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AUTOMATED FAULT DETECTION AND DIAGNOSIS FOR HVAC&R SYSTEMS: FUNCTIONAL DESCRIPTION AND LESSONS LEARNT

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ABSTRACT

From the last two decades, the development of robust automated fault detection and diagnosis (FDD) methods applicable to HVAC&R equipment has been an area of active research, and several papers have been written on this issue. However, the use of these systems is not prevalent in the industry as yet, and some reasons for this status are presented in this paper. This paper also provides a description of the various functions and capabilities of an automated FDD system and summarizes pertinent lessons learnt from previous research studies. It is not meant to be a bibliographic review but a clear description and succinct assessment of the various issues which impact this topical area.

Keywords: fault detection and diagnosis, HVAC&R equipment and systems, building energy systems.

Background

Operating problems associated with degraded equipment, failed sensors, improper installation, poor maintenance, and improperly implemented controls plague many building systems. These factors lead to inefficient operation (increased energy costs), discomfort (loss of productivity and loss of tenants), and increased wear of components (reduced reliability and shorter equipment life). Today, most problems with building systems are detected as a result of occupant complaints or alarms provided by building automation systems. Building operators often respond by checking space temperatures or adjusting thermostat settings or other set points. The root cause of an operation problem is often not diagnosed, so problems reoccur, and the operator responds again by making an adjustment (Katipamula et al., 2001). Such adjustments are often based on rudimentary or incorrect physical reasoning and rules-of-thumb built on personal experience. For a skilled operator to diagnose problems more carefully by inspecting equipment, controls, or control algorithms requires more time than he/she has available. Often a properly operating automatic control is overridden or turned off, when it *appears* to be the cause of a problem. Moreover, some "latent" problems do not manifest themselves in conditions that directly affect occupants in obvious ways and, as a result, go undetected (such as simultaneous heating and cooling). These undetected problems may affect energy costs and indoor air quality. On the other hand, unwarranted maintenance leads to excessive maintenance costs, and may in many cases increase the risk of failure. Such considerations led to interest in applying automated fault detection and diagnosis (FDD) methods to building systems and equipment since it promises to remedy these problems and improve building operation by automatically and continuously detecting performance problems and bringing them to the attention of building operators.

Functional Description of an Automated FDD System

Issermann and Balle (1997), while performing a comprehensive literature review of FDD papers, suggest an overall classification of FDD techniques, which is deemed too comprehensive for our purpose. The classification proposed below is a reorganization of the schemes suggested by Himmelblau (1978), International Energy Agency (IEA) studies (Hyvarinen and Karki, 1993,1996; Dexter and Parkanen, 2001), Venkatasubramanian et al. (2003 a,b,c), Katipamula et al. (2001) and Katipamula and Brambley, (2005 a,b). An on-line automated process supervision of an engineering system in general comprises of six elements or steps as described below (see Table 1).

Step 1: Design and installation of sensor network. This phase involves identifying the type of faults to be tracked (done based on either published studies or based on discussion with service personnel); evaluating the location and accuracy of existing sensor networks, installing additional sensors as necessary, and commissioning the data collection system.

Step 2: Pre-processing of sensor data. The raw data from the sensors are first subject to data filtering that involves removing spikes and bad signals. Subsequently, the data stream needs to be proofed for quality that involves range checks, and mass and/or heat balance checks. This would automatically flag the occurrence of hard sensor faults which are caused by failed equipment and sensors. Most commercial data collection software programs developed by HVAC control companies have such filters built-in to some extent. This issue, though seemingly straightforward, needs perhaps to be re-investigated. A report by Piette et al. (1999) which involved monitoring a chiller for an extended period of time at a 1-minute time scale showed unexplained brief electric use spikes even when the chiller was supposed to be operating normally. The authors speculated that this could be a type of chiller fault, which has not been identified previously.

The filtered data is then sampled, saved and/or recorded at predetermined frequencies. For example, all sensors could be sampled at, say 5-second intervals and then averaged and saved in files at say, one-minute intervals. Instead of recording this data in permanent files, one could adopt a scheme called "recording by exception" where the data are recorded in permanent files only if a fault has been detected (Katipamula et al., 2001). These data are used for FDD. If no fault is recorded, the data could be averaged and recorded, say every 15 minutes to create historic performance data.

