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Perceptron network fault diagnosis on the shutdown of the fan in fan-coil unit

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Abstract: Fault diagnosis is an important method of improving the safety and reliability of air conditioning systems. When the fan in fan-coil unit is shut down, there are temperature variations in the conditioned space. The heat exchanger efficiency is lower and the temperature in the room will change while the heat load of the room is stable. In this study, fault data are obtained in an experimental test rig. Thermal parameters as suction pressure and room temperature are selected and measured to establish a characteristic description to represent states of system malfunction. A new approach to fault diagnosis is presented by using real data from the test rig. Using the artificial neural network (ANN) in self-learning and pattern recognition modes, the fault is diagnosed with the perceptron (one type of ANN model) suitable for pattern classification problems. The perceptron network is shown to distinguish types of system faults correctly, and to be an artificial neural network architecture especially well suited for fault diagnosis.

Key words: Shutdown of the fan, Fault diagnosis, Perceptron, Neural network
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INTRODUCTION

The extensive research that has gone into fault diagnosis of air conditioning systems thus far has been motivated by several concerns, ranging from the need to reduce power consumption and energy costs, improving comfort levels in buildings, reducing wear on air-conditioning equipment, reducing the magnitude of greenhouse emission, to assisting in optimal building operation (Wang and Xiao, 2004; Yoshida and Kumar, 2001; Soteris, 2001). When faults are diagnosed and eliminated, the comfort level and reliability of building air conditioning system will improve, thus enabling buildings to be more occupant friendly.

Several researchers have applied fault diagnosis methods to air conditioning systems. Wagner and Shoureshi (1992) evaluated two different fault diagnosis methods when applied on a small scale experimental heat pump. Rossi and Braun (1996) presented an air-conditioner fault diagnosis method based on a statistical rule which takes 9 measured temperatures and a relative humidity as input data. This method successfully diagnosed 5 faults, including air-side fouling of the condenser, air-side fouling of the evaporator, partial blockage of the refrigerant flow, and leakage of the compressor valve plate. However, this prior work only provides fault diagnosis demonstration; a fully functional fault-diagnosis system is not completed. These fault diagnosis systems are all based on system models, and their diagnosistic fidelity is strongly dependent on the precision and accuracy of the model. Model-based fault diagnosis systems require that every sub-system or component can be described in quantitative functional form. Meanwhile, air conditioning systems are nonlinear, multi-parameter systems. It is challenging to develop a precise and general model for all kinds of air-conditioning systems. Therefore, model-based fault diagnosis systems are not extensively applied, because of system complexity and equipment-specific features of system behavior.

In this paper, a fault diagnosis method for air-conditioning systems is presented; the method is different from model-based methods. It makes use of the pattern-classification capabilities of percepron networks, and introduces artificial neural networks as a fault diagnosis method for air-conditioning systems.

FAULT SIMULATION TEST RIG

For a fault diagnosis system to work, the criteria used to represent the system must be established. As far as air-conditioning systems are concerned, the thermal parameters such as temperatures and pressures of the system are of importance to characterize the fault. These parameters provide self-contained information about the system running state. So, a characteristic description formed from some typical thermal parameters can be the input data for fault diagnosis (House *et al*., 1999; Chia *et al*., 1999; Gordon and Ng, 1995). These characteristic vectors belonging to various running state are used as the training examples for the fault diagnosis purpose neural network.

To obtain a dataset for training the neural network, a test rig was used. During the fault simulation test, important thermal parameters are measured to form characteristic descriptions that represent abnormal running state.

Test rig

Experiments and fault diagnosis system development were carried out on an air-conditioning test rig, shown in Fig.1. This apparatus is based on a reciprocating air-conditioning system using refrigerant R-22 with a cooling capacity of 2.2 kW.

Components of the air-conditioning system include a hermetic reciprocating compressor, a refrigerant-to-water plate heat exchanger (PHX) acting as a condenser, and a fin-tube outdoor heat exchanger acting as an evaporator. The system is equipped with a thermal expansion valve (TEV). Using a circulation pump and a hot-water supply, an air-conditioning load is supplied to the room.

