five data sets were averaged in order to use as input data.

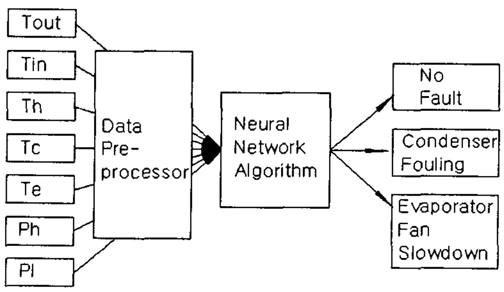

Fig. 2 Fault detection scheme.

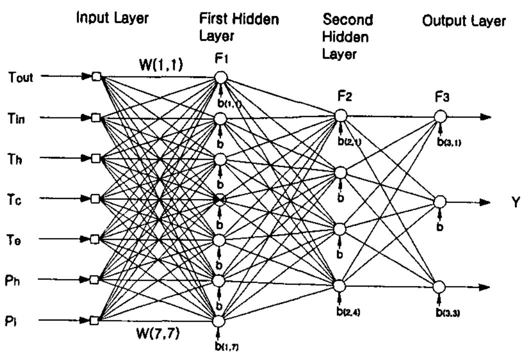

Fig. 3 Neural network architecture.

3.2 Neural network algorithm

Fig. 3 shows the NNA structure selected for this study. T_{out}, T_{in}, T_h, T_c, T_e, P_h, and P_l, are seven inputs, and F is the activation function. The neural network is composed of one input layer, two hidden layers, and one output layer. The first hidden layer has the seven neurons and uses the tangent-sigmoid activation function, and the second hidden layer has four neurons and uses the log-sigmoid activation function. The output layer has three neurons and uses the linear activation function.

3.3 Neural network training

In order to train the neural network, experimental data obtained under the normal condition, the condenser fouling condition, and the evaporator fan slowdown condition were used. Data used for the neural network training consists of uniformly spaced 18 data sets.[8] The indoor and outdoor relative humidities were 41% and 50%, respectively. The indoor air temperature was between 21℃ and 37℃, and the outdoor air temperature was between 25℃ and 40 ℃. Table 1, 2, and 3 show the five sets of data among eighteen sets of data obtained for the normal operation, the condenser 30% fouling operation, and the evaporator fan 25% slowdown operation.

Values for synaptic weights and biases were calculated by a back-propagation algorithm. Fig. 4 shows the back-propagation algorithm. Synaptic weight and bias values are initialized, and target values and error limits are set. After calculating output values by given activation func-

Table 1 No fault data sets

	Set1	Set2	Set3	Set4	Set5
T_{out}	36.43	36.43	36.43	36.43	36.43
T_{in}	16.77	21.31	24.50	28.89	32.49
T_h	108.01	112.86	114.22	115.49	117.89
T_c	44.65	45.16	45.52	45.44	45.90
T_e	0.86	2.53	3.47	5.00	6.05
P_h	17.63	17.80	17.89	17.92	18.05
P_l	3.35	3.47	3.56	3.68	3.73

Table 2 Condenser fouling data sets

	Set1	Set2	Set3	Set4	Set5
T_{out}	36.18	36.18	36.18	36.18	36.18
T_{in}	17.71	21.33	25.39	28.56	31.88
T_h	109.26	115.72	120.65	122.19	123.28
T_c	45.89	47.08	47.73	47.24	47.25
T_e	0.87	2.08	3.26	3.84	4.71
P_h	18.14	18.66	19.00	18.80	18.80
P_l	3.35	3.49	3.56	3.63	3.68

Table 3 Evaporator fan slowdown data sets

	Set1	Set2	Set3	Set4	Set5
T_{out}	35.36	35.36	35.36	35.36	35.36
T_{in}	18.11	21.68	26.00	29.84	33.23
T_h	96.23	95.83	96.24	99.05	100.46
T_c	41.81	42.02	42.35	43.50	43.50
T_e	-3.88	-3.47	-2.39	-1.08	-0.40
P_h	16.30	16.37	16.53	16.98	17.27
P_l	2.68	2.69	2.76	2.87	2.96