Step 3: Fault detection. The screened data are analyzed in order to determine whether the performance of the monitored system has deviated from expected performance, i.e., whether the system has developed a fault. This step involves two sub-elements:

Step 3-1: **Generation of actual performance indices** using the sensor data representative of the actual performance of the engineering system consistent with the type of FDD method used subsequently (this is usually straightforward using arithmetic or algebraic transformations, and may involve thermodynamic property calculations);

Step 3-2: The **baseline or fault-free performance predictor** uses the screened sensor data from Step 2 to predict the fault-free values of the same performance indices deduced in step 3-1. There are essentially two types of predictor groups:

(a) model-free methods (also termed, qualitative), which can be further sub-divided into:

(i) range checks on the primary variables (or on the characteristic quantities or on the characteristic parameters). Examples are system indices, such as COP or kW/ton index for chillers or component performance of the system (say, effectiveness of heat exchanger);

(ii) physical redundancy where two different sensors measuring essentially the same system state (one could use, say pressure and temperature sensors for an evaporating/condensing fluid) are compared;

(iii) trend analysis methods using statistical time series methods and Auto Regressive Moving Average (ARMA) models of one or more of the sensor data or the performance indices (such methods, however, require that baseline or fault-free data sets be available against which to evaluate actual performance);

(iv) information flow graphs (such as fault tree analysis, event-tree analysis, failure mode and effect analysis-FMEA)- these methods are more suitable for reliability and risk analysis than for FDD.

(b) model-based methods (also termed quantitative or analytical redundancy methods) can be subdivided into:

(i) time-domain forward models (detailed transient models, lumped transient models, detailed steady-state models) based on mechanistic mathematical models which allow simulating the performance of the various components and of the system. Though specific and detailed guidelines are lacking at this time, the general approach is to first calibrate the simulation model with fault-free system operation, and then use it to generate expected performance;

(ii) time-domain inverse models which can be statistical (based on multi-variate methods), black-box models (polynomial, Artificial Neural Network (ANN), Auto Regressive Integrated Moving Average with Exogenous variables (ARIMAX) or grey-box models which rely on monitored data under fault-free system performance to establish the appropriate model structure and identify the model parameters characterizing fault-free system operation (for example, Grimmelius et al., 1995); and

(iii) frequency-domain signal model-based methods (such as correlation function, band-pass filters, spectral analysis)- these methods are more suited for vibration and acoustic analysis of rotating machinery with high frequency data sampling.

Step 3-3: The **FD trigger** analyzes the data generated by the FD pre-processor and flags the onset of a fault by looking at differences, or innovations, between fault-free and faulty performance indices. The logic upon which the FD trigger is based could consist of **heuristic rules** (crisp or fuzzy) for range checks, **statistical hypothesis testing** (which could be single tests or multiple tests), **Bayesian-based probabilistic methods, control chart techniques** if time series data is being analyzed, and **pattern recognition** techniques or pattern recognition classifiers (such as k-nearest neighbors, k-nearest prototype and ANN). With model-based pre-processors, **innovation**-based methods or **hypothesis testing** applied to the various physical parameters estimated from fault-free and actual system operation have been widely used (Gertler, 1998 a, b). Note that the FD trigger may not be activated based on say, the deviation of a single performance index; rather a FDD method which collectively evaluates system performance based on several performance indices is likely to reduce the number of false alarms; this however, would require a more sophisticated statistical approach.

A basic issue is the specification of threshold levels to flag deviations between current and normal system performance. Usually, one is unable to assign absolute threshold levels. There is always a trade-off between detection sensitivities and false alarm rates (Reddy, 2007). Tighter thresholds result in being able to detect smaller faults (i.e., provide greater FD sensitivity), but are also likely to lead to more false alarms. However, incorrect detection leading to false alarms can have very negative consequences, such as the operator disabling the system altogether. Several detection methods have been suggested to reduce the probability of a false alarm. Some schemes use heuristic thresholds (Salsbury and Haves, 1996), while others use statistical thresholds (Rossi and Braun, 1997), hypothesis testing (Dodier et al., 1998) or even simple and two-step fuzzy model-based methods (Dexter and Benouarets, 1997; Dexter and Ngo, 2001).

Step 4: Fault diagnosis. Once a fault has been flagged, we need to determine the exact location of the fault, i.e., isolate the faulty component and determine the magnitude or severity of the fault. Also of interest is the time at which the fault occurred, and how the severity of the fault varies over time (for example the fault could progressively get worse, or exhibit cyclic behavior in case the system operation is variable over time). Fault diagnosis can be broken up into two blocks.