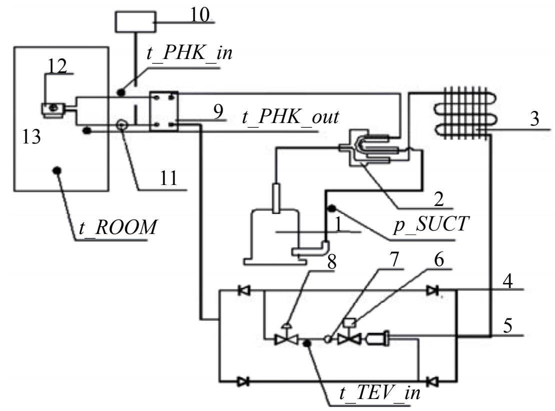


Fig.1 Diagram of the air conditioning system test rig
1: Compressor; 2: Four-way-reversing valve; 3: Outdoor heat exchanger; 4: Check valve; 5: Drier and filter; 6: Solenoid valve; 7: Sight glass; 8: Thermal expansion valve; 9: Plate heat exchanger; 10: Expansion vessel; 11: Circulation pump; 12: Fan coil unit; 13: Conditioned room

Instrumentation and data-acquisition system

The instrumentation of the test rig is composed of four platinum resistance temperature detectors (RTDs) (tolerance: (±0.25+0.0042) °C), and one pressure transducer is given in Table 1.

Table 1 Measured variables

Variables	Descriptions
t_TEV_in	Entering temperature of TEV (°C)
t_PHX_in	Entering temperature of PHX (°C)
t_PHX_out	Leaving temperature of PHX (°C)
t_ROOM	Room temperature (°C)
p_SUCT	Suction pressure (kPa)

Dry surface-mounted RTDs are used. This type of installation was chosen not only to avoid problems with refrigerant leaks, but also to duplicate the most likely way in which RTDs would be installed in the field. Pressure is measured using an optical pressure transducer (accuracy: ±6.5 kPa) mounted in the manner usually employed for pressure gauges and as close to the desired point as conditions would allow; the measurement point is also shown in Fig.1.

Data acquisition is carried out using a computer-based system that enables the user to establish sampling frequencies of up to 1 Hz. The output data files can be stored on the computer serving the test unit and can be transferred to other platforms with specialized software applications for further analysis as shown in Fig.2.

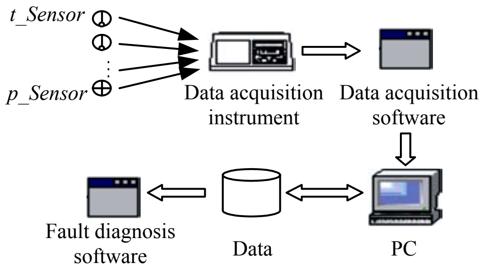
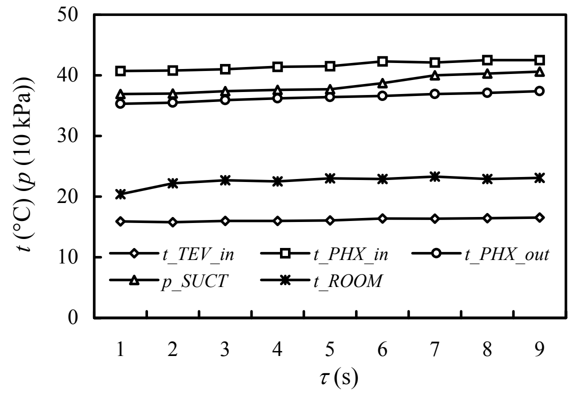


