Development of Fault Diagnosing System for Air-conditioning Systems

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Abstract—This paper proposes probabilistic neural network (PNN) to monitor the operation statues for the compressor of air-conditioning systems. The field data including the high/low pressures and the high/low temperatures of refrigerants are measured in a practical system. PNN analyses the refrigerants' pressures/temperatures of air-conditioning systems to monitor the operation conditions of compressor and identifies the abnormal status, while using the ratio of refrigerants' pressures/temperatures to create training data-set. PNN method is suitable for application in a dynamic environment by using new data-set and new hidden without doing any computed iteration. The commonly used EXCEL was integrated to provide a convenient man-machine interface. Computer simulations were conducted with refrigerants' records, test results showed the effectiveness of the proposed system.

Keywords— Probabilistic Neural Network (PNN), Air-Conditioning Systems, Compressor.

1. Introduction

The capacity of air-conditioning apparatus has occupied more than 40% of overall energy consumption in Taiwan. The air-conditioning systems used promoted not only comfortable environments but also the quality of products. Although some techniques [1-3] have been effectively applied in saving energy, the system operation need still have potential to ensure the comfort of building occupants and the reliability of equipment. Preventive techniques for early detection can find out the incipient faults and avoid outages during the operating periods. Parameters available, such as the high/low pressure and high/low temperature of refrigerants in an air-conditioning, compressor, and so on, can tell the conditions of air-condition systems. Based on the operating data, it is the important information to identify the faults. Although there are few concerns on the faults diagnose of air-conditioning system [4-6], they generally have high development costs and relatively high initial hardware and software costs. Therefore, its designs need high efficiency, simplicity, and low cost for faults diagnose is need.

The compressor of air-conditioning systems moves the refrigerant molecules from low-pressure side to high-pressure side during the compression cycle. The pressure and temperature of refrigerants are the sum of bombarded molecules and the speed of molecules motion, respectively. In normal operation, the pressure and temperature of refrigerants are maintained on an interval. If the abnormal pressure or temperature of refrigerants were produced in any compression refrigeration system, it will be led to a fault in the air-conditioning systems. For example, the operated pressure of R12 refrigerant are served on 50psi~70psi and 220psi~280psi for low-pressure side and high-pressure side, respectively. If the low-pressure of refrigerants is under 50psi, the system may be occurred the abnormal operation of electromagnetic valves. Similarly, the abnormal pressure and temperature of refrigerants can produce the various alarms and faults in the system. The purpose of this paper is to discriminate the behaviors of refrigerants in order to diagnose the operating status of the air-condition systems. To reduce the outage duration and promptly restore power services, fan effective tool is helpful for fault estimation.

In literatures, artificial neural network (ANN) have been applied in the fault diagnosis [7-10]. ANN is very useful owing to its parallel distributed process, training capacity, implicit knowledge representation, and pattern recognition capability. However, ANNs have some drawbacks, including the determination of network architecture and network parameters assignment. When networks are applied in dynamic environments, especially for online applications, traditional networks can become the bottleneck in adaptive applications [11]. Considering these limitations, probabilistic neural network (PNN) is proposed in this paper for faults identification. Accordingly adaptation methods such as PNN and general regression neural networks (GRNN) have been presented [12-14], and are recognized as having expandable or reducible network structure, fast learning speed, and promising results. PNN can function as a classifier, and it has the advantage of a fast learning process, requiring only a single-pass network training stage without any iteration for adjusting weights, and it can adapt itself to architectural changes [14].

In this paper, the PNN-based diagnosing system is used to monitor the operation conditions and identify six abnormal types. Experimental results are provided to show the effectiveness of the proposed method.

