Applications of fault detection and diagnostic techniques for refrigeration and air conditioning: a review of basic principles

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Abstract: During the 1990s a number of different prototype Refrigeration and Air Conditioning (RAC) Fault Detection and Diagnostic (FDD) systems have been developed and subsequently presented in various research publications. This interest in RAC FDD systems is generally a result of the potential benefits, such as reducing equipment downtime and avoiding energy wastage, these systems can bring to new and existing RAC installations. With the exception of a few reports produced by the International Energy Agency (IEA) Annex 25, no other publications or texts exist that bring together the various FDD concepts directly associated with RAC applications. However, the reports produced by the IEA are far from comprehensive enough to be of use to typical industry personnel. Therefore, the aim of this review is to present RAC personnel with a clearer understanding of the fundamental principles associated with the application of RAC FDD. The paper will initially highlight various relevant areas before presenting examples of typical FDD systems applicable to RAC systems.

Keywords: refrigeration, air conditioning, fault detection and diagnostic, knowledge-based modelling, artificial neural networks, expert systems

NOTATION

c	specific heat capacity of water
COP	coefficient of performance
E	heat exchanger effectiveness
m	mass flow rate of water
P	pressure
q	rate of heat losses
Q	heat transfer rate or volume flow rate
R	residual value
SC	degree of subcooling
SH	degree of superheat
T	temperature

Subscripts

c	condenser
e	evaporator
HX	heat exchanger

Superscripts

in	inlet
out	outlet

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1 INTRODUCTION

The subject area of Fault Detection and Diagnostic systems (FDD) in Refrigeration and Air Conditioning (RAC) is extremely diverse, including topics associated with adaptive filtering, artificial intelligence, qualitative, quantitative, and fuzzy modelling, and so forth. However, since most industry personnel such as contractors, maintenance and design engineers, sales representatives, etc. will not be in possession of the associated specialist knowledge, some difficulties naturally arise when attempts are made to develop an 'overall' understanding and appreciation of the applications of FDDs in RAC. In view of this, this paper has been written to review and illustrate fundamental principles and concepts such that:

- It does not serve merely as a summary of FDD terminology and, more importantly
- It can be better understood by industry personnel having varying backgrounds.

Faults arise for a number of reasons, including [**1**]:

- Incorrect design, installation, and operation of systems, in addition to
- Aging, wear, and corrosion during normal operation.

In general terms a fault can be defined as: 'a non-permitted deviation of a characteristic property which leads to the inability of a system to fulfill an intended purpose' [2]; or alternatively, as: 'an undesired change that tends to degrade the overall performance of a system' [1]. To detect a fault, a decision must first be made based on the fact that: 'either something has gone wrong or everything is fine' [3]. This 'either, or' binary decision process regarding the status of a system's operation is in fact the fundamental principle behind any fault detection system [2]. Once a fault within a particular system has been detected, it is advantageous to determine the source (location) of the fault. The technique of locating a fault is commonly known as fault isolation [4]. Fault diagnosis is generally considered as consisting of both fault detection and fault isolation.

1.1 Types of faults that occur within systems

In general, different FDD techniques (and therefore systems) are used to detect different types of faults [5]. These faults are usually random and can potentially occur at any point in time. However, in many situations most faults arising within a system can be classified according to:

- The location at which each fault develops [4, 6],
- The design and subsequent use of a system [7],
- The type of fault signal produced [5], and
- The 'concealed' nature of a fault [8].

1.1.1 Fault location

Components utilized in large and complex RAC systems can be split into four categories, and thus the fault locations can be distinguished as [9]:

- Sensor faults,
- Actuator faults,
- Computer/controller faults, and
- Physical component faults.

Sensor faults usually take the form of discrepancies between measured and actual values of individual plant variables, while faults associated with actuators are usually discrepancies between the input command of the actuator (from a controller) and its actual output. Computer/controller faults may be due to problems with software and programs as opposed to computer hardware. Consequently, these faults may affect a variety of control systems (e.g., cooling and heating coil subsystems, etc.). Malfunctions in physical components can generally occur in a variety of ways and for a multitude of reasons, such as lack of maintenance.

1.1.2 Design and user faults

Design faults occur as a result of the inadequate design of a particular installation, such as under-sizing of equipment, while user faults occur when an end user misuses a particular part of a system [7].

1.1.3 Fault signals

Most faults (with the exception of hidden ones) will provide some type of 'indication' to a fault detection mechanism that something within the system is not performing properly. Various types of indications or fault signals exist.

Bias and drift fault signals can be associated with sensors [10]. A sensor bias occurs when it produces incorrect readings, while with drift, a bias within the sensor continuously changes in a given direction over a specific period of time. For the prime purpose of system fault detection, sensor faults should be differentiated from system faults. Proper functioning of sensors can only be ascertained by means of regular inspection and calibration, and by estimation of their useful working life.

A slowly varying fault is also known as a soft or incipient fault (e.g., gradual fouling in water-cooled condensers), while abrupt faults are commonly referred to as hard or suddenly occurring faults [11]. These faults can also be individually described in some texts as multiplicative process faults [9]. In general, slowly varying faults are more difficult to detect than other types of fault, mainly because they do not cause sudden changes in the monitored system's behavior, but instead result in a gradual deterioration of the plant's performance over a given period of time [11]. Conversely, examples of hard faults include the sudden seizure of a pump or the total loss of electrical power.