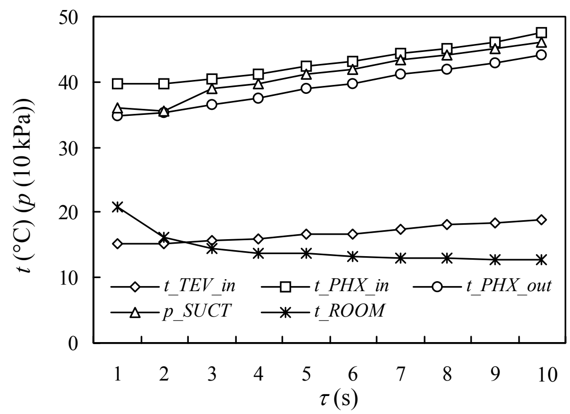
Fig.2 Data-acquisition system

Experimental methodology

The air-conditioning system is at its normal state for times less than t=9 min, and data are recorded as in Fig.3a. At t=9 min, the fan of fan-coil unit in the air-conditioning room is shut down. The temperature of the air in the conditioned space changes because the heat load to the room is steady. The refrigerant temperature at the plate heat exchange increases, owing to insufficient heat rejection at the evaporator. The COP of the system decreases because of the high condensing temperature, and the cooling capacity of the system is reduced. The thermal parameters are shown in Fig.3a. By analyzing the experimental results, characteristic descriptions can be developed for the faults, distinguishing one fault from another. Analysis of Fig.3 shows that two of the parameters can represent the malfunction. Suction pressure is the most quick to respond to the fault, and conditioned-space temperature is an important parameter because controlling the air temperature is the function of the system. Suction pressure and temperature of the conditioned space are selected as the parameters to provide a characteristic description.



(a)



(b)

Fig.3 Thermal parameters of the normal state (a) and the fan shutdown of fan-coil unit (b)

PERCEPTRON NETWORK FAULT DIAGNOSIS

Artificial neural networks can classify patterns, using distributed information distributed storage and parallel computation features. The ANN has batch calculation capacity and self-learning ability. The ANN is a powerful tool for solving many nonlinear mapping problems which cannot be solved with conventional methods (Peitsman and Bakker, 1996; Mohamed *et al*., 2005).

Perceptron network

The general approach to solving real-world complex classification problems that relies upon an MLP (Multi-Layer Perceptron) network is adopted (Weng and Wang, 2002), which is more precisely the so-called BP (Back Propagation) network. However, there is no theoretical basis for deciding how many neurodes to use, nor is there an established theory for deciding network architecture, such as the number of layers and neurode distribution for each particular problem. In most cases, finding workable networks are implemented through a trial-and-error procedure.

The perceptron is one of the most classical artificial neural networks (Rosenblatt, 1961). The simplest perceptron network is a single-layer network, with its input weights and biases set by training. After that, when an input vector is presented to the trained perceptron network, the desired output target can be obtained. The algorithm used in the training process is called the perceptron learning rule. If the problem is linearly separable, the perceptron network is always the most powerful and reliable problem-solving network. It is especially well suited for solving simple pattern classification problems.

Perceptron neurode

A perceptron neurode using the hard-limit transfer function *hardlim* (Rosenblatt, 1961), is shown in Fig.4. Each external input is weighted with an appropriate weight W_{1j}, and the sum of the weighted inputs is sent to the hard-limit transfer function, which also has an input of 1 transmitted to it through the bias. The hard-limit transfer function, which returns a 0 or a 1, is shown in Fig.5. The perceptron neurode produces a 1 if the net input into the transfer function is equal to or greater than 0; otherwise it produces a 0. The hard-limit transfer function gives the perceptron the ability to classify input vectors by dividing the input space into two regions. Two classification regions are formed by the decision boundary line, which is determined by Eq.(1). This line is perpendicular to the weight matrix $\boldsymbol{W}$ and shifted according to the bias $\boldsymbol{b}$.

$$\boldsymbol{Wp}+\boldsymbol{b}=0. \tag{1}$$

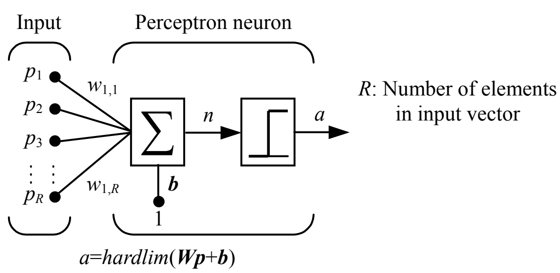


Fig.4 Perceptron neurode

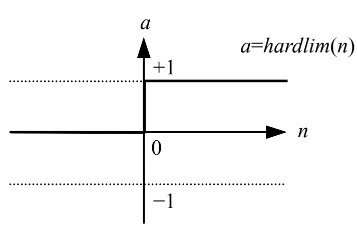


Fig.5 Hard-limit transfer function

Implementation of perceptron diagnosis network

Assume that there are finite possible running states which an air-conditioning system can take. For instance, there are n types of possible system faults. Let S_0 represents the normal state, and $S_1, S_2, S_3, \ldots, S_n$ each represent one type of fault state. When the system is running at state S_i, the corresponding observable vector is $\boldsymbol{Y}_i=(Y_{i1}, \ldots, Y_{im})$. Therefore, the process of fault diagnosis can be considered as finding the state S_i according to the given measurable characteristic vector $\boldsymbol{Y}_i=(Y_{i1}, \ldots, Y_{im})$ of the system. To some extent, fault diagnosis can be considered as one kind of pattern classification problem. The output values of a perceptron can take on only one of two values (0 or 1) due to the hard-limit transfer function. It is suitable in the above fault diagnosis (Zhang, 2006).