2. Methodological Description

PNN consists of the input, hidden, summation, and output layer as shown in Figure 1. PNN can function as a classifier, used to learn to place test examples into one of two or more categories for classification tasks. The input vector $X=[x_1, x_2, \ldots, x_i, \ldots, x_n]$, $i=1, 2, 3, \ldots, n$, is connected to the input layer, and inputs are the

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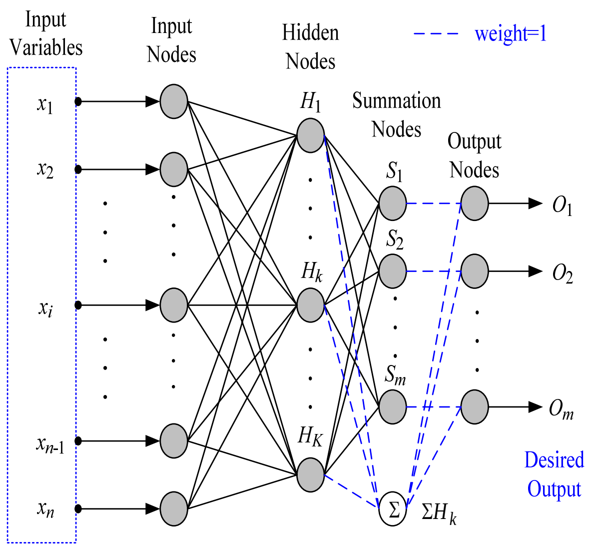


Figure 1. Architecture of the PNN

detectionunknown variables. The number of hidden nodes H_k (k=1, 2, 3, …, K) is equal to the number of training data, while the number of summation nodes S_j and output nodes O_j (j=1, 2, 3, …, m) equals to the classified types. The weights w_{ki}^{IH} (connecting the kth hidden node and the ith input node) and w_{jk}^{HS} (connecting the jth summation node and the kth hidden node) are determined by K input-output training pairs [11, 14]. The final output of node O_j is

$$H_k = \exp[-\sum_{i=1}^{n} \frac{(x_i - w_{ki}^{IH})^2}{2\sigma_k^2}] \quad (1)$$

$$O_j = \frac{\sum_{k=1}^{K} w_{jk}^{HS} H_k}{\sum_{k=1}^{K} H_k} = \frac{S_j}{\sum_{k=1}^{K} H_k} \quad (2)$$

The optimal σ_k can be performed to obtain the minimum misclassification error based on the testing data. The optimization method is used to adjust parameter σ_k with iteration process, and adjust the σ_k would refine the accuracy in the dynamic environment [13, 15]. The algorithm of the PNN contains two stages: "Learning Stage" and "Recalling Stage".

2.1. Learning Stage

Step 1)For each training data $X(k)$= [$x_1(k)$, $x_2(k)$, …, $x_i(k)$, …, $x_n(k)$], k=1, 2, 3, …, K, i=1, 2, 3, …, n, create weights w_{ki}^{IH} between input node and hidden node H_k by

$$w_{ki}^{IH} = x_i(k) \quad (3)$$

Step 2)Create weights w_{jk}^{HS} between hidden node H_k and summation node S_j, j=1, 2, 3, …, m, by

$$w_{jk}^{HS} = \begin{cases} 1 \\ 0 \end{cases} \quad (4)$$

where the values of w_{jk}^{HS} are the predicted outputs associated with each stored pattern w_{ki}^{IH}. The value of w_{jk}^{HS} will be equal to either "1" or "0". The value will be set to "1" when the kth training data relates to jth type. Connection weights from hidden nodes H_k to summation node Σ are set 1.

2.2. Recalling Stage

Step 1)Get network weights w_{ki}^{IH} and w_{jk}^{HS}.
Step 2)Apply input vector X=[x_1, x_2,…, x_i, …, x_n] to the input layer. Compute the output of hidden node H_k, k=1,2, 3, …, K, by Gaussian activation function

$$H_k = \exp[-\sum_{i=1}^{n} \frac{(x_i - w_{ki}^{IH})^2}{2\sigma^2}] \quad (5)$$

where $\sigma_1=\sigma_2=\cdots=\sigma_k=\cdots=\sigma_K=\sigma$, the optimal value can be obtained by using optimization method, and can be adjusted to minimize misclassification error.
Step 3)Compute the sum of overall outputs of hidden nodes in the node Σ, and then compute the outputs of node O_j by using the equation (2).