A single fault signal usually occurs when a particular component fault causes a system to malfunction [12], while a multiple fault signal may be caused by the failure of two or more components [13]. Fault signals that are always present and 'relatively constant' within a system are commonly referred to as static faults [13]. Conversely, fault signals that vary with time are known as intermittent faults [13].

1.1.4 Concealed faults

Some faults, known as hidden or concealed faults, can develop within a system without being detected. Normally when a hidden fault occurs within a system the overall symptoms generated can be difficult to identify, hence this type of fault can often result in energy being wasted [8]. An example of a hidden fault could be a stuck motorised damper in the fresh air intake duct of an air-handling unit. If the motorized damper associated with the enthalpy control system was stuck, then full use of free cooling could not be achieved, thus wasting energy, and the occupants would not notice the presence and the effect of the fault.

2 CATEGORIES OF FDD SYSTEMS

Many different types of FDD systems have been developed as a result of the fact that no particular technique is capable of detecting every type of fault [5, 7, 13]. Fundamentally, FDD systems can be grouped into three major categories [1] (although various techniques exist that incorporate principles adopted from each of these categories).

2.1 Model-based FDD techniques

In general there are various types of models that can be used to replicate real systems, examples of which include descriptive and functional models [**14**]. These models can be further subdivided into quantitative and qualitative models [**15**]. Quantitative models are essentially described by parameters or variables, while qualitative models are usually described by categorical data [**14**]. (Categorical data can be regarded as data that is easily grouped into predefined categories.)

A wide range of FDD techniques incorporating qualitative modeling exist. For example, Qualitative Bond Graphs [**16**] have been used to model thermal systems. This particular technique is fully capable of describing a particular system's structural information and correct operation in addition to any changes, which may account for a malfunction within the system.

Quantitative models are commonly referred to in some texts as analytical or mathematical models [**5**, **17**]. These models can be used to describe the mathematical relationship between quantities or system variables (i.e., temperatures, pressures, flow rates, etc.) in terms of a variety of mathematical expressions, including difference or differential equations [**17**]. These expressions can be used to provide computer-based descriptions of entire systems on a component-by-component basis. However, modelling errors are unavoidable, since no model can describe a given system perfectly [**7**]. Today one of the main uses of mathematical models within FDD techniques is to predict the behavior of a particular system.

Often the philosophy underlying this type of technique is based upon the idea that when any type of fault develops that fault will change a number of physical parameters associated with the system [**5**]. This in turn will lead to changes in various model parameters or states. Thus, by monitoring and comparing the measured system output variables (e.g., temperatures, etc.) with the predicted outputs (via the models), the presence of faults can be determined.

A residual is a term often used in FDD to describe the difference between measured and predicted variables [**8**]. Residuals normally have a near zero value under fault-free conditions and a high value when a fault develops. The magnitude of the generated residual will usually be taken into account in order to determine if a fault has developed within a given system. This is achieved by the assignment of thresholds [**18**].

A threshold is a preset limit, which, if exceeded by the residual value, declares the presence of a fault. In setting up thresholds there is normally a trade-off between the fault detection sensitivity and false alarm rate [**18**]. Tight (smaller) thresholds result in greater sensitivities (i.e., the detection of smaller faults), but will lead to more false alarms (an indication of a fault that does not exist) [**18**].

2.2 Knowledge-based techniques

In general, a knowledge-based system can be regarded as consisting of a collection of facts, rules, inferences, and procedures, which, when combined, produce the information required to solve a variety of problems [**5**]. In the case of a knowledge-based FDD system, faults can only be isolated once the relevant information applicable to a system has been collected and fed into a computer, and the constructed knowledge subsequently tested [**19**]. The testing strategies can, for example, incorporate qualitative models to predict the behavior of a process during both normal and faulty operating conditions.

Examples of relevant information include observations and measurements made from a system while a particular fault is occurring, fault symptom patterns that are recognizable to experts, normal system operational behavior patterns, design data, fault trees, system models, etc. Typically, knowledge-based FDD techniques do not rely on accurate quantitative information about a particular system [**1**].

Some knowledge-based techniques necessitate the use of residual signals (a quantitative model-based approach) both to detect and isolate potential faults. However, by adopting a qualitative approach, some fault symptoms (e.g., noise or vibration) could be identified which otherwise would be difficult to describe by parameter deviations or residual signals.

Knowledge-based FDD systems can be classified into four categories [**20**]: (i) Shallow knowledge systems generally consist of information that is not represented by mathematical modeling; (ii) Deep knowledge systems incorporate various mathematical models in order to detect and diagnose faults; (iii) Compiled knowledge systems utilize rules (derived from deep knowledge); (iv) Rule-based knowledge systems derive the necessary rules from a combination of both shallow and compiled knowledge. Rule-based knowledge is generally used when expert systems are utilized for FDD [**21**].

2.3 Signal processing techniques

FDD techniques that do not fundamentally fit into either the model- or knowledge-based categories are commonly known as signal processing techniques [**1**]. An example of three techniques that fall into this category include:

- Physical redundancy,
- Limit checking, and
- Spectrum analysis

Physical/hardware redundancy is used primarily for sensors. These utilize multiple lanes of sensors to facilitate the measurement of a particular variable. For example, if one of the sensors measuring evaporating temperature in a refrigeration system has an unusually high value compared to the other two sensor values (which are nearly equal), a fault would be associated with the individual sensor showing the high reading, therefore enabling the sensor fault to be discriminated from a potential system fault.

When limit checking is used, measured variables (e.g., temperature, pressure, etc.) are compared (using a computer) with predetermined limits. If a measured variable exceeds a particular limit, a fault condition is declared. Two levels of limits are usually set, one for the pre-warning and the other to set off, say, an alarm.

