Fault detection methods for vapor-compression air conditioners using electrical measurements

by

Christopher Reed Laughman

S.B., Massachusetts Institute of Technology (1999) M.Eng., Massachusetts Institute of Technology (2001)

Submitted to the Department of Architecture in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Architecture: Building Technology

at the

MASSACHUSETTS INSTITUTE OF TECHNOLOGY

September 2008

© Massachusetts Institute of Technology 2008. All rights reserved.

Author	
	Department of Architecture 8 August 2008
Certified by	

Leslie K. Norford Professor of Building Technology Thesis Supervisor

Certified by

Steven B. Leeb Professor of Electrical and Mechanical Engineering Thesis Supervisor

Accepted by Julian Beinart Professor of Architecture Chair of the Department Committee on Graduate Students

Thesis Committee

Thesis Supervisor: Leslie K. Norford Title: Professor of Building Technology University: Massachusetts Institute of Technology

Thesis Supervisor: Steven B. Leeb Title: Professor of Electrical and Mechanical Engineering University: Massachusetts Institute of Technology

Thesis Reader: Leon R. Glicksman Title: Professor of Building Technology University: Massachusetts Institute of Technology

Thesis Reader: James L. Kirtley Title: Professor of Electrical Engineering University: Massachusetts Institute of Technology

Thesis Reader: Steven R. Shaw Title: Associate Professor of Electrical Engineering University: Montana State University

Thesis Reader: Peter R. Armstrong Title: Professor of Mechanical Engineering (?) University: Masdar Institute of Science and Technology

Fault detection methods for vapor-compression air conditioners using electrical measurements

by Christopher Reed Laughman

Submitted to the Department of Architecture on 8 August 2008, in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Architecture: Building Technology

Abstract

Abstract goes here. Yadda yadda yadda.

Thesis Supervisor: Leslie K. Norford Title: Professor of Building Technology

Thesis Supervisor: Steven B. Leeb Title: Professor of Electrical and Mechanical Engineering

for Katie

Acknowledgments

"You need the willingness to fail all the time.

You have to generate many ideas and then you have to work very hard only to discover that they don't work. And you keep doing that over and over until you find one that does work."

- John W. Backus

thanks to steve leeb, les norford. also thanks to prof. k and leon. thanks to peter armstrong, rob, and steve shaw. thanks to jim, warit, roderick lafoy, ryan bavetta. thanks to lau fan, dudes at abco, dudes at uri, dudes at purdue thanks to friends, glass lab. thanks to family thanks to katie.



Contents

1	Intro	troduction		17
	1.1	1 Fault Detection and Diagnostic Systems		20
		1.1.1	Fault Detection	21
		1.1.2	Fault Diagnosis	27
		1.1.3	Fault Evaluation and Decision	29
	1.2	Previc	bus Work	31
		1.2.1	Air Conditioning System Overview	31
		1.2.2	Common Faults in Air-Conditioners	33
		1.2.3	FDD Methods for Air-Conditioners	38
	1.3	Electri	cally-based FDD techniques	42
	1.4	Resear	rch Overview	45

List of Figures

1-1	The basic structure of an FDD system (adapted from [29])	20
1-2	Fault detection using a signal model-based approach (adapted from [29]).	23
1-3	Fault detection using a system model-based approach (adapted from [29])	23
1-4	caption	27
1-5	caption	27
1-6	Schematic diagram of the air-conditioner	32

List of Tables

Chapter 1

Introduction

Whether the motivation is environmentalism, money, or just an interest in thermodynamics, the topic of energy conservation is presently receiving a great deal of attention. Such considerations can arise in a wide variety of different contexts: the amount of energy needed to manufacture a product, the amount of energy needed to operate a piece of equipment, and the amount of energy needed for transportation are just a few of the the different types of concerns which can arise. Moreover, one common concern at a time during which the price of oil exceeds \$140 a barrel is to account for and minimize the amount of energy consumed by a given task, allowing energy to be better allocated or saved.