Step 4-1: **Fault isolation** entails the determination of the kind, location and possibly the time of occurrence of the fault. In certain on-line monitoring protocols, the individual components are so extensively instrumented that the fault detection directly isolates the fault as well, and no additional data processing is required. However, such a monitoring protocol is not common and may not apply to all the various faults, which may arise. Hence, the diagnostic step is necessary. Note that certain authors differentiate between fault classification and fault isolation (for example, Isermann, 1984), but we chose not to do so following Gertler (1998b). The primary function of the fault isolator is to identify the specific fault from a list of possibilities based on some feature of the fault or faults.

Fault isolation is perhaps the most demanding of the various tasks. In certain cases, one is unable to isolate certain types of faults, i.e., separate one from another because they act on the physical plant in an undistinguishable way (Gertler, 1998b). In other cases, the onset of one fault could trigger other faults resulting in having to perform the more difficult task of multi-fault isolation.

Step 4-2: **Fault identification** involves determining the severity and time variability of a fault. Hence, quantitative estimation is required. For example, a restriction in a chiller line would increase the pressure drop and reduce mass flow rate. However, most fault processes are not linear, and so physical modeling is required based on either a forward-based model or a gray-box model.

Though there are several fault diagnosis methods (also called fault classifier methods), most of them can be viewed as either **(i) knowledge based, or (ii) association-based.** While the latter methods has been said to be more powerful than the former, they are still in their infancy, and need more theoretical development before they can be considered for practical evaluation. **Knowledge-based techniques** are of two types (Rossi and Braun, 1997, section 2.3 of IEA Annex 25, Hyvarinen and Karki, 1993) **:**

(a) rule-based, where knowledge is used in the form of "IF-THEN-ELSE" rules;
These can be either simple heuristic methods, or based on expert systems. In the engineering field, expert systems have been applied for design, equipment selection, and operation (Culp, 1989; Culp et al., 1990; Kaler, 1990; Klima, 1990; Maor, 2002). In building applications, most research has focused on detection and diagnosis of faults (but not evaluating them) with the exception of Rossi and Braun (1997), Katipamula et al. (2001) and Dodier and Krieder (1999). Patel and Kamrani (1996) have tabulated over 75 predictive maintenance research projects developed around the world (mostly related to manufacturing and process control). Most of these projects are based on some form of expert system which underlines the great and continued importance of heuristic and model-free methods in current FDD systems.

(b) statistical pattern recognition, which can be of several sub-types: sign directed graphs (or fault direction graphs)- also called diagnosis rules, clustering methods, Bayesian methods, fault dictionaries, analytical, such as ANN models.

Knowledge-based techniques have two basic elements: a **knowledge base**, and an inference engine. Hence, these techniques can be distinguished into how the underlying rules or knowledge are generated/determined, i.e., how the knowledge base is created:

a) simple heuristic rules based on rules-of-thumb (such as kW/ton,….)
b) rules gained from experience by "domain experts" who would develop these rules based on an engineering or physics understanding of the system operation;
c) rules developed by codifying the knowledge gained by running a deterministic forward model simulation program under a wide range of operating conditions and under different types and magnitudes of faults;
d) statistical rules identified from intentional introduction of faults in a laboratory setting.

Finally, the inference engine could be one of the following:

(i) using a commercial knowledge based shell within which to encode the rules,

(ii) developing a program in a convenient language (say C or Matlab) where the "if-then" rules are programmed in,

(iii) using a statistical pattern recognition program, such as ANN (Bailey, 1998).

Step 5: Fault evaluation entails assessing the impact of a fault on system performance and on the associated annualized cost of operating the engineering system. The evaluation could be done based on simple **heuristic rules** gathered from previous experience and imbedded in an expert system, to the application of **operation research techniques**, and using **probabilistic approaches**. Furthermore, most current FDD systems for buildings applications do not implement or discuss the fault evaluation and decision steps. Fault evaluation is particularly important when the performance of a component is degrading slowly over time.

Step 6: Actions initiated. Depending on the outcome of the fault evaluation process, one of several actions can be undertaken. In case of a catastrophic fault involving danger to human life or heavy damage to equipment, one could immediately shut the entire system down. HVAC&R manufacturers usually provide such safety controls in their equipment. Other hues of fault levels could entail undertaking repairs as soon as the system can be shut-down (say, at night when the demand for the system output is low), or during scheduled downtime for preventive maintenance. There are certain types of faults that can be rectified by on-line control (provided such capabilities exist). Finally, a fault that is barely discernable could be tolerated until it grows to a degree that justifies the cost of repair.