The computer simulation routines of the preceding diagnosis neural network are implemented within the MATLAB computational environment (Wasserman, 1993). It includes the network foundation, training program *newtrainfdp.m*, and the diagnosis program *simfdp.m*. The decision boundaries of the trained neurodes within the perceptron network are shown in Fig.6. The characteristic description of the fault through suction pressure and temperature of the conditioned space are given.

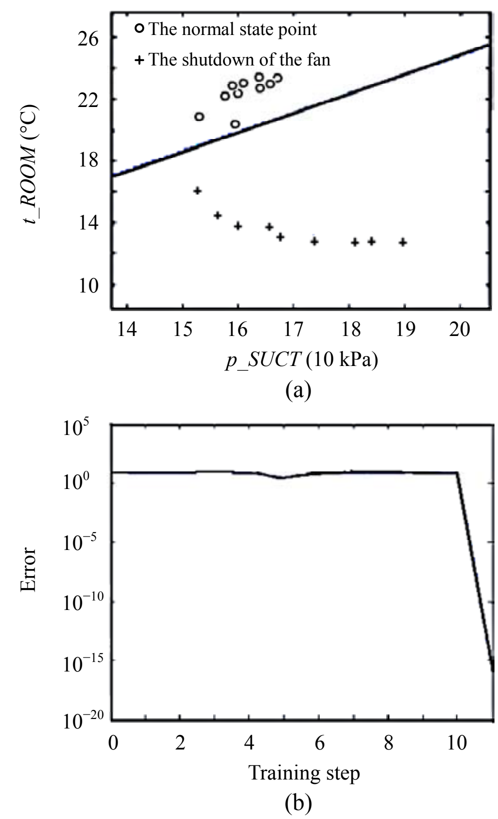


Fig.6 Results of the network training and identification. (a) Results of classification; (b) Result of obtaining error

It can be seen that after several iterations in the training procedure, the ANN separates the fault state successfully from the normal state. That is to say, the trained perceptron network is ready for future diagnostic tasks. Moreover, taking the experimental data as test inputs to validate the diagnosistic ability of the network, the diagnosis outputs are correctly identified by the ANN. In a second phase of testing, a set of experiments was designed and carried out on the real system. In this way, the methods were tested in real situations. One strength of the ANN approach, as opposed to a full system model, is that it does not require long computational time. Once the network is trained, the ANN provides fast and precise fault diagnosis for faults under conditions similar to the experimental conditions.

After making a summary of other researchers' works and the present test rig, six typical faults are simulated and the thermal parameters that represent their running state are sampled to form the characteristic description shown in Table 2.

Table 2 Characteristic description for the other 6 faults

Fault	Characteristic description
Compressor shutdown	Discharge temperature, leaving temperature of PHX
Pump halt	Leaving temperature of PHX, suction pressure
TEV too broad	Entering temperature of PHX, suction pressure
TEV too narrow	Suction temperature, suction pressure
Refrigerant too few	Discharge temperature, suction pressure
Refrigerant too much	Discharge temperature, suction pressure

The ANN diagnostic tool can distinguish each fault correctly. Moreover, using the experimental data as testing inputs to validate the diagnosis network, the diagnosis outputs are correct. The fault diagnosis neural network based on the perceptron approach described above can diagnose the system faults rapidly and precisely, in real time. The perceptron architecture is very well suited for fault diagnosis of air-conditioning systems.

CONCLUSION

Using an experimental apparatus, a database of system response to a range of system faults is obtained. By analyzing the experimental results, characteristic descriptions of each fault, embodied in the behavior of the suction pressure and temperature of the conditioned space are developed. Perceptron neural network fault diagnosis can diagnose the faults precisely, and map the fault symptoms to the fault using pattern classification techniques. When no model of the system is available, or when the model is too complex, the use of ANN-based pattern classification methods can provide a convenient approach to solving the fault diagnosis problem. The work presented here can serve as a basis for the further development of fault-diagnosis systems based on neural-network frameworks for air-conditioning systems.

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