Buildings represent one particularly important and common consumer of energy. Even neglecting the myriad uses of energy which take place inside of buildings, the energy required to heat, cool and provide light in buildings amounts to billions of kilowatt-hours every year. Especially apropos to considerations of energy conservation is the fact that the installation of air conditioning in buildings is becoming increasingly commonplace. Over half of the industrial and commercial buildings currently in existence are air conditioned, while approximately 90% of newly constructed homes have central air installed. Similar statistics are cited in [63], in which 14% of the U.S. primary energy consumption is dedicated to HVAC systems for commercial and industrial buildings, and 32% of the electricity generated is consumed to heat, cool, ventilate, and light commercial buildings. This profusion of air conditioners uses a great deal of energy; by one estimate, 76 billion kWh per year are consumed by packaged air conditioning equipment [51]. Of the types of air conditioners sold, packaged rooftop units (RTUs) form the largest segment of the

market, cooling 45% of the 58.7 billion square feet of commercial space in the U.S.

While air-conditioning has long been popularly viewed as a luxury [16, 45], it serves many essential functions in buildings today. Perhaps the application which comes to mind most readily is that of increasing the level of thermal comfort in buildings via a reduction in air temperature and/or humidity, resulting in benefits both to the health and the productivity of the building occupants. Commercial and industrial applications also abound, as air-conditioning is often essential to process control in chemical or manufacturing plants, and it is also needed for many businesses, such as those which deal with the preparation, storage, and sale of food products. Medical applications of air-conditioning are also very common, as hospitals require it for the comfort and well-being of their patients.

This dependence of so many applications on air-conditioning brings a corresponding need for the air-conditioners to operate within specified bounds on its performance. The many potential consequences of faulty operation depend on the application and the severity of the fault; for faults which result in a loss of air-conditioning, the effects can range from discomfort for home or business occupants, to ruining foodstuffs or temperature-dependent products, to directly affecting the health of hospital patients [10]. Less dramatic faults might not have such extreme short-term consequences, but they can still cause size-able reductions in equipment efficiency and corresponding increases in energy consumption, or the shortening of equipment life, resulting in increases in service costs. Factors which can cause or contribute to such poor behavior are legion, including neglect and improper installation and maintenance, as well as unforeseen electrical and mechanical failures. Field studies suggest that such faults are widespread, as a study of 4,168 air-conditioners found that 72 percent of the air-conditioners had the incorrect refrigerant charge, and 44 percent had improper airflow [**?**].

Methods for monitoring and evaluating the operation of air-conditioning systems are gaining in importance as air-conditioning becomes more common. Systems which are designed to implement these methods, often referred to as condition monitoring or fault detection and diagnostic (FDD) systems, have a variety of potential uses, including monitoring the performance of the equipment over time, alerting users of the presence of a fault, improving the quality of service by identifying the cause of faulty operation, or even changing the operation of the equipment to reduce the effect of the fault. The functionality of these FDD systems can thereby greatly improve the performance of the underlying air-conditioning system and assist the service technician in expeditiously fixing and maintaining equipment.

While the users of air-conditioning systems which incorporate FDD methods will see a direct benefit due to the reduced downtime and improved performance of the air-conditioner, these FDD systems also benefit a number of other parties. For example, an effective FDD method can help a service technician to quickly identify malfunctioning components and reduce the time required to troubleshoot ambiguous problems. This will assist both users and service technicians in ensuring that the system was installed correctly, and providing prognostic capabilities in identifying and monitoring faults which can be addressed during scheduled service calls, rather than in emergency situations. Equipment manufacturers also benefit from the installation of such an apparatus, in that it could enable them to better understand how and when faults occur.