In this paper, the inputs are the ratios of high-/low-pressures and high-/low- temperatures (n=4), and outputs represent eight types (m=8) as normal, over-load, below load, refrigerant overmuch, refrigerant deficiency, immediate frequency reduced in high/low pressure status, and abnormal electromagnetic valve in low-pressure pass as shown in Table 1. Training data creation will be shown with discussions provided in the next section.

3. The Proposed Diagnosis System

3.1. The Creation of Training Example

The detection of abnormal conditions for air-conditioning systems requires the evaluation of refrigerant states. In operation condition, liquid refrigerant under high-pressure side flows from liquid receiver to vapor (low-pressure side). The temperature and pressure of refrigerants are different between high-pressure side and low-pressure side. Either a temperature or a pressure in refrigerant tube must operate in a state of equilibrium, and the pressure of the refrigerant at any particular temperature can be found by using the pressure-temperature curves [16]. If the abnormal operation occurred in system, either temperatures of refrigerants or pressures of refrigerants will violate their limitation. Each abnormal type produces certain conditions that may indicate the existence of thermal and electrical faults. In an air-conditioning compressor, key-data involving high-/low-pressures and high-/low-temperatures are the important information for fault diagnosis. The key-data could be obtained from the field test by operating experiences, and gives the values for the four key-data ratios (Normalization) corresponding to the suggested fault diagnoses. When key-ratios exceed specific limits, faults can be expected in an air-conditioning compressor. Ranges of ratios are assigned to classify the fault types as shown in Table 1.

Table 1. The abnormal status corresponding to the suggested limitations

Fault Type	*F1*	*F2*	*F3*	*F4*	*F5*	*F6*	*F7*
High Pressure	$> PH_{max}$	$< PH_{min}$	$> PH_{max}$	$< PH_{min}$	$> PH_{max}$	—	—
Low Pressure	$> PL_{max}$	$< PL_{min}$	$> PL_{max}$	$< PL_{min}$	—	—	$< PL_{min}$
High Temperature	$> PHT_{max}$	—	—	$> PHT_{max}$	—	—	$> PHT_{max}$
Low Temperature	$> PLT_{max}$	$< PLT_{min}$	$< PLT_{min}$	$> PLT_{max}$	—	$< PLT_{min}$	—