Most of the variables associated with a given system will exhibit a given frequency spectrum during the normal operation of a plant. Over a period of time, different variable spectra for normal operation can be recorded and stored. Fault detection can be achieved by comparing the recorded spectra with those of the existing system, a large deviation usually signifying the presence of a fault. Generally speaking, however, signal processing techniques are rarely used within the FDD applied to RAC industry.

In order to provide further insight into the various FDD systems, a review of the fundamental principles incorporating mathematical models, expert systems, and artificial neural networks will be highlighted. Various examples and diagram illustrations are taken from published literature. However, in some cases they have been simplified and altered to increase clarity.

3 DETECTING FOULING IN FLOODED EVAPORATORS AND WATER-COOLED CONDENSERS USING THERMODYNAMIC MODELS

Research work associated with the modelling of vapor compression reciprocating chillers [**22–35**] can be divided into three groups using a variety of different assumptions:

1. Endoreversible chiller models [**25–35**],
2. Endoreversible chiller models with heat leaks [**36**], and
3. Thermodynamic models incorporating all sources of irreversibility [**35**].

The term 'endoreversible' describes a particular internally reversible system, with the only irreversibilities residing in the coupling of heat flows to the surroundings [**36**]. However, the model does not fully characterize the operating performance of a real chiller because a practical system will have various irreversibilities (other than heat transfer in evaporator and condenser [**35**]) such as fluid friction, throttling losses in the expanding device, etc. Experimental results obtained from a commercial system have demonstrated that endoreversible chiller models fail to provide accurate chiller coefficients of performance [**37**, **38**].

Even when endoreversible models were supplemented with heat leaks [**26**, **37**, **38**] (*Note*: heat leaks could stem from refrigerant suction and discharge piping or compressor casing), they still failed to account for the principal losses associated with internal irreversibilities [**38**]. Consequently, the operating performance inaccuracies associated with pure endoreversible chiller models also tended to apply to these modified models incorporating heat leaks.

Individual thermodynamic models in the third group can be used as diagnostic tools to identify faults. This is achievable mainly because the models characterize the performance of real chillers for a wide range of operating conditions. Thus, any deviation in their performance characteristics over a period of time (which can be illustrated graphically) will signify the presence of a fault within the system. These thermodynamic models are often invaluable for diagnosing incipient types of faults.

Using a thermodynamic model to detect an incipient fault within a vapour compression chiller, Gordon and Ng [**39**] and Gordon *et al.* [**40**] presented their models for fault diagnosis.

When the system performance, equation (1), is coupled with the characteristics of the condenser and evaporator, the performance can be expressed in terms of the chiller flow temperature (T_e^{out}) and condenser cooling water inlet temperature (T_c^{in}) (equation (2)).

$$\frac{1}{\mathrm{COP}} = -1 + \frac{T_c}{T_e} + \frac{1}{Q_e}\left(\frac{q_e T_c^{in}}{T_e^{out}} - q_c\right) \tag{1}$$

where Q_e = rate of heat transfer to evaporator
q_e = rate of losses from evaporator
q_c = rate of losses from condenser
Q_c = rate of heat transfer from condenser

$$\frac{1}{\mathrm{COP}} = -1 + \frac{T_c^{in}}{T_e^{out}} + \frac{1}{Q_e}\left(\frac{q_e T_c^{in}}{T_e^{out}} - q_c\right) + f_{HX} \tag{2}$$

where

$$f_{HX} = \left[\frac{q_e(1-E_e)}{(mcE)_e} + \frac{q_e T_c^{in}}{T_e^{out}(mcE)_c} + \left(\frac{T_c^{in} q_e}{T_e^{out}} - q_c\right) \times \left(\frac{1}{(mcE)_c} + \frac{(1-E_e)}{(mcE)_e}\right)\right] / T_e^{out}$$

E = heat exchanger effectiveness
m = water mass flow rate
c = water specific heat capacity

Equation (2) is a good approximation of the chiller COP, and the term f_{HX} is independent of the cooling rate; yet at the same time it is very much dependent on the heat exchanger properties. Typically, this particular term is relatively small, and negligible in comparison to unity. However, when fouling occurs within flooded evaporators or water-cooled condensers, the magnitude of this term increases until it becomes non-negligible, indicating an incipient fault due to fouling (assuming the chiller is not operating with any other faults). The values of f_{HX} can be obtained using a variety of mathematical methods.

4 ARTIFICAL NEURAL NETWORKS (ANNs)

A number of papers [**8**, **41–43**] on the application of ANNs for FDD have been published. These papers all tend to follow similar patterns whereby the ANNs are used either for residual generation or pattern recognition. Fundamentally ANNs can be regarded as:

- A crude artificial model of a brain incorporating various unique characteristics [**44**], or
- A computer algorithm that can be used to mimic a learning process of a human brain [**45**].

ANNs are totally different from other more conventional computer software since they learn directly from example data instead of depending on programmed rules. ANNs essentially contain masses of parallel, interconnecting information processing units, technically known as neurons [**46**], which interact with one another and can be located in multi-layers: for example an input layer, an output layer, and the intermediate layers consisting of Hidden (intervening) Neurons.

A basic neuron model [**47**] (Fig. 1) consists of the following three fundamentally important elements:

1. A set of connecting weights from respective input terminals,
2. A linear combiner, and
3. An activation function.

The numerous interconnections between neurons can be regarded as information transport mechanisms, allowing neurons to both send and receive information. In addition, the interconnections are also used to store knowledge within ANNs. This is achieved through the assignment of weights (W_{j1}, W_{j2}, etc., Fig. 1) to individual interconnections, and gives some indication as to the importance of a particular neuron input value.