Interest in the theoretical and experimental development of FDD methods in general is growing, due to the dependence of society on systems of increasing complexity. These systems can be found nearly everywhere in the early 21st century, from buildings to cars to airplanes to consumer electronics to traffic control systems. The traditional attitude of the designer, that the system will function reliably for a long period of time if the design is "good enough", is slowly giving into the realization that many systems will be operated in conditions unforeseen by the designer, and that the cost of faults in such systems can sometimes be greater than the system itself. The implementation of FDD and condition monitoring systems is vital in such circumstances, to ensure that the system will continue to function well in the face of considerable operative uncertainty.

The research presented here investigates and develops FDD methods for residential air-conditioners using electrical measurements. Such an approach inherently has a variety of both benefits and challenges, which will be discussed in this introductory chapter. In order to provide context for this development of the FDD method, however, many of the factors and possible approaches which must be considered when designing FDD systems will be reviewed in the following section.

1.1 Fault Detection and Diagnostic Systems

In developing an FDD method, it is useful to identify the constituent tasks which are performed. A useful and intuitive general framework for FDD methods is outlined by Isermann in [28,29] in which the FDD process is broken down into four steps: fault detection, fault diagnosis, fault evaluation, and decision, as seen in Figure 1-1.



Figure 1-1: The basic structure of an FDD system (adapted from [29]).

In the fault detection block, measurements of the system are made and then processed in order to determine if a fault has occurred. Since the reported faults could potentially be caused by a variety of circumstances, the fault diagnosis block processes the information from the fault detector and determines the cause of the fault. Once this has been determined, the fault evaluation and decision block assesses the significance of the fault determines the proper course of action, be it to continue operating in a faulty state, shut down, change operation so that the effect of the fault is mitigated or eliminated, or any other option.

While this is a useful general framework, the construction of the particular blocks will vary widely in any specific implementation of an FDD method. For example, many such methods only implement the fault detection block in hardware and software, and rely upon the expert knowledge of a system user to perform the fault diagnosis and evaluation steps. Due to such concerns, the performance of FDD system is often dependent on both the performance of the individual blocks as well as the interactions between the blocks. Each of the constituent components of the overall FDD system must therefore be designed while considering the operation of the other components.

A variety of issues which can affect the performance of the FDD method must also be considered during the design stage. For example, the reliability of the FDD system itself is critical to its performance, as situations in which the FDD system erroneously reports a fault can often be as problematic as those in which faults are reported correctly. The FDD method must correspondingly be designed and specified so that its reliability and performance in the field environment can be assessed and understood.

The cost of developing and implementing an FDD method is also an important consideration. These costs may be justified by examining the savings collected by keeping the system running efficiently, servicing faults before they increase in magnitude, or by the convenience of scheduling service visits on a non-emergency basis. They might also be justified because of the consequences of not detecting the faults; even if the faults are inexpensive and easy to repair, situations in which system failure could have significant ramifications for the health of individuals or a business can be a powerful incentive for installing an FDD system. As many of these issues shaped the design and implementation of the FDD methods discussed in this research, each block of the general FDD method will be discussed briefly in the following sections in order to better provide context for the design decisions which were made.

1.1.1 Fault Detection

The structure of a fault detector can generally be broken down into three different pieces. The first of these takes a set of input measurements of the system which are obtained from a sensor or set of sensors and uses these measurements to characterize a model or generate an expected response of the system. The output of this model is then processed to generate a set of fault signatures, which make it easier to observe the effect of the fault and which are known to be directly related to the fault or faults of interest. These fault signatures effectively project the observations onto a space which enhances the detectability of the fault. Once these fault signatures have been obtained, they are processed by a change detector which compares the observed fault signatures to the expected signatures that are generated by normal behavior, and generates an output which indicates the existence and/or size of the mismatch, also called a symptom. These symptoms are output to the fault diagnosis block, which assesses the presence or the severity of the fault.

While there are a number of different types of models which may be used in the fault detector, they can generally be grouped into one of two different types: signal-based models, and system-based models. Signal model-based fault detection techniques do not incorporate any knowledge about the monitored system itself; instead, the sensor output is characterized solely by a model of the signal, and the presence of a fault is identified by looking at attributes of the signal model. This approach is illustrated in Figure 1-2. In comparison, system model-based fault detection techniques incorporate models of the underlying system that generate the observed sensor data, and use this data to characterize the proposed system model and to examine model characteristics which are indicative of a fault. This alternative strategy for fault detection is illustrated in Figure 1-3. As each of these approaches has relative strengths and weaknesses, so both will be used in this research depending on the needs of the particular application.