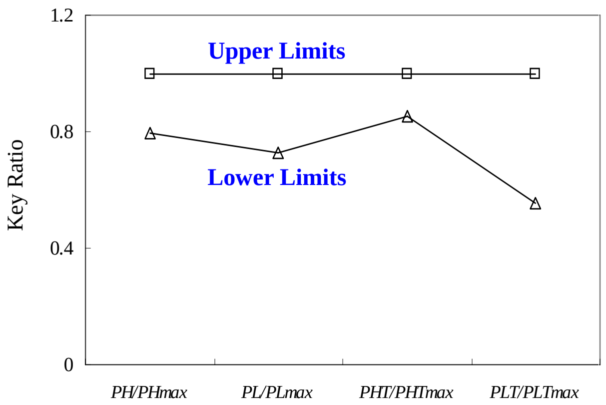


Figure 2. Specific range of normal condition

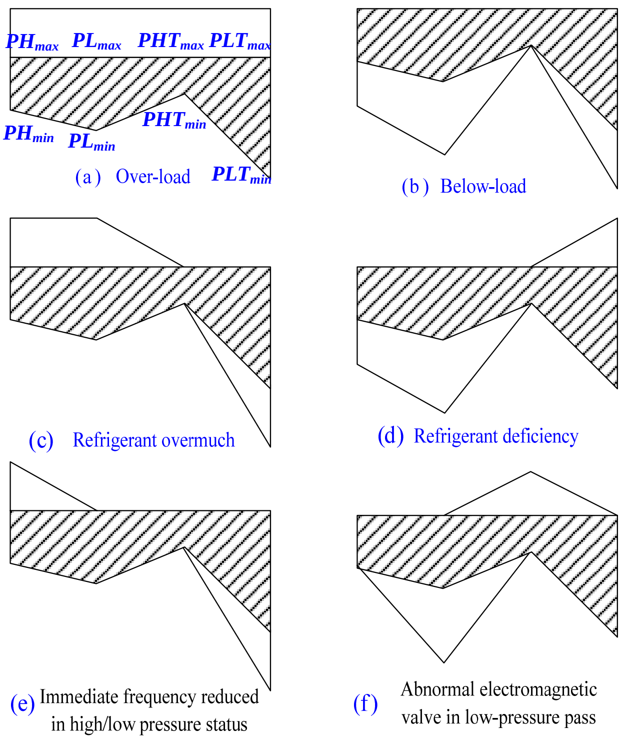


Figure 3. The abnormal ratio distribution

The ranges of key-ratios are used to create the training data. Four key-ratios *R1* to *R4* are defined as follows

$$R1 = PH/PH_{max} \tag{6}$$
$$R2 = PL/PL_{max} \tag{7}$$
$$R3 = PHT/PHT_{max} \tag{8}$$
$$R4 = PLT/PLT_{max} \tag{9}$$

R1 and *R2* are the ratios of refrigerant's high-pressure and low-pressure. *R3* and *R4* are the ratios of refrigerant's high-pressure temperature and refrigerant's low-pressure temperature. Each pre-selected ratio *R1* to *R4* has a specific range with upper and lower limits as shown in Figure 2. Based on the field experiences, the abnormal operations are built by using a ratio distribution as shown in Figure 3. We can sample points for the four selected ratios with four sampling stages including "*a*", "*b*", "*c*", and "*d*" points in the distribution ranges [17]. More points can be sampled for wider ranges. Considering the four stages, an event can be defined by multiplication rule with

$$Event = a \times b \times c \times d \tag{10}$$

The training data can be created from among all possible events. For example, for the event "refrigerant over", we have a=3 for *R1*, b=3 for *R2*, c=2 for *R3*, and d=3 for *R4*, and the number of possible events are 54. We can create 54-set data for training PNN. The number of training data for all the other faults is shown in Table 2. The events and sampled points construct curves giving cobwebby patterns as shown in Figure 4. In the other words, according to the patterns, we can systematically create numerical training data for the PNN.

Table 2. Training data for the PNN

Fault Type		The Number of Training Data
N	Normal Condition	108
F1	Over-Load	81
F2	Below-Load	54
F3	Refrigerant Overmuch	54
F4	Refrigerant Deficiency	81
F5	Immediate Frequency Reduced in High-Pressure Status	48
F6	Immediate Frequency Reduced in Low-Pressure Status	36
F7	Abnormal Electromagnetic Valve in Low-Pressure Pass	54
Total		516