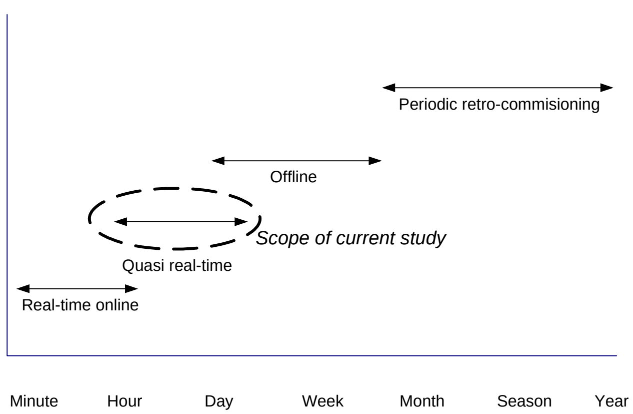

Figure 1. Broad classification of FDD applications based on latency period, i.e., time from which data are collected to the time they are analyzed. The scope of the current study is limited to thermal performance degradation FDD for which 1-2 day latency periods are deemed most appropriate practically. One would expect about 10-20 steady state data points to be screened together for occurrence of faults

Figure 1 is our attempt at a broad classification of FDD applications. We contend that a strict real-time online FDD method is unlikely to be the one which will be implemented initially, and that one which involves analyzing collected data at the end of a 1-2 day latency period is more likely to be implemented practically.

Lessons Learnt

There are several textbooks (such as those by Himmelblau, 1978; Chen and Patton, 1999) which describe in great mathematical detail the various tools and techniques appropriate for FDD. Unfortunately, these techniques have limited success with real-world data. Further, the real challenge is not the lack of modeling and analysis techniques for FDD, but the lack of proper appreciation as to which method is most appropriate for the given circumstance (Davies, 1998).

An ASHRAE technical bulletin assembling 10 papers on FDD for HVAC systems (ASHRAE, 1996) provides a good perspective of the state of art in this area at that time. In the early 1990s, the International Energy Agency (IEA) commissioned the Annex 25 collaborative research project on real-time simulation of HVAC&R systems for building optimization, fault detection, and diagnostics (Hyvärinen and Kärki, 1993, 1996). The Annex 25 study identified common faults for various types of HVAC&R systems, and a wide variety of detection and diagnosis methods were investigated including physical models of HVAC&R systems and black-box models. The black-box models use classification techniques such as artificial neural networks, fuzzy models, and rule-based expert systems. The selected methods proved to be successful in detecting and diagnosing faults with simulated data. However, the effectiveness of the FDD systems in real building systems was not assessed. A followup study was initiated by IEA to demonstrate FDD systems in real buildings (Dexter and Parkanen, 2001). A handbook review article of FDD methods as applied to HVAC&R equipment with three detailed FDD case studies (none of which pertain to chillers) has been prepared by Katipamula et al. (2001). A comprehensive document containing a literature search on FDD applied to vapor compression cooling equipment has already been compiled by Comstock et al. (1999). Faults can be divided into the following categories: (a) sensor faults, (b) actuator faults, (c) process faults- this is our primary focus, and (d) control loop or controller faults. Till now, category (c) has been the most studied, while a few studies do address category (a).

Selection of method(s) for FDD plays a critical part in the development of the FDD systems. There are several approaches to detecting and diagnosing faults in building systems. Most of them perform more than adequately in the laboratory or test setting, but not many of them may be suitable for field implementation. Some methods need few data need requirements, while others require extensive data. It is very important to note that one could use different model approaches for fault detection and for fault diagnosis. For example, Haves et al. (1996) suggested a fault detection method involving a hybrid approach that used a physical model along with a radial basis function ANN model to capture the former's structural deficiencies. Anderson et al. (1989) adopted a statistical approach for fault detection and a rule-based method for fault diagnosis.

The FDD methods differ widely depending on the type of system they are applied to, the necessary degree of knowledge about the diagnosed object, cost-to-benefit ratio (including monetary as well as life safety related issues), the degree of automation, and the input data required. Most classical methods use alarm limits as fault criteria, whereas the advanced methods apply accurate mathematical models of the process. Between the two groups are various simplified empirical and heuristic knowledge-based methods of fault detection and diagnostics.

The following insights have been gleaned from our study of the various FDD papers on HVAC&R equipment and systems:

(1) Heuristic FDD systems: As mentioned earlier, most of the 75 predictive maintenance projects identified by Patel and Kamrani (1996) worldwide are based on some form of expert system. Such expert systems have been in use for a wide variety of systems (CIGRE,1992, 1995). Whether model based FD methods yield superior diagnostics (as stated in most books) than model free methods is uncertain. Model based FD methods have been found to be superior in their FDD capability to limit checking by Fasolo and Seborg (1995), while the results of Wagner and Soureshi (1992) and Carling (2002) did not seem to support this. Given that model-free methods may be more easily acceptable by HVAC&R professionals, there seems to be a need to determine the conditions under which model-based FDD methods are advantageous. These thoughts suggest that this very important class of FDD techniques should not be overlooked in this research.