Signal model-based fault detection methods are often the most straightforward fault detection methods to implement, since little additional information about the current state of the system is needed for the operation of the method. Two common approaches look strictly at the time-series data obtained from the sensors; the first of these analyzes the observations as they are obtained and uses a simple thresholding or limit-checking algorithm for fault detection. Observed changes in the signal which crosses an established limit are deemed to be indicative of a fault. Such simplicity in a fault detector is attractive because it minimizes the fault detector's complexity, which has benefits for both the FDD system reliability and cost. An alternative approach is to analyze trends in the time-series history of the observed data, rather than looking solely at the instantaneous values of the data. Such an approach is useful when the observations are expected to change over time in a well-understood manner.

While the simplicity of this type of fault detector is attractive, it also imposes limitations on the performance of the detection method. These fault detectors are typically sensitive



Figure 1-2: Fault detection using a signal model-based approach (adapted from [29]).





to noise and bias, as there is no apparatus for differentiating between a spurious event which has no appreciable effect on the system and a fault condition. These detectors are also highly dependent on the equipment installer and FDD method designer to ensure that the sensor accurately characterizes the system performance over its lifetime, and that the threshold is set appropriately for the particular instance of the system, with its attendant variations in performance.

An additional limitation of such threshold-checking fault detectors is that faults may not appear in an abrupt manner, so that changes in the system as it "wears in" over time must be distinguished from slowly appearing faults. In drawing a distinction between faults which appear over a long period of time and faults which occur abruptly, it is helpful to borrow terminology from [11] in which the slowly developing faults will be referred to as "soft" faults, while the abrupt faults will be labeled "hard" faults. Using this terminology, hard faults tend to be conducive to detection with a threshold detector because they represent an abrupt change in the variable of interest, while soft faults tend to be much more difficult to identify with a threshold detector because they are difficult to differentiate from characteristics of the system, which will gradually change with continuing use.

Alternative methods for processing the sensor data can also increase the amount of fault information obtained from the sensor array. While many extant fault detection systems rely solely on data obtained when the system is operating in quasi-steady-state, data acquired during transient changes in the state of the system can provide a great deal of information about its behavior. Analyzing the sensor data via other signal representations can also help to identify changes in the signal which would be difficult to observe in the time-series data. Common techniques include analyzing the signal with the Fourier transform or a multi-resolution basis such as wavelets, or fitting the data with radial basis functions.

In contrast to the signal modeling approach, the system modeling approach to fault detection involves constructing a mathematical or computational model of the system being monitored. Models are constructed with a given structure and a set of parameters, which are either set when the model has been chosen, or are initialized with a set of characterization data which is known to accurately represent the behavior of the working system. After the model has been initialized, faults can be identified by driving the model with inputs that are related to the inputs of the real system and comparing the output of the model of the simulated system with the output of the real system. One of the principal advantages of this approach is that it makes it possible to draw inferences about the system which are not directly visible, but are instead tied to the the relationship between a number of different changes which are related by an unobservable variable or fault condition.

Naturally, these models can take a wide variety of different forms. One common class of models is referred to as black-box models, which require no information about the system being modeled. Perhaps the simplest type of black-box model is a simple polynomial, using sensor observations as the independent variable and the coefficients of the sensor observation terms being the model parameters. Other common types of black-box models are based upon machine learning techniques, such as neural nets and fuzzy logic-based models. The parameters for these models are generally obtained by a learning process that collects training data which is known to characterize the normal operating behavior; this step either occurs at the time that the model is constructed with a verified set of data, or after installing the system in the field, when the system is assumed to be fault-free.