The adder ($\sum$) or (combiner) is used to sum all the weighted input signals of a particular neuron (Fig. 1), and thus produce an activation value. However, before the neuron can produce (or transmit) an output, it must 'activate itself' by the application of the activation value and a signal transfer function. The signal transfer function of the neuron then determines precisely how its output is calculated. Three typical signal transfer functions [**48**] are:

- A step function,
- A linear threshold function, and
- A Sigmoid function.

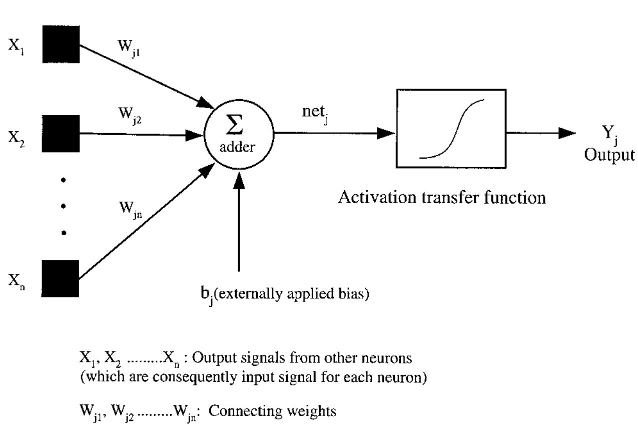

Fig. 1 A typical neuron model (adapted from [**47**])

A step function will activate a neuron if its weighted sum is greater than zero. The linear threshold function enables a low constant output value to be produced until the weighted input sums reach an initial activation threshold. The output value is then increased linearly until a final activation threshold is reached. The Sigmoid transfer function is widely used due to the fact that it is continuous and differentiable at every point [**49**]. These features in turn enable a popular training algorithm known as 'back propagation' to be applied [**49**]. The Sigmoid function contains high and low saturation limits and is approximately proportional in between. Its output value is zero when the activation value is a large negative value, and has a value of one when the activation value is a large positive number.

4.1 Typical model structures

Although neurons can be combined in various ways to form different types of interconnecting structures, only feed forward structures have featured predominantly in fault diagnostic research papers. This structure generally has no connections from the output neuron back to the input neuron, and two formations of structure layers exist [**49**], namely heteroassociative and autoassociative.

In heteroassociative structures (Fig. 2), input, hidden, and output neurons are located in the input, intermediate, and output layers, respectively. Conversely, in autoassociative structures, the input neurons are also the output neurons. The number of neurons in the input or output layer is generally dependent on the number of input or output values available in the training dataset. There are many suggestions as to how the number of neurons in the hidden layer might be chosen. However, in general, the greater the number, the more the characteristics contained in the training data will be captured by the ANN (although the ANN will take longer to train).

4.2 Training ANNs

The conditions for ANNs to learn can be created by the application of a learning (training) algorithm, usually incorporated into computer software. Training is essentially the

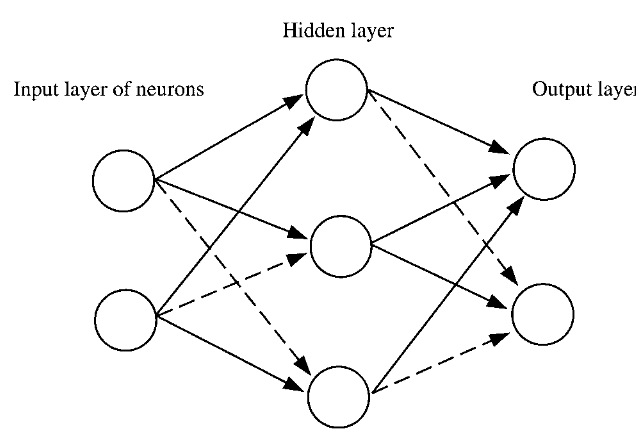

Fig. 2 A feedforward heteroassociative artificial neural network

process of modifying the connection weights of a network in an orderly fashion [**45**]. Three types of training algorithm exist, and these are generally referred to as [**45**]:

1. Supervised learning,
2. Unsupervised learning, and
3. Reinforcement.

Many FDD techniques incorporating ANNs utilize supervised learning. When supervised learning is undertaken, input–output training data of past and present variables (obtained from a system or an experimental setup over a wide range of operating conditions) are used. The input data are read into an appropriate structure or neural network, thus allowing an output to be generated. The value of this output is then compared with the correct (or desired) output value contained in the training data. If a difference exists, then the network connection weights are altered in order to decrease the value of the error and encourage convergence to a specified tolerance. The training is then complete and the ANN is ready for use. The initial values of the connection weights are usually randomly chosen to be small (around zero) positive and negative values, since large values tend to result in slow learning. A very common technique for adjusting the weights is known as the back propagation learning rule [**3**], which is essentially a gradient descent algorithm [**49**].

4.3 Application of ANNs in FDD systems

When using ANNs for residual generation to help detect faults, a system is declared faulty where the magnitude of the residual exceeds a predefined threshold. Similarly, in order to isolate a fault within a system, a secondary ANN can be utilized to examine patterns in the various system residuals; for example, a particular residual pattern would correspond to a specific fault location. In order to highlight the use of ANNs in air conditioning fault diagnostic systems, the work by Lee *et al.* [**43**], will be used to demonstrate how ANNs might be utilized to both detect and diagnose three specific faults located within an air handling unit (Fig. 3).