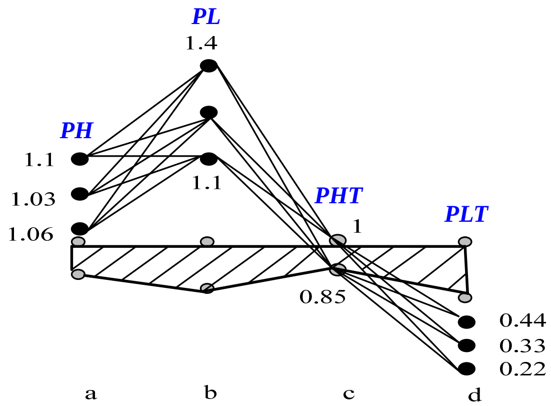


Figure 4. Cobwebby training pattern

3.2. Architecture of diagnosis system

The architecture of the diagnosis systems based on the

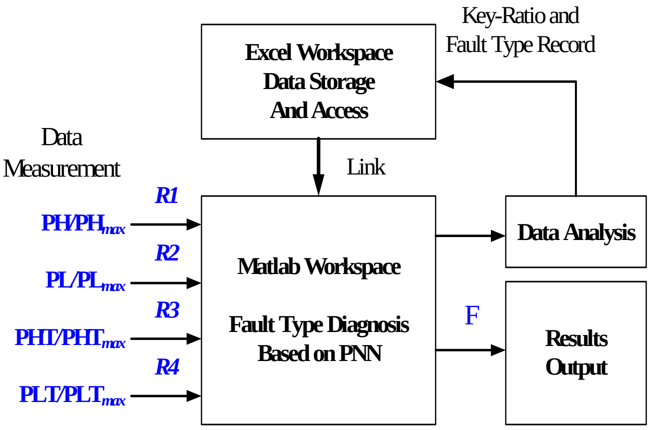


Figure 5. The architecture of the diagnosis systems

Table 3. Related data of the PNN

Method	Related Parameters	
PNN	Input layer	4 nodes
	Hidden layer	516 nodes
	Output layer	8 nodes
	Ranges of σ	0.1~ 0.2

PNN is shown in Figure 5. The diagnosis system has been implemented according to the 516 samples with associated fault types. 516 records for the PNN are stored in Database, and the diagnosis system can further record new generated samples. The PNN has four input nodes *R1~R4*, eight output nodes *N* and *F1~F7*, and 516 hidden nodes being equal to the number of training data. According to the various training patterns, the weights between input nodes and hidden nodes are determined by training data. The weights between hidden nodes and summation nodes are the predicted outputs associated with each input pattern by encoding signal "1" for "*Abnormal*", when a training data relates to its fault type, and "0" for "*Normal*". The procedure for diagnosis system is described below.

Step 1) Obtain the key-data from air-conditioning system and calculate the key ratios *R1~R4* by equations (6)~(9). Define the test vector *X*=[*R1*, *R2*, *R3*, *R4*].
Step 2) Calculate the outputs of the PNN as $O=[O_1, O_2, O_3, O_4, O_5, O_6, O_7, O_8]$=[*N*, *F1*, *F2*, *F3*, *F4*, *F5*, *F6*, *F7*].
Step 3) Find the maximum value $F_{\max}$=**max**{*N*, *F1*, *F2*, *F3*, *F4*, *F5*, *F6*, *F7*}.
Step 4) Maximum value $F_{\max}$ indicates fault type.

The PNN is responsible for fault identification. Output vector *O*=[*N*, *F1*, *F2*, *F3*, *F4*, *F5*, *F6*, *F7*] is evaluated by the PNN, and a threshold value 0.5 is designed for element O_j (j=1, 2, 3, …, 8) to separate normal from abnormal values. The output values are between 0 and 1, where a value close to 0 means "*Normal*", and 1 means "*Abnormal*", and maximum F_{max} then indicates the possible fault type.

In a real world, training data could be collected from the field data. The new training data are presented to the PNN, and the corresponding hidden nodes will continue to grow, and use equations (3) and (4) to create the network weights without re-iteration to corrupt the previous database or structure. This process results in very fast training, and the network is adaptive to data changes. The diagnosis system is always database enhancible with each new sample added to the current database [15, 17]. Training data in the database can be selected for diagnosis, addition and deletion with Matlab-Excel link to construct the PNN. Matlab-Excel Link is a software add-on to integrate Matlab computing environment and Excel workspace. It also provides data management with data from the Excel workspace and the evaluation command from Matlab workspace. Excel workspace becomes a data-storage and application-development front end for Matlab, which is a computational processor for developing the diagnostic tool.

4. Test Results and Discussions

The proposed diagnosis system was designed on a P-IV PC with 256-MB RAM and Matlab software. The Excel file was used to store 516 training data, with Matlab-Excel Link to construct a computational process. We have 516 training data for the PNN with eight types, and relative smoothing parameter σ=0.1 is chosen in this study. The related data of PNN are shown in Table 3. To show the effectiveness of proposed diagnosis system, three cases were chosen for investigation, as follows:

4.1. Condition 1: *Normal Operation Condition*

The performance of the diagnosis system was tested with unrecorded data. In normal operation condition, *PH*=256.7*psi*, *PL*=58.6*psi*, *PHT*=67.3°*C*, and *PLT*=18.4°*C* are measured from field data, the diagnostic procedures can be shown below:

Step 1) Calculate the test vector: *X*=[*R1*, *R2*, *R3*, *R4*]= [0.9168, 0.8371, 0.9095, 0.8361].
Step 2) Calculate the output of the PNN: *O*=[*N*, *F1*, *F2*, *F3*, *F4*, *F5*, *F6*, *F7*]=[0.9976, 0.0000, 0.0000, 0.0000, 0.0000, 0.0024, 0.0000, 0.0000].
Step 3) Find the maximum value $F_{\max}$: $F_{\max}$=**max**{*O*}= 0.9996 → "*N*".
Step 4) Maximum value $F_{\max}$ indicates "*Normal Operation Condition*". It takes 0.031 seconds (CPU Time) to identify the fault with learning and recalling stage.

The operated pressure of "R12 refrigerant" are served on 50*psi* ~70*psi* and 220*psi* ~280*psi* for low-pressure side and high-pressure side, and the operated temperature are located on 73.3°*C*~63.3°*C* and 12.2°*C*~21.1°*C* for low-pressure side and high-pressure side. The proposed method provides high confidences for judging the normal condition.

4.2. Condition 2: *Immediate Frequency Reduced in High-Pressure Status*

Test data are also obtained from the field data in March, 2006, as follow: *PH*=311.9*psi*, *PL*=39.8*psi*, *PHT*=73.3°*C*, and *PLT*=15.6°*C*. The diagnostic procedures can be shown below:

Step 1) Calculate the test vector: *X*=[*R1*, *R2*, *R3*, *R4*]= [1.1139, 0.5686, 0.9905, 0.7091].

Step 2) Calculate the output of the PNN: *O*=[*N*, *F1*, *F2*, *F3*, *F4*, *F5*, *F6*, *F7*]=[0.0564, 0.0000, 0.0000, 0.0000, 0.0000, 0.9371, 0.0000, 0.0065].
Step 3) Find the maximum value F_{max}: F_{max}=**max**{*O*}= 0.9371 → "*F5*".
Step 4) Maximum value F_{max} indicates "*Immediate Frequency Reduced in High-Pressure Status*". It also takes 0.031 seconds to identify the fault.

The proposed method also provides confident results for judging the fault, and agrees with providing a suggestion to trip the air-conditioner by the electromagnetic valve.

4.3. Condition 3: *Refrigerant Deficiency*

Test data are also obtained from the field data in April, 2006, as follow: *PH*=206.7*psi*, *PL*=58.6*psi*, *PHT*=97.3°*C*, and *PLT*=29.4°*C*. The diagnostic procedures can be shown below:

Step 1) Calculate the test vector: *X*=[*R1*, *R2*, *R3*, *R4*]= [0.7382, 0.8371, 1.3149, 1.3364].
Step 2) Calculate the output of the PNN: *O*=[*N*, *F1*, *F2*, *F3*, *F4*, *F5*, *F6*, *F7*]=[0.0000, 0.0000, 0.0000, 0.0000, 1.0000, 0.0000, 0.0000, 0.0000].
Step 3) Find the maximum value F_{max}: F_{max}=**max**{*O*}= 1.0000 → "*F4*".
Step 4) Maximum value F_{max} indicates "*Refrigerant deficiency*". It takes 0.015 seconds to identify the fault.

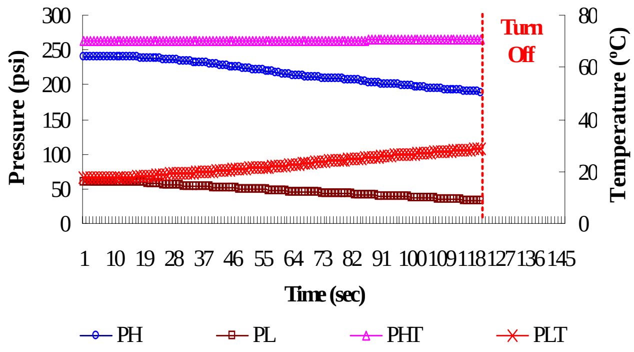
The proposed method judges the fault and provides a suggestion to trip the compressor of air-conditioner due to the refrigerant deficiency.