One of the shortcomings of these types of models is that they do not take advantage of any of the physical understanding of the system which is based upon fundamental constitutive laws. There are many benefits to using these physically-motivated, or greybox, models, such as the ability to incorporate intuitive knowledge about the behavior of the system into the mathematical dynamics of the model, as well as set the parameters of the model ahead of time, rather than relying solely upon the data. Linear and nonlinear Kalman filtering [56, ch. 4] are perhaps the best known application of this approach to fault identification. These type of models can also be applied to processes, rather than physical systems, allowing fault detection methods to be implemented on systems which are driven by random inputs [17].

The system-modelling approach is also useful when used to track system parameters as the system performance changes over time. Rather than driving the model with the same input as the physical system and then analyzing the differences between the model output and the system output, this alternative approach drives the model with the same input, but instead adjusts the parameters of the model to successfully reproduce the system output, so that both the model input and output match the system input and output. The resulting changes in the model parameters will reflect the underlying changes in the system, and analysis of these changes can be used to determine the presence of a fault. The appeal of such an approach is that fault signatures can be generated for unmeasured parameters of the model which are of interest, rather than the measured variables which, by themselves, may not provide enough information to identify a fault. Physical models are particularly useful in this context, as it allows the designer to detect faults based upon his intuition regarding the changes in the physical model of the system.

In designing the fault detector, due consideration must also be given to the possibility that aspects of the FDD method will not function as expected, either by not reporting faults which are present, or by reporting faults which are not present. Both of these scenarios are problematic because the service requirements of the system will not be addressed correctly, and because they will cause the user to lose confidence in the accuracy of the FDD method. It is therefore imperative that the reliability of the FDD method be well understood.

Failure of or faults in the FDD method can arise for a few different reasons. Malfunctioning sensors clearly have significant ramifications for the FDD method, both in the case that the sensors stop providing data to the fault detector altogether, or in the case that the output of the sensors acquires noise or bias which prevents the sensor output from accurately representing the true behavior of the system. Model inaccuracies also represent a significant challenge. For example, if the behavior of the fault-free system cannot be described by the model due to unplanned changes in the system, discrepancies between the expected and observed data could be reported as a fault. Moreover, many fault detection methods rely upon baseline data collected after the system is installed and its functionality is tested and verified (also referred to as commissioning) by a technician. If the technician does not install or commission the system accurately, the baseline data for the FDD system will represent faulty, rather than fault-free, behavior of the system. The possibility of emergent behavior which arises in complex systems must also be considered, as unforeseen circumstances might interact with highly complex FDD systems to produce unexpected results. These phenomena can only be mitigated or avoided through extensive testing.



Figure 1-5: caption.

1.1.2 Fault Diagnosis

Historically speaking, most FDD systems have been designed to monitor a small number of variables and alert the system user to the presence of a fault when a fault symptom is generated by the fault detection module. This can be an effective tool in some types of systems, where the user is interested only in knowing the presence of a fault, rather than knowing what the actual cause of the fault is. For many types of complex systems in use today, however, such systems are insufficient. Fault diagnosis modules can be used to determine the cause of faults in such systems by analyzing the observed set of fault symptoms.

The central challenge which must be addressed by any fault diagnosis module is that faults are not related to fault symptoms in a one-to-one relationship. This fact is illustrated in Figures 1-4. As can be seen on the right hand side of this figure, a given fault may be manifested via a number of different symptoms. While some of these symptoms may be easier to distinguish from normal operating behavior than the others, each fault could

manifest itself in multiple ways. The diagram on the left hand side of this figure illustrates the other complicating factor for fault diagnosis, which is the fact that multiple different faults can manifest themselves with the same set of fault symptoms. This fact can make it difficult to guarantee the occurrence of a particular fault if only one set of fault symptoms is monitored.