(2) **Steady-state data**. It is tempting to use transient chiller data in some form or another during the FDD process, especially since this data is being collected anyway. However, the two studies relating to chillers which we have been able to identify (Bruecker and Braun, 1998a,b and Stylianou, 1997) use such data in a cursory and non-rigorous manner. More importantly, there are several published articles on FDD applied to AHU (see review articles by Katipamula et al., 2001, or Comstock et al., 1999). What is striking is that despite more sophisticated FDD methods evaluated in previous years, the three studies which stand out in recent years (those by Visier et al., 1999, House et al., 1999, and Carling, 2002) have fallen back to simple steady state FDD methods. One study used two averaged data points over the day, and the other used averaged moving data which is so filtered that, at most, only a few data points satisfy the criteria on a daily time scale.

(3) Single measurement versus time series approach. As depicted in Fig.1, one would expect quasi real-time FDD methods to be implemented initially. This would imply that a small number of performance points along with their evolution over time would be analyzed together for onset of faults. There are well-known statistical techniques which fall under the general category of "control chart" techniques (see for example, Himmelblau, 1978) which have been developed intentionally for this purpose. Hence the sequence in which the data were collected, i.e., retaining the time series behavior of the incoming data over a day becomes important. Unfortunately, to date, the majority of chiller FDD studies deal with individual single points.

There are three studies, however, (other than the rather preliminary study by Stylianou and Nikanpour,1996) which have tried to use the time series behavior to advantage during the FDD process. Pape et al. (1991) explored different statistical methods (namely, static or single-measurement) as well as time series measurements to determine the existence and location of faults in HVAC systems. The study was more conceptual in nature, and was meant to propose and conceptually illustrate these techniques with limited data. Riemer et al. (2002) analyzed data from a commercially operated water plant in the framework of an exploratory study involving the use of four variants of the sliding window ARIMA models to data collected at 1 min intervals. Another study by Schein and House (2003) describes a fault detection tool called VAV Box Performance Assessment Control Charts (VPACC) which can be embedded directly in VAV box controllers. It uses the CUSUM algorithm, a well known procedure in statistical process control literature suited for detecting gradual shifts in the process mean. The procedure applies the CUSUM algorithm to a small number of sensor data variables so as to detect eight different faults. The paper presents results of applying the tool to emulation, laboratory and field data sets.

(4) Lumped numerical model. A transient simulation model for simulating chiller faults is available (Bendapudi, 2004). However, using this model for the fault detection by first calibrating it with the monitored data of a specific chiller and then using it for generating the necessary fault dictionaries is not practical. Calibrating such a model is extremely tedious and cumbersome as several researchers have pointed out (for example, Castro, 2002). Hence, it would be more suitable to adopt a lumped numerical model for this purpose. Several such models are available; for example, the Primary HVAC Toolkit (Bourdouxhe et al., 1999), and those by Comstock and Braun (1999), McIntosh et al., (2000), Browne and Bansal (1998) to name a few. Such lumped models are easier to calibrate, and hence more appropriate for FDD implementation. Since it is difficult to intentionally introduce known faults in field-operated chillers in order to create the database required for diagnosis, such forward simulation approaches offer a particularly attractive means for performing FDD.

(5) Component isolation approach. Calibrated simulation model approaches for FDD are best suited for systems where limited sensor data are available (such as those by Rossi and Braun, 1997; Brueker and Braun, 1998a,b and Castro, 2002). This is the case for smaller unitary equipment.