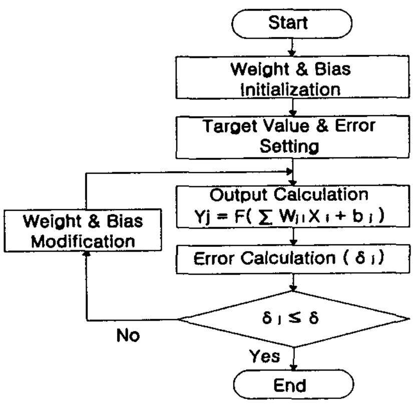

Fig. 4 Back-propagation algorithm.

tions, values for synaptic weights and biases are modified repeatedly until calculated errors (δ_j) are within given tolerance error boundaries (δ). For this study, tolerance error boundaries were set to 10^{-3} and output target values were set to $[1\ 0\ 0]^T$ for the normal operation, $[0\ 1\ 0]^T$ for the condenser fouling operation, and $[0\ 0\ 1]^T$ for the evaporator fan slowdown operation.

4. Test results

In order to verify the fault detection algorithm, outdoor test conditions were 35℃ and 41% (RH), and indoor test conditions were 24℃ and 50% (RH).

Figs. 5 and 6 show temperature and pressure

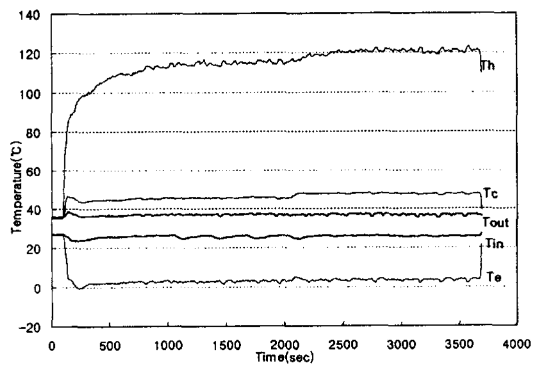

Fig. 5 Various temperatures at the 30% condenser fouling test.

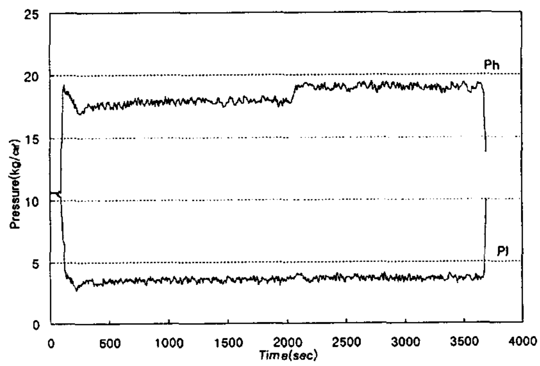

Fig. 6 Various pressures at the 30% condenser fouling test.

readings from a condenser fouling simulation test.

Fig. 7 shows fault detection results for the case of using a generic neural network. The first 1000-second time interval was assumed as a preparation period. The normal operation test was started since the first 1000 seconds and lasted for the next 1000 second. The condenser 30% fouling test was started from the 2100th second and lasted for the next 1500 seconds.

Fig. 8 shows the fault detection results for the case of using a data preprocessor. The Fault detection rate is defined as the percentage of detected faults for a given time period by assuming the ±5% fault tolerance interval. Compared with the result of Fig. 7, the result of Fig. 8 shows the performance improvement from 84.4% to 95.9% of detection rate. The moving average neural network improved the detection rate by 11.5%.

Figs. 9 and 10 show temperature and pressure readings from the simulation test of evaporator fan 25% slowdown.

Fig. 11 shows the fault detection results for the case of using the generic neural network. The first 1000-second time interval was assumed as a preparation period. The normal operation test was performed between the 1000th second and the 2200th second. The evaporator

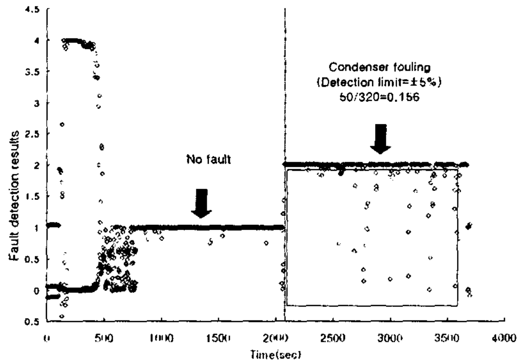

Fig. 7 Fault detection results at the 30% condenser fouling test without the data preprocessor.