The extent of the potential difficulties facing the fault diagnosis module can be seen in Figure 1-5, in which multiple faults could be occurring simultaneously. Often referred to as the multiple-simultaneous fault problem, the FDD method must ideally be able to analyze a given set of fault symptoms and identify which faults, of all possible options, are affecting the system at any given point in time. This is particularly challenging because the fault symptoms are not necessarily binary quantities, so that the diagnostic module must infer the relative contributions of different faults to the observed magnitude of a given symptom. A pseudo-mathematical analogy to this situation suggested by [40,41] takes the following form:

$$\begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \text{fault 1} \\ \text{fault 2} \\ \text{fault 3} \end{bmatrix} = \begin{bmatrix} \text{symptom 1} \\ \text{symptom 2} \\ \text{symptom 3} \end{bmatrix}.$$
 (1.1)

In general, the technique used by FDD methods solve this problem is called fault isolation. In the context of (1.1), this can be understood as diagonalizing the fault diagnostic matrix containing the terms a_{ii} , though it is important to note that this diagonalization is not carried out computationally, but rather is only performed analogically. This step can be greatly assisted by properly designing the sensor network for the FDD system; by carefully selecting the type and location of these sensors, it is often possible to capture fault signatures which are strongly correlated to the fault of interest and only weakly correlated with other faults. Similarly, the proper sequencing of the fault diagnoses can also be helpful by using the process of elimination to reduce the number of conflicting fault symptoms.

A number of different approaches can be taken to implementing this fault isolation and diagnostic strategy. These approaches generally fall under the umbrella of classification problems, since the problem is essentially one of classifying a set of observed fault symptoms as corresponding to one or multiple faults. There is a rich body of literature on the different types of classification techniques, including Bayes classification, geometric classifiers, decision trees, neural networks, and clustering algorithms. Each of these methods has its own strengths and weaknesses, and the "right" technique for a given FDD method can only be chosen by evaluating them in the context of the system of interest.

Two other factors must also be considered when designing an FDD method. One situation which can arise occurs when the faulty behavior of one system component causes faults in other system components, so that the faults cascade. An FDD method must therefore be able to diagnose both the proximate faults as well as the source fault; if only the proximate faults are diagnosed and repaired, the system will continue to operate in a suboptimal manner because undiagnosed fault will cause the repaired components to fail as well. The design of the FDD system should also account for the fact that the complete set of all possible system faults may not be known. In this case, the attribution of a fault symptom to a particular cause will not be accurate, because of model inaccuracies. While the only information which can be given to the system user in such a circumstance is that there is a fault, but that it is not one of the faults implemented in the method, this information can still be of assistance to a service technician.

1.1.3 Fault Evaluation and Decision

Once the existence of a fault has been detected and the cause of the fault has been identified, the proper course of action must be determined. In many situations, this is chosen by the system user or service technician. As an assessment of the severity of the fault is essential to this decision process, the principal function of the fault evaluation system is making this assessment, which is commonly called the "fault level". The type of fault level can vary, as some faults are binary in nature, while other vary in a continuous manner. The fault evaluation module must therefore analyze the information provided by the fault detection module, which tells it that there is a fault, as well as the information provided by the fault diagnostic module, which tells it what the fault is caused by, in order to estimate how bad the fault is.

Once the fault level has been evaluated, the FDD method must select of the proper course of action. In the described FDD framework, this step is designated as the fault

decision module. The following options provide a sense of the possible choices which could be made by this module, depending on the exigencies of the particular situation.