Large chillers come equipped with a large array of sensors installed by the chiller manufacturers (which are cursorily, if at all, used by service personnel and energy managers). A new chiller modeling approach, based on the component isolation approach, was developed by Jia and Reddy (2003), and independently by McIntosh et al. (2000). This approach, called the **characteristic parameter approach**, basically allows a baseline or fault-free model of each of the primary sub-components of the chiller to be identified from the performance data of the numerous sensors available. The basis of the characteristic parameter approach is to characterize each and every primary component of the chiller (the electrical motor, the compressor, the condenser heat exchanger, the evaporator heat exchanger and the expansion device) by one or at most two performance parameters, the magnitude of which is indicative of the health of that component. These quantities are not constants during normal operation. For example, (UA) values of the flooded type of evaporators and condensers vary as much as 15-20%. A hybrid inverse model is set up based on the theoretical standard refrigeration cycle in conjunction with statistically identified component models that correct for non-standard behavior of the characteristic parameters of the particular chiller. Such an approach has the advantage of using few physically meaningful parameters (as against using the numerous sensor data directly), thus simplifying the detection phase while directly providing the needed diagnostic ability. Another advantage of this generic approach is that the identification of the models that capture the non-standard behavior is simple and robust since they require model parameters to be identified directly by regression rather than calibration involving a numerical search. This modeling approach has been evaluated with two chiller data sets by Reddy et al., (2001) and effect of sensor accuracy has also been investigated. Thus, the component isolation approach while being cost effective, is much more robust than calibrated simulation model-based FDD, and concurrent with fault detection directly provides the needed diagnosis as well.

(6) Inverse baseline models. Inverse modeling can also be used for FDD of HVAC&R equipment. The inverse model has to meet requirements very different from the forward model. The limited and often repetitive information contained in the performance data (for example, building and cooling equipment operation from one day to the next is fairly repetitive) can only support inverse models with relatively few model parameters. The inverse model is thus a much simpler model (than a model used to simulate equipment or system performance) that contains fewer terms representative of aggregated or macroscopic parameters (such as overall heat loss coefficient, time constants,...). Since the model parameters are deduced from actual equipment performance it is much more likely to accurately capture the as-built system performance, thus allowing more accurate prediction of future system behavior (provided that the operating range during model calibration is complete enough to encompass normal system operating conditions). Performance data collection and model formulation need to be appropriately tailored for the specific circumstance which may often require a high level of skill and expertise of the user. In general, inverse models are more limited as compared to the flexibility which forward models offer in evaluating energy implications of different design and operational alternatives, and so they are not a substitute in this regard.

(7) Grey-box models. Our past research indicates that grey-box models (as against black-box models such as multi-linear polynomial models MP, ARIMAX or ANN) are the best choice to model chillers. The report by Reddy et al. (2001) presents the research results of comparing the suitability of four different chiller performance models to be used for on-line automated FDD of chillers. The models were limited to steady-state performance and models linear in the parameters (except for ANN): (a) Black-box models: linear empirical models, usually tri-quadratic multivariate polynomial models , (b) Artificial neural network models: radial basis function (RBF) and multi-layer perceptron (MLP), (c) Gray-box model: the generic physical component model approach (Jia and Reddy, 2003), and (d) Gray-box model: Lumped physical GN model (Gordon and Ng, 2000). The two online training models were evaluated: Ordinary Recursive Least Squares (ORLS) where all data are given the same weight in readjusting the parameter estimates, and Weighted Recursive Least Squares (WRLS) where more weight is given to newer data. The evaluation was done based on 5 month of data from a 220 Ton (T) field operated chiller from Toronto (a data set of about 800 data points), and 14 day data from a 450 T field operated chiller (a set of about 1120 data points) located on an university campus, which was instrumented, and data collected specifically for this research. It was concluded that the best candidates for implementing on-line chiller FD schemes are those based on model predictions rather than model parameters, using either MLP models (with 2-3 hidden neurons) or the GN model, using ORLS sliding window schemes of 100-200 data points. However, the ANN modeling approach is probably an overkill for chiller modeling, and also requires much more training data.

(8) Output innovations, and not parameter innovation. The fault detection using the innovation approach can be done either by output values or by model parameters (Salsbury and Haves, 1996). The latter approach seems attractive and has been described in several textbooks. It is said to offer additional sensitivity in the fault detection process. However, previous research (see Reddy et al., 2001) found that the model parameters, even when grey-box models, such the linear Gordon-Ng model (2000) with only three model parameters are used, vary greatly during on-line model training indicating lack of robustness. Hence, innovation based on output quantities (such as chiller COP, or heat exchanger overall heat loss coefficients or UA values,…) would be a much more robust option to evaluate in this research.

(9) Fuzzy logic. Classical innovation-based thresholds use crisp logic methods to flag the onset of faults. Detection of faults using fuzzy logic offers several advantages over the crisp approach, as described by Dexter and Ngo (2001). It can account for modeling errors, ambiguous data, and sensor bias, and could minimize the generation of false alarms.