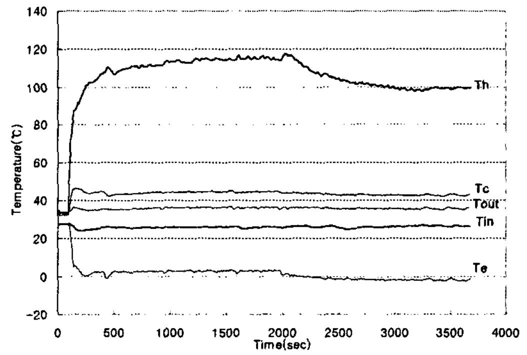

Fig. 9 Various temperatures at the 25% evaporator fan slowdown test.

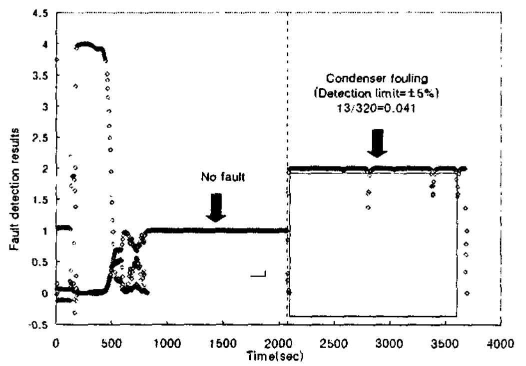

Fig. 8 Fault detection results at the 30% condenser fouling test with the data preprocessor.

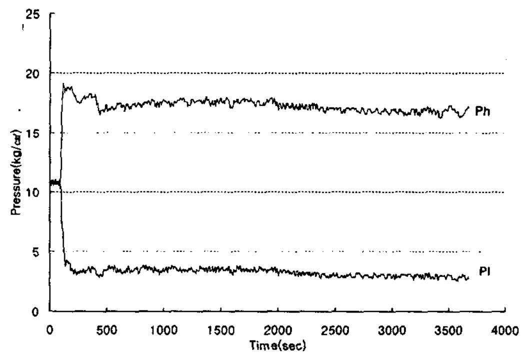

Fig. 10 Various pressures at the 25% evaporator fan slowdown test.

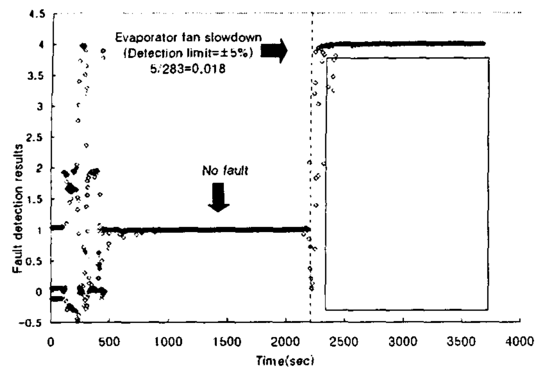

Fig. 11 Fault detection results at the 25% evaporator fan slowdown test without the data preprocessor.

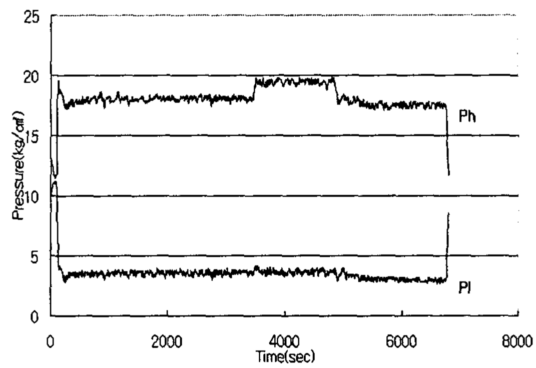

Fig. 14 Various pressures at the 30% condenser fouling and the 25% evaporator fan slowdown test.