- 1. Notify the user of the existence of a faulty condition, as well as the particular fault which has been diagnosed. Information about the fault detection signature and/or other potential faults may also be communicated to the user to properly convey information about the relative uncertainty of the diagnostic, in order to properly characterize the chance that the fault detection or the fault diagnostic modules did not correctly identify the fault. This fault evaluation procedure might be useful if the equipment owner or user has direct control over the system, and is able or desires to make his own evaluation of the status of the equipment as well as how to proceed with repairing it.
- 2. Record the existence of the fault, as well its diagnosis, in a logfile. This logfile might simply reside in the onboard computational framework of the FDD method, or it could be located in a remote location. Information about the confidence of the fault diagnosis could also be recorded. This procedure might be useful if the fault level is not high, or if it is either unnecessary or not practical to inform the user of the fault; when the service technician or the manufacturer examines the output of the logfile, they will be able to use this information most effectively.
- 3. Contact a service company directly, via a remote connection. This approach could dovetail with the previous approach, in that the service company could receive the information otherwise logged in the datafile regarding the nature and severity of the identified fault. Under such a framework, an FDD method which contacted a maintenance company directly for service could ensure that the system being monitored would be operating in a faulty state for a minimal amount of time. Obviously, such an approach would require a high degree of confidence in the FDD method's ability to correctly detect and diagnose faults, so as to prevent unneeded service calls.
- 4. Directly change the operation of the system in response to the presence of the diagnosed fault. Such a course of action might only be necessary or justifiable under the most extreme of fault conditions, e.g. if the system will undergo irreparable damage

if allowed to continue operating in its present state. The FDD method could also modify the system performance if it was integrated with the control system, so that the system performance is modified to compensate for the effects of the fault.

Clearly, a variety of other courses of action exist, depending on the system being monitored, the particular application of the system, and the structure and implementation of the FDD method. Nevertheless, consideration of the particular approach taken to evaluate the effects of the fault and provide the appropriate response is an important element in the job facing the designer of the FDD method.

1.2 Previous Work

While the previously discussed framework is useful in developing a general understanding of FDD methods, it will be primarily applied to FDD methods for air-conditioning systems in this research. As a wide variety of FDD methods have been implemented for air-conditioning and refrigeration systems, it is helpful to survey this body of work to gain a sense of the advantages and disadvantages of these approaches. In order to provide context for these studies, the general operation of air-conditioning systems will first be reviewed, and will be followed by a summary of a number of surveys which examined the frequency and types of faults which occur in field-installed air-conditioning equipment.

1.2.1 Air Conditioning System Overview

A schematic diagram of a vapor-compression air-conditioner is illustrated in Figure 1-6. The overall objective of the ideal vapor compression refrigeration cycle is the transfer of thermal energy from the air passing through the evaporator to the air passing through the condenser via the refrigerant. To see how this occurs, consider the refrigerant leaving the compressor, travelling toward the condenser in the direction of the boldface arrow. Having just been compressed, this vapor is at both a high temperature and a high pressure. As the vapor travels through the condenser and is cooled by the air blowing over the coils, it gradually gives up enough of its thermal energy to cause it to change from 100% vapor at the top of the condenser to 100% liquid by the bottom of the condenser.



Figure 1-6: Schematic diagram of the air-conditioner.

Once the refrigerant has fully condensed, it has the capacity to absorb more thermal energy via conversion back to a gas. This process is accomplished in two stages; first, the the refrigerant passes through an expansion valve into the evaporator coil. The expansion valve (typically a thermostatic expansion valve, or TXV) serves the dual purposes of regulating the flow and reducing the pressure of the refrigerant. This drop in pressure causes a corresponding reduction in the saturation temperature of the refrigerant, or the temperature at which the liquid refrigerant evaporates. As this low pressure refrigerant flows through the evaporator coil, the process of its evaporation causes it to absorb thermal energy from the air traveling past the evaporator coil. This process causes the air flowing over the coil to become cooler. After leaving the evaporator as 100% low pressure vapor, the refrigerant is compressed and returned into the condenser, completing the refrigeration cycle [6].

Due to the wide variety of requirements and applications which exist, many different types of air-conditioning systems have been constructed which implement this basic refrigeration cycle or variations thereof. Window air-conditioners satisfy the requirements for small room-size residential applications. Air-conditioning systems which serve the entire house are often constructed with either centralized air-conditioning systems, which place an evaporator at a central location and distribute the cool air through a ventilation system, or split air-conditioning systems, which distribute refrigerant lines throughout the house and cool the air locally. A variety of types of compressors are used in these units, including reciprocating compressors, scroll compressors, and rolling piston compressors; the particular compressor used also depends on the size of the cooling load and the application. Still other types of mechanical cooling systems exist for larger buildings, including systems which incorporate single and multi-stage chillers and cooling towers [5].