The air handling unit consists of supply and return air fans, outdoor exhaust and recirculation air dampers, a cooling coil, temperature and air flow sensors, and proportional-integral and derivative (PID) controllers. These components operate in combination to provide cool supply air to Variable Air Volume (VAV) boxes. A constant static pressure is achieved at each VAV box inlet by sensing the static pressure within the ductwork and varying the speed of the supply air fan. The air temperature supplied to each VAV box is maintained and controlled by a three-port chilled water control valve.

4.4 Residual definitions

Some of the residuals used in this diagnostic technique include:

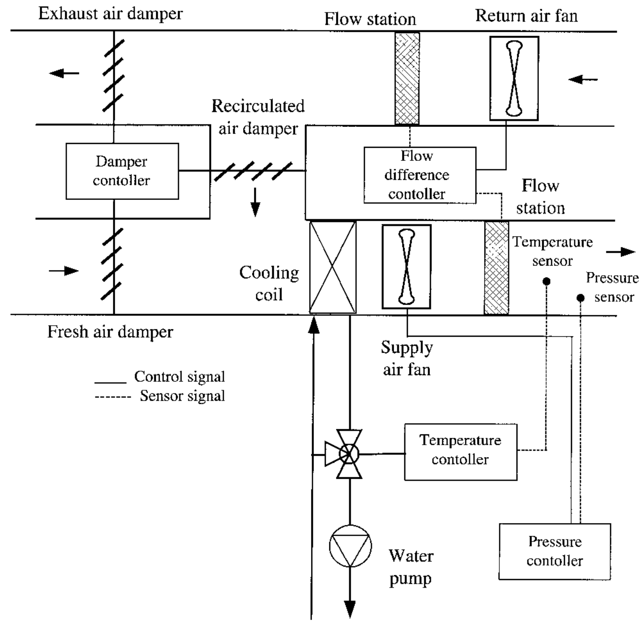

Fig. 3 Schematic of an air handling unit (adapted from [**43**])

Supply air temperature (R_T), where $R_T = T_S - T_{S.SP}$
Supply air pressure (R_P), where $R_P = P_S - P_{S.SP}$
Airflow rate difference (R_Q), where $R_Q = Q_D - Q_{D.SP}$
Control signal to the cooling coil valve (R_U), where

$$R_U = U_{CC} - U_{CC.EV}$$

Supply air fan (R_{NS}), where $R_{NS} = N_S - U_S$
Cooling coil valve position (R_V), where $R_V = V_P - U_{CC}$

R	residual value,
T_S	supply air temperature
P_S	supply air pressure,
Q_D	airflow rate difference in the supply and return air ducts,
$T_{S.SP}$	set point value of T_S,
$P_{S.SP}$	set point value of P_S,
U_{CC}	actual control signal to the cooling coil valve,
$U_{CC.EV}$	expected value of U_{CC},
N_S	measured value of the supply fan speed,
U_S	control signal for supply fan,
V_P	two-way cooling coil valve position,
$Q_{D.SP}$	airflow rate difference in the supply and return air ducts set point.

4.5 Fault descriptions

Some of the example faults to be diagnosed within the AHU are:

Fault No.	Description
1.	Supply air fan failure
2.	Stuck cooling coil valve
3.	Supply air pressure sensor (transducer) failure

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Fault No. 1 represents the failure of the supply air fan. The static pressure in the supply air duct is maintained at a predefined fixed value by modulating the supply air fan speed. Thus the failure of this fan significantly influences the static pressure in addition to various other parameters. Hence, in order to detect this particular fault the supply air fan speed residual, the static air pressure residual, the flow difference residual, and the supply air temperature residual are used.

Fault No. 2 gives notice of the condition whereby the cooling coil control valve is stuck in one position, allowing the fault to be detected over a period of time via a change in the control signal residual in addition to the cooling coil valve position residual.

Fault No. 3 denotes the complete failure of the static pressure transducer in the supply air duct, giving a zero output to the supply fan controller. In turn, the controller will maximize the supply fan control signal in an attempt to maintain the feedback pressure signal at the set point value. As a consequence, the supply fan operates at its maximum speed, resulting in an increase in the static air pressure within the supply air duct (ultimately resulting in an increase in the pressure residual). In addition, other residuals will be influenced, including airflow difference, supply air temperature, cooling coil control signal, and supply fan input control signal.

4.6 Developing an ANN to diagnose faults within the AHU

In order to develop an ANN to diagnose faults, the ANN itself must first be trained using data that are representatives of normal as well as faulty operating conditions of the AHU. Once the ANN has been trained, the detection and diagnosis of faults becomes a pattern recognition task.

4.6.1 Input/output data representative of the normal operating condition of the AHU

For normal operation (i.e., without faults), the residuals should be assigned a value of approximately zero as the training input data.

R_P	R_Q	R_T	R_U	R_{NS}	R_{NR}	R_V	System operation
0	0	0	0	0	0	0	Normal

The output data associated with this characteristic signature are generally chosen to enable the ANN to perform pattern recognition. Thus, by codifying the output data using a unique numerical pattern, the condition 'normal operation' can be defined. Each element of the output data associated with this diagnostic system will possess four terms (since there are three fault conditions and one normal operating condition). Each term constitutes a value of an output neuron. In order to codify output data, two numerical values 0 and 1 are used to develop a totally unique numerical pattern.