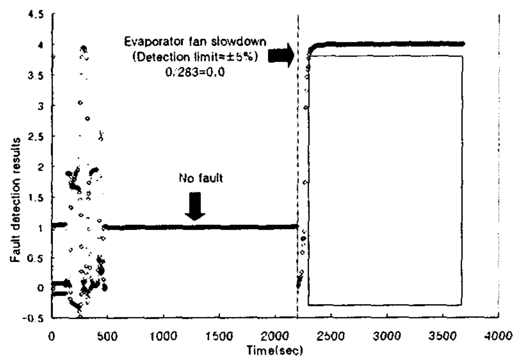

Fig. 12 Fault detection results at the 25% evaporator fan slowdown test with the data preprocessor.

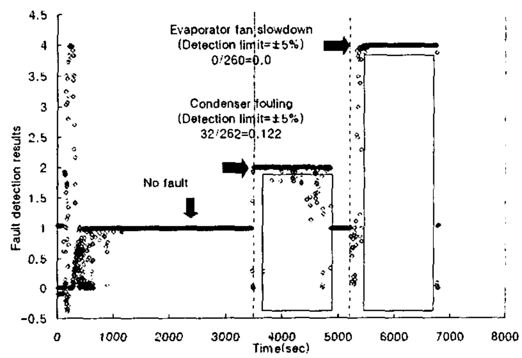

Fig. 15 Fault detection results at the 30% condenser fouling and the 25% evaporator fan slowdown test without the data preprocessor.

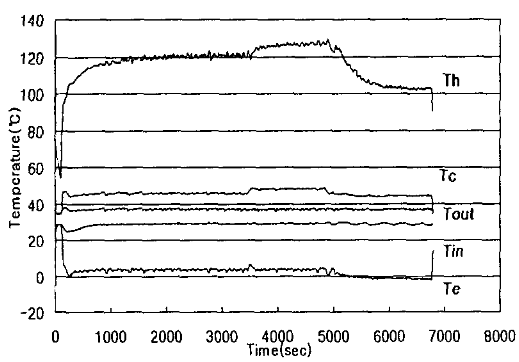

Fig. 13 Various temperatures at the 30% condenser fouling and the 25% evaporator fan slowdown test.

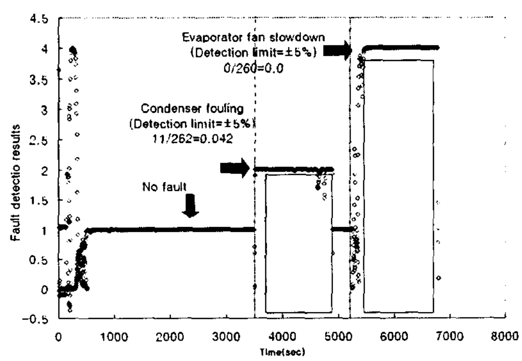

Fig. 16 Fault detection results at the 30% condenser fouling and the 25% evaporator fan slowdown test with the data preprocessor.

fan 25% slowdown test was performed between the 2300th second and the 3700th second.

Fig. 12 shows the fault detection results for the case of using the data preprocessor. Compared with the result of Fig. 11, the result of Fig. 12 shows the performance improvement from 98.2% to 100% of detection rate. The moving average neural network improved the detection rate by 1.8%.

Figs. 13 and 14 show temperature and pressure readings from the simulation test of normal operation, condenser 30% fouling, and evaporator fan 25% slowdown.

Fig. 15 shows fault detection results for the case of using the generic neural network. After the first 1000-second preparation time interval, the normal operation test was performed for the next 2500-second time interval, and the condenser 30% fouling was followed by the 3600th second for the next 1300-second time interval. And then, the normal operation test was performed for the next 400-second time interval, and the evaporator fan 25% slowdown test was followed from the 5400th second for the next 1300-second time interval.

Fig. 16 shows the fault detection results for the case of using the data preprocessor. Compared with the result of Fig. 15, the result of Fig. 16 shows the performance improvement.

5. Conclusions

A moving average neural network was developed. The selected architecture of the neural network was a [7×7×4×3] structure. Selected input variables were various temperature and pressure readings. Input data were filtered through the preprocessor by a moving average method.

Performances of the developed system using preprocessor was compared with those of a generic neural network by experimental tests. Test results showed that the moving average neural network was outperformed the generic neural network in the detection of the condenser fouling by 11.5% and the evaporator fan slowdown by 1.8%. Therefore, the developed moving average neural network may be effectively used for the partial fault detection of the air-conditioning system.

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