(10) Source of fault-free data. Having fault-free performance data is essential for all FDD methods. For AHU units which are often assembled at site and highly installation-specific, such data is not forthcoming from the manufacturer, and hence, FDD tools for AHU need to contain sophisticated classification capability whereby such data can be gleaned from in-situ performance data. This was the reason for the study by House et al. (1999) wherein different classification techniques were compared in terms of their ability to distinguish between faulty and fault-free data. This issue is also important for unitary equipment (vapor compression and boilers) and for larger chillers. Manufacturers do gather extensive fault-free performance data from in-house testing, but this may not properly characterize actual field operation for the specific chiller under consideration. It is better to carefully design and perform customized start-up commissioning tests in the field specific for FDD purposes for both new chiller installations and those which have already been in service for some time. Though some guidance is available (see Corcoran and Reddy, 2003), the exact field procedures adopted by chiller manufacturers and service companies is not properly documented in the professional literature.

(11) Source of faulty data. Fault diagnosis involves isolating the cause of the fault. This is based on the observation that different types of faults cause different characteristic features to behave differently from their fault-free behavior. Hence, one ought to know these fault patterns for each fault in advance. Such prior symptom-to-fault behavior patterns can be identified by one (or a combination) of the following:

(a) <u>prior studies</u> which have identified such fault patterns (perhaps in a generic sense) for HVAC&R equipment in question; our opinion is that some amount of customization is necessary;

(b) in a <u>laboratory setting</u> where known faults are introduced into the system and the monitored data is used to identify the characteristics which describe the particular fault (as done by numerous HVAC&R studies; for example, Bailey (1998), Brueker and Braun (1998 a,b), Castro (2002), and Rossi and Braun (1997). The lab chiller tests documented by Comstock and Braun (1999) are an excellent example of this type of learning. However, this approach is hardly practical for each and every equipment being considered for FDD monitoring, and hence, is most beneficial when no knowledge is available at all;

(c) based on <u>physical mathematical models</u> of the equipment and/or system which is structured such that it explicitly contains input parameters likely to be affected when different faults occur. Here the model is calibrated with fault-free performance data, and the numerical values of specific parameters characterizing a specific fault can be modified to simulate the occurrence and magnitude of that fault (McIntosh et al., 2000);

(d) by <u>online in-situ learning</u> whereby the characteristics of different faults as they arise over time are learnt (provided one is able to identify the faults through a different route), say by manual supervision or using a sophisticated classification algorithm which can separate fault-free and faulty performance, such as that studied by House et al., (1999).

Usually routes (a), (b) and (c) may be complemented by some amount of tuning once the FDD system is in place since minor modifications may be needed to the generic knowledge patterns (especially to fault detection threshold).

(12) Sensor accuracy: The accuracy of the sensors used in commercial cooling plants as well as those provided by chiller manufacturers is an important issue in FDD. There are only a few studies in the published literature dealing with this issue (for example, Wang and Cui, 2004). More accurate sensors will provide more robust and sensitive FDD, but at a higher cost. Usually one can consider three types of categories: laboratory, industrial and commercial. ANSI/ASHRAE standard 150-2000 (ASHRAE, 2000) stipulates the required accuracy, precision, and resolution of various types of instrumentation. It also requires that practitioners field-verify the installed accuracy of temperature and flow sensors according to ASHRAE standard 150.

A study detailed in two reports (Fromberg and d'Albora, 2001a,b), performed cost-benefit analysis which, among others, included improving temperature difference accuracies in chilled water plants from 2.0^0F to 0.5^0F. The annual cost of installing and maintaining more accurate equipment was assumed to be $150/yr per temperature sensor. The intended application of these studies was not for automated FDD, but rather for operation, control, diagnostics and commissioning. General conclusions were:

(a) For chiller performance and heat balance measurements, chilled water temperature measurements should be 0.25^0F accurate, and those for chilled water flow should be 1% accurate. For all other uses, they should be 0.5^0F and 2% accurate, respectively.

(b) For chiller heat balance measurements, condenser water temperatures should be 0.25^0F accurate, and the condensate flow should be 1% accurate. For all other uses, temperatures should be 0.5^0F accurate.

(c) Chiller power should be 0.5% accurate if performance or heat balance calculations are to be performed.

The potential chiller energy savings from implementing these recommendations was estimated to be from 1.6% to 7.7% of the total energy costs at the buildings studied. Also, for diagnosis problems using plots, the study found that data storage frequencies for cooling tower, pump and condensate data should be every 1-2 minutes (instantaneous data), while for chiller readings, storage frequency should be every 15 min (averaged data). From the above study, it would seem that industrial grade sensors, rather the current practice of using commercial-grade sensors, ought to be preferred.