Y_1	Y_2	Y_3	Y_4	System operation
1	0	0	0	Normal

4.6.2 Input/output data representative of the AHU's operating condition in the presence of faults

When a fault occurs, some residuals will possess higher values in relation to others, and thus will 'dominate' them. However, by normalising each individual residual by dividing by the maximum value obtained from measurement (e.g., $R_{NS} = (N_S - U_S)/|N_S - U_S|_{max}$), dominant residuals will have the same value, $+1$ or -1, for the various fault events. A non-dominating residual is assigned a value of 0.

If a malfunction occurs within the supply air fan, the fan speed and supply air pressure will both be zero. Additionally, the control signal for the supply air fan will be at its maximum value (*Note*: these and other conditions can be deduced by deliberately introducing faults into the AHU). Under these conditions the residuals R_{NS}, R_P, and R_Q will be influenced. Thus if $N_S = 0$ (i.e., the supply air fan speed is zero), the normalized value for $R_{NS} = -1$. Accordingly, both the normalized residuals R_P and R_Q also become -1. In addition, the residual R_U and R_T will be assigned a normalized value of 1, while residuals R_{NR} and R_V will all be assigned values of 0.

Consequently, the following normalized residual pattern (or fault characteristic signature) would be produced and form part of the overall input training data required for the ANN.

R_P	R_Q	R_T	R_U	R_{NS}	R_{NR}	R_V	AHU operating condition
-1	-1	1	1	-1	0	0	Supply fan fault

Normalized residual patterns for the other faults can be dealt with in the same way, thus producing complete residual patterns (which can be used as input training data) for all other faults, as well as in the pattern depicting a fault-free AHU.

The corresponding neuron outputs consist of various permutations of zeros and ones for each fault occurrence. Since the ANN is designed to detect only one fault at any one time, each category will contain different permutations of one unity value and three zeros.

Once the ANN has been trained using the input/output data sets contained in the table below, fault diagnosis within

Net inputs							Net outputs				
R_P	R_Q	R_T	R_U	R_{NS}	R_{NR}	R_V	Y_1	Y_2	Y_3	Y_4	Fault diagnosis
0	0	0	0	0	0	0	1	0	0	0	Normal
−1	−1	1	1	−1	0	0	0	1	0	0	Supply fan
0	0	0	−1	0	0	1	0	0	1	0	Cooling coil valve
−1	1	1	1	−1	0	0	0	0	0	1	Pressure transducer

the AHU is achievable via pattern recognition. For example, if any one of the three faults occurs, the output pattern will be matched against predefined patterns, which ultimately correspond to particular faults.

5 EXPERT SYSTEMS

Expert systems are relatively popular within the RAC FDD research domain. They can be described as 'computer-based systems which utilize specialist knowledge (usually obtained from a human expert) to perform such problem-solving tasks as diagnosis, advice-giving and interpretation' [**50**]. Expert systems can be considered as a product of artificial intelligence, since techniques developed for artificial intelligence can also be used to design knowledge-based expert systems [**1**].

Artificial intelligence is a branch of computer science that focuses on how to enable computers to learn, reason, and make judgements [**1**]. Any system whose development is based on artificial intelligence must be capable of performing three important tasks. These are:

- Storing knowledge,
- Using stored knowledge to solve problems, and
- Acquiring new knowledge.

These fundamental tasks also define the overall objectives of expert systems when used in a variety of applications today. It is common practice for knowledge stored in expert systems to be contained in knowledge bases. These knowledge bases can be set up to contain 'if–then' rules to represent a human expert's 'understanding' of a particular problem [**51**]. These rules can be extracted from various sources, including interviews with engineers, etc. [**52**]. They can also be developed using published sources such as engineering data [**53**]. Rules associated with knowledge bases can be modified, removed, or increased in number. Hence if a human expert's 'understanding' of a particular problem changes with time, any associated knowledge base can be modified easily.

In general, rules incorporated in expert systems are interpreted by another part of the expert system called the inference engine [**51**]. When the expert system is run, the inference engine analyses the various rules in order to arrive at a particular conclusion.

5.1 Fault detection and diagnosis incorporating if–then rules and flow diagrams

A variety of RAC fault diagnostic techniques have been developed based on the use of expert systems [**54–57**]. In view of these papers, and to further highlight the application of expert systems in RAC systems, a technique by Yoshimura and Noboru [**58**] incorporating if–then rules and flow diagrams (based on commercially available packaged comfort cooling and heating systems, Fig. 4) will be examined.

The FDD technique, like many others, is based on the principle that an abnormality (due to a fault) within the system will influence the values of many different parameters. Thus, by measuring various diagnostic parameters any component causing a particular fault condition can be isolated (assuming some advance knowledge of the equipment's related fault symptoms).

For this particular fault diagnostic technique, the diagnostic parameters related to predefined faults were obtained by measurement based on the Experimental Design Method [**59**]. The faults chosen were 'potentially' considered by industry experts to be some of those likely to occur within the packaged system under review. Three examples of such faults are considered here:

- An abnormality in the compressor,
- A shortage of refrigerant within the system, and
- An insufficient air volume in the evaporator.