4.4. On-line analysis

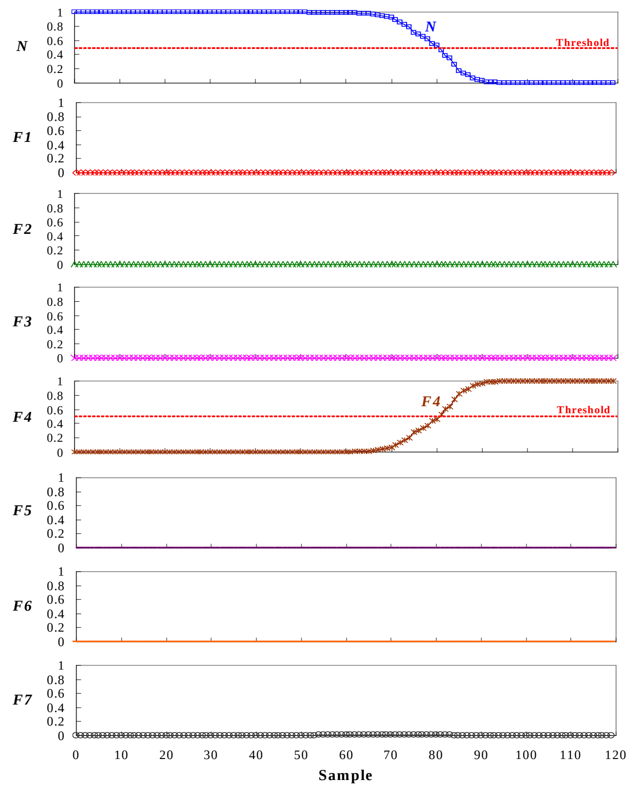
On-line analysis was also conducted to detect the proposed method with 120 samples (about 120 sec) as shown in Figure 6(a). The experimental data are obtained in the laboratory with a sampling rate of 1 sample/sec. Figure 6(a) shows that the high-pressure *PH* and low-pressure *PL* decrease gradually, and low-pressure temperature *PLT* gradually increases from 25th sample to 120th sample. PNN can monitor the overall duration including the beginning and ending samples. For 120 detection samples, Figure 6(b) shows that the proposed method has the high detection confidence for on-line analysis. The results can be observed for "*Normal Operation Condition*" as *PH*=223*psi*~278*psi*, *PL*=51*psi*~70*psi*, *PHT*=73°*C*~64°*C*, and *PLT*=12.4°*C*~21°*C*. Type *F4* was gradually identified with pressures and temperature exceeding the upper and lower limits. This confirms that proposed method have higher confidence value of detection results in the tests.

5. Conclusions

A diagnosis system of air-conditioner with a PNN has been developed in this paper. With field data, the diagnosis system provides fast and easy manipulation tool to detect the fault types. The diagnosis system uses a minimal number of connections, requires less computation time for operation, and doesn't need more weight settings. It is based on a Matlab-Excel Link. By connecting Excel and Matlab, we can process the numerical computation, and data is easy to manage and maintain. Computer results can be shown that it could be very effective to identify faults from the field data.



(a) The variations of high-/low-pressure and temperature



(b) Detection results of on-line analysis

Figure 6. Related data for on-line analysis

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7. Biographies

Ming-Tong Tsay was born in 1964. He received the B.S. degree from the Feng-Chia University, Taichung, Taiwan, in 1988, the M.S. degree in electrical engineering from the National Sun Yat-Sen University, Kaohsiung, Taiwan, in 1990, and the Ph.D. degree in electrical engineering from National Sun Yat-Sen University in 1994. Currently, he is the professor of department of electrical engineering, Cheng-Shiu University, Kaohsiung, Taiwan, where has been since 1994.

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