Status of FDD in HVAC&R

While FDD is well established in the process, nuclear, aircraft, and automotive industries, it did not enter the building and HVAC&R industries until the mid 1990s (Braun 1999). High reliability and safety are relatively less critical in building operations; therefore, FDD did not receive the same level of interest among the building researchers, owners, and operators. The primary driver of building costs is still the operating cost and capital investment. Although FDD has been an active area of research among the building and the HVAC&R community for several years, it is not widely deployed in the field. The primary reasons for slow adoption of FDD in the buildings and the HVAC&R areas are numerous, and the major ones are described below:

(a) The cost-to-benefit ratio for a FDD implementation is relatively high, partly caused by the lack of extensive instrumentation in the building and HVAC&R systems, and lack of data to quantify the benefits (Braun, 1999). The lack of such "bridge" research is one of the major hurdles which has impeded the widespread development of FDD equipment in HVAC&R equipment.

(b) Further, Dexter and Ngo (2001) point out that the problems associated with identifying and isolating faults in HVAC systems are more severe than those that occur in most process control applications. The behavior of HVAC plants and buildings is more difficult to predict due to lack of accurate mathematical models because most HVAC designs are unique, and financial considerations restrict the amount of time and effort that can be put in deriving a model.

(c) Detailed design information is seldom available, and measured data from an actual plant are often inadequate indicators of the overall behavior, since test signals cannot be injected during normal operation (Haves et al., 1996) because of potential occupant discomfort, unacceptable energy penalties, and possibility of equipment damage.

(d) Another problem is that many variables cannot be measured accurately, and some measurements, needed for proper modeling, are not even available. Finally, the issue of fault diagnosis can be problematic since several faults may have the same symptoms.

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Table 1. ELEMENTS OF AN ON-LINE SUPERVISION AND FDD SYSTEM

<table>
<tr><td rowspan="3">Designing and installing sensor network</td><td>Select faults to track</td><td colspan="6">Done either from published studies or from discussions with service personnel</td></tr>
<tr><td>Design network</td><td colspan="6">Evaluate existing sensor network, and determine critical sensors</td></tr>
<tr><td>Commission</td><td colspan="6">Install new sensors as necessary, calibrate and commission sensor network and data collection system</td></tr>
<tr><td rowspan="3">Pre-processing of sensor data during day-to-day operation</td><td>Data acquisition</td><td colspan="6">Measurements from sensors (could be from a few seconds to hourly)</td></tr>
<tr><td>Data screening</td><td colspan="6">Screen data for hard sensor faults
Perform range and balance checks to detect soft sensor faults</td></tr>
<tr><td>Transient data filtering</td><td colspan="2">Steady-state</td><td colspan="2">Time series trends</td><td colspan="2">Transient data</td></tr>
<tr><td rowspan="3">Fault Detection</td><td>Generation of actual performance indices</td><td colspan="6">Using the senor data, generate the necessary indices representing actual performance (this is usually straightforward using arithmetic or algebraic transformations, and may involve thermodynamic property calculations</td></tr>
<tr><td>Baseline or fault-free performance predictor</td><td colspan="2">Model-free

- range checks
-physical redundancy
-trend analysis</td><td colspan="2">Forward model-based

Calibrated lumped simulation model</td><td colspan="2">Inverse model-based
- Statistical (discriminant)
- Black-box regression Model (Polynomial, ARIMAX, ANN)
- Grey box model)</td></tr>
<tr><td>Logic of threshold trigger</td><td colspan="2">Crisp/fuzzy Heuristic bounds

(user defined)</td><td>Statistical hypothesis testing

- single
- multiple</td><td>Probabilistic and/or Bayesian</td><td>Pattern recognition detectors</td><td>Control charts

- Shewart
- Cusum
-EWMA</td></tr>
<tr><td rowspan="2">Fault Diagnosis</td><td>Isolation</td><td colspan="2" rowspan="2">Heuristic rules</td><td colspan="4" rowspan="2">Statistical pattern recognition
- Signed directed graphs
- Clustering methods
- Bayesian methods
- Fault dictionaries
- Analytical methods, such as ANN</td></tr>
<tr><td>Identification</td></tr>
<tr><td>Fault Evaluation</td><td></td><td colspan="2">Heuristics used to extrapolate to season/year</td><td colspan="2">Hourly simulation over season/year</td><td colspan="2">Modified bin method</td></tr>
<tr><td>Possible actions</td><td></td><td>Shut down</td><td>Repair ASAP</td><td>Repair whenever convenient</td><td>Repair during scheduled maintenance</td><td>Software tuning of controller</td><td>Tolerate fault</td></tr>
</table>