In addition to the room air temperature, the measured variables consisted of evaporating and condensing pressures, inlet and outlet condenser cooling air temperatures, discharge air temperature leaving the direct expansion evaporator, suction refrigerant temperature to the compressor, and the refrigerant inlet temperature to the expansion device (Fig. 4). The five relevant diagnostic parameters established were:

High pressure coefficient
$$\left(CPH = \frac{\text{measured condensing pressure, absolute}}{\text{rated condensing pressure}}\right)$$
Low pressure coefficient
$$\left(CPL = \frac{\text{measured evaporating pressure, absolute}}{\text{rated evaporating pressure}}\right)$$
SH (degree of superheat)
SC (degree of subcooling)
TCL (evaporator air-on and air-off temperature difference)

By monitoring (either manually by maintenance personnel or automatically by a microprocessor-controlled data logger)

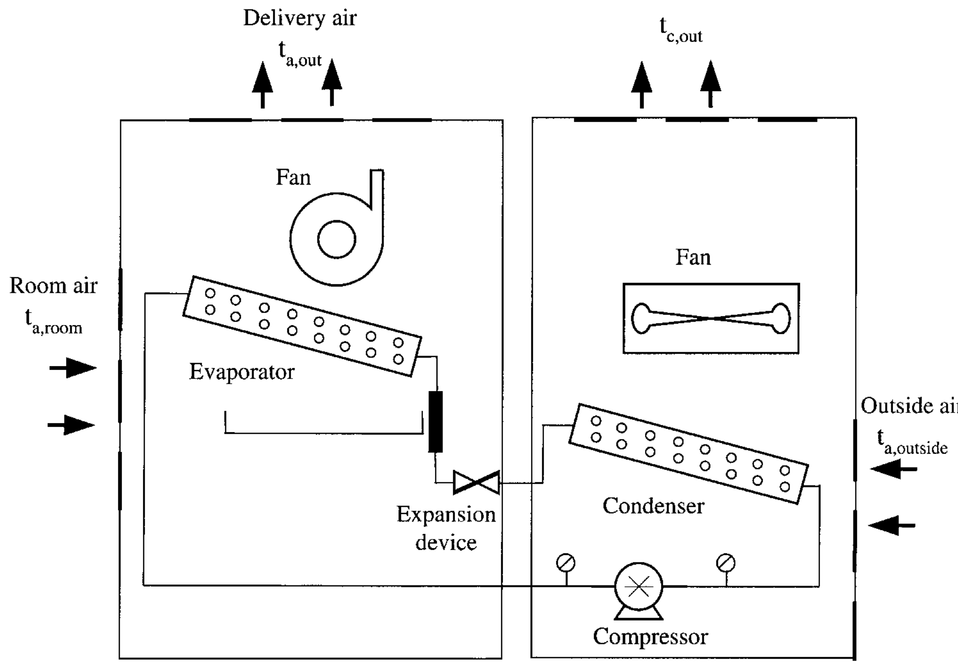

Fig. 4 Schematic of an air-cooled packaged air conditioner (adapted from [**58**])

the values of each of the various diagnostic parameters previously determined, predefined faults can be diagnosed.

In order to achieve this, the monitored diagnostic parameters are compared with set threshold values. The threshold values (C1, . . . , C5) are essentially values of the various diagnostic parameters (obtained during the experiments) in the absence of any faults. The fault diagnostic procedure used in this particular system is based on the flow chart presented in Fig. 5, which is based on if–then rules as follows:

If the value of the low pressure coefficient (*CPL*) is equal to or greater than the threshold value 'C1', then an abnormality in the compressor is declared.

However

- if the value of the low pressure coefficient is less than the threshold value 'C1', but
- greater than the threshold value 'C2', then
- the system is declared to be operating normally.

Conversely, if

- the value of the low pressure coefficient is less than the threshold values 'C1' and 'C2', and
- the degree of superheat is greater than the threshold value 'C3', and
- the degree of subcooling is greater than the threshold value 'C5', then
- the fault 'shortage of refrigeration' is declared.

However, if

- the value of the low pressure coefficient is less than the threshold values 'C1' and 'C2', and
- the degree of superheat is less than the threshold value 'C3', and
- the temperature difference between the inlet and outlet air temperatures in the air cooler is greater than the threshold value 'C4', then
- the fault 'insufficient air volume in the evaporator' is declared.

6 DISCUSSION

There can be little doubt there are limitations associated with various individual RAC FDD techniques. Despite the fact that model-based techniques are viable in theory, in general the procedure illustrated assumed that only one fault is diagnosed and no other fault exists within the system (otherwise the mathematical model would be unrepresentative of the actual system under observation). In fact, any conclusions drawn from subsequent measurements (of temperatures, pressures, etc.) would not enable the end user to deduce a particular fault — certainly a disadvantage when being considered for practical application. Thus, if any other faults developed within the chiller, this diagnostic procedure would be unsuitable.

FDD expert systems incorporating if–then rules have the benefit of not requiring any qualitative or quantitative models. However, they do rely heavily on the accuracy and reliability of various sensors. A faulty sensor (see sections 1.1.3 and 2.3) can render an entire FDD procedure inconclusive. Another limitation of this technique is its overall 'usability'. In general, the application of a large number of if–then rules to diagnose a large variety of faults

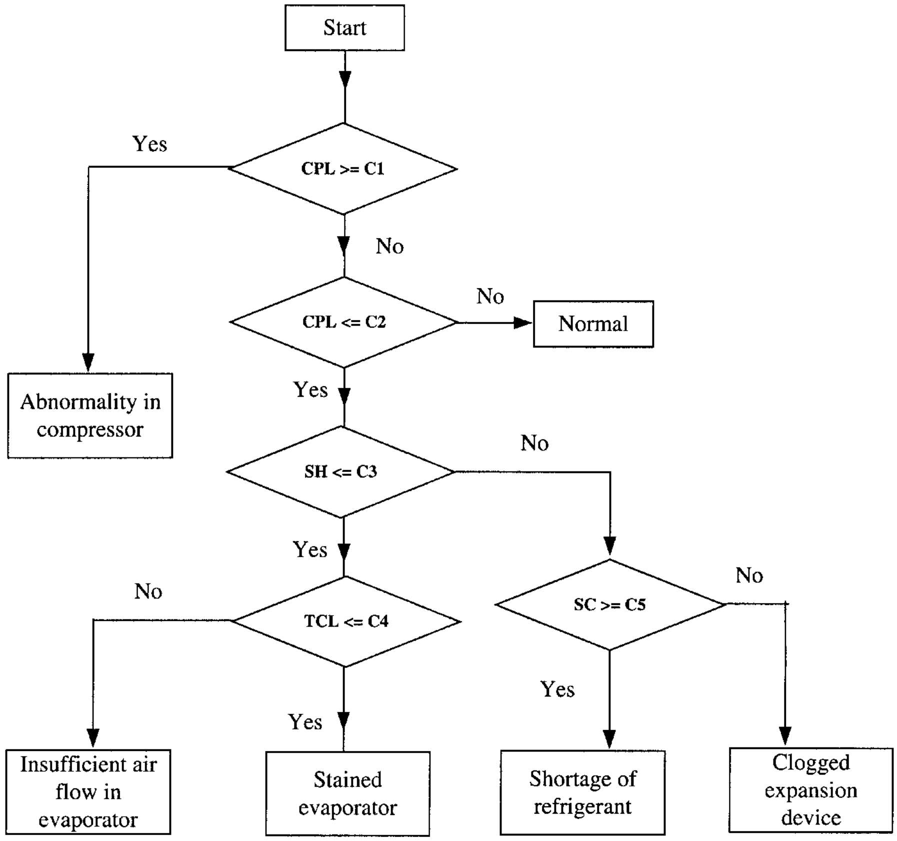

Fig. 5 Diagnosis flow diagram for an air-cooled packaged air conditioner (adapted from [**58**])

can be cumbersome and difficult to implement in real situations.

The incorporation of ANNs in RAC FDD systems can have various advantages. As an example, individual ANNs can be trained to diagnose faults within a variety of sub-circuits associated with a large complex system. However, it must be borne in mind that the training of ANNs will involve a trade-off between the accuracy of a given model and the overall computational requirements. Thus the more accurate the ANN in terms of modeling (i.e., the more hidden units and layers contained within the ANN) the greater the computational requirements. Furthermore, it is extremely important that when ANNs are initially trained, the conditions corresponding to the various system faults are incorporated in the training data. Once an ANN has been fully trained, additional faults cannot be added to it unless it has been retrained totally from inception. This inflexibility constitutes a significant problem when training ANNs using incomplete training data.

Today, very few commercial RAC FDD systems actually exist [**60**], and those that do are only appropriate for specific types of systems. A survey amongst various manufacturers in the UK indicated that FDD systems are currently available for vapour compression chillers and split comfort cooling/heating systems. However, they are not available for other air conditioning sub-units such as fan coil units. Braun [**60**] suggested that RAC FDD systems must be incorporated in controllers used for chillers and other packaged air conditioning equipment before being incorporated in other controllers that are integrated with the devices they control. The first point is evident from commercial chillers and comfort cooling/heating split systems available today, while the second point is yet to be seen in practice.

The lack of development in practical applications may have been caused by the need for low cost installations, cheaper sensors, etc. [**60**]. Another, equally decisive factor is a lack of understanding among industry personnel regarding the overall concept and benefits of FDD. These shortcomings must be addressed thoroughly if the further development and commercial utilization of FDD systems is to be realized.

In general, RAC FDD is still in its infancy when compared to other counterpart systems used in industries, such as nuclear, power, and aeronautical engineering. However, today, other related subject areas are now beginning to attract more and more attention from industry (e.g., the IEA Annex 34 programme, 1997–2001: Computer Aided Evaluation of HVAC System).

7 CONCLUDING REMARKS

This paper was prepared in order to provide RAC industry personnel, with:

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- A better overall understanding of fundamental RAC FDD concepts,
- Insight into a variety of RAC FDD systems, and
- An appreciation of the overall status of commercial RAC FDD systems in use today.

In order to achieve these aims and objectives, this paper initially highlighted various fundamental and pertinent concepts associated with RAC FDD before introducing three different types of FDD technique. A review of these techniques was presented in order to provide the reader with an overall appreciation of the various principles employed.

The principles and issues raised in this paper have effectively enabled a number of conclusions to be drawn. These conclusions infer that:

- A large variety of FDD research publications available today are extremely difficult to understand without specialist knowledge in certain topic areas (e.g., Kalman filtering, fuzzy modeling, etc.),
- A single RAC FDD system cannot be used to detect and diagnose all the various types of faults that could develop within a system,
- The accuracy associated the mathematical models (used to describe a particular system or component) will influence the overall reliability of model-based FDD systems, and
- Commercial 'off-the-shelf' RAC FDD systems are available for certain types of equipment, including split type comfort cooling/heating split systems and vapor compression chillers (all FDD systems associated with these types of equipment are incorporated in microprocessor-based controllers).

Although these concluding remarks are applicable to the overall subject area of RAC FDD (as opposed to individual systems), one further point must be made here. Studies of this kind are set to continue, and in time this additional research will provide further insight into the many different aspects of this subject area. In the meantime, however, this paper can be read for its validity as an aid to mechanical engineering, building services engineering, and RAC personnel within the industry who are unfamiliar with RAC FDD techniques.

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