While the function of real refrigeration equipment is theoretically equivalent to that of the ideal refrigeration cycle described above, the behavior of the physical realization of such a system differs from that of the idealized system in a number of aspects which can have a significant effect upon the unit's performance. Some of these differences are expected, and their effects can be minimized or otherwise compensated for in the design of the unit. Other differences may be unforeseen by the design engineer, and are the result of aberrant behavior due to atypical environmental conditions or malfunctioning equipment. These undesirable behaviors are precisely what FDD methods seek to characterize and eliminate.

1.2.2 Common Faults in Air-Conditioners

Faults typically develop in air-conditioners via three different mechanisms: improper commissioning, premature component failure, and wear due to normal usage. Each of these fault mechanisms results in a degradation of the air-conditioner's performance, either because the air-conditioner ceases to function (hard faults), because of a reduction in the efficiency of the air-conditioner, or because the increased rate of wear for the air-conditioner components (soft faults). These faults can be manifested in the electrical, mechanical, or thermal interactions of the air-conditioner.

In order to avoid the consequences of malfunctioning and broken air conditioning equipment, studies have been performed to enumerate the different types of faults to which packaged air-conditioners are susceptible. These studies classify the faults according to a range of different criteria, such as cost to repair, importance to the overall function of the unit, and the tendency of a given fault to accelerate the onset of other faults. While their methods of comparison might differ, all of these studies are useful when attempting to understand the scope of faults which occur in package air conditioning units. Given the near ubiquity of RTUs, it may be surprising to find that only three major studies have been published in enumerating these faults. One possible reason for this fact is that failure information is often quite valuable, and this proprietary information is therefore not made public by equipment manufacturers. These studies were authored by Cunniffe, James, and Dunn in 1986 [18], Stouppe and Lau in 1989 [54], and Breuker and Braun in 1998 [11]. An additional study which examined both heating and air-conditioning equipment was published by Hasan in 1974 [25]; as this study focuses on larger types of equipment, such as cooling towers and chillers, it will not be considered here.

In [18], Cunniffe, James and Dunn conducted a survey of vapor compression refrigeration plants in a variety of different applications, such as low temperature refrigeration applications, air conditioning systems, and vehicle refrigeration systems, in order to quantify and enumerate the common faults which occur. Rather than quantify the statistics of particular faults, the ultimate causes of the faults were classified; of the 851 systems which were studied, 32% of the mechanical faults and 29% of the electrical faults were caused by unforeseen operating conditions. In comparison, 38% of the mechanical faults and 44% of the electrical faults were caused by faulty materials, manufacture, design, installation, service, commissioning, or maintenance. The remainder of the faults were either due to normal deterioration or remained unclassified.

As these statistics were collected, the authors observed that a number of operational faults overloaded the compressor, which consequently failed and was diagnosed as the faulty component. This type of failure is problematic because the compressor is often repaired without fixing the underlying fault. In order to address this concern, the authors identify a number of fault classes which cause overloading. High discharge temperatures represent one class of faults which account for 9-15% of the failures in reciprocating compressors, which are in turn caused by faults such as high intermittent plant operation, fouled condenser surfaces, non-condensible gases, or other unforeseen operating conditions. Liquid return to the compressor housing and refrigerant migration, in which liquid refrigerant accumulates in the compressor shell and then boils up into the compressor cylinders, can also cause a host of problems, ranging from increased discharge temperatures, to major mechanical damage, to the degradation of winding insulation. Poorly controlled expansion valve or evaporator dynamics, excessive equipment cycling, and inadequate system cleanliness also caused compressors to fail prematurely.

Another set of researchers [54] who systematically investigated the faults which are responsible for malfunctioning air conditioning equipment were Stouppe and Lau [54]. They examined 15,760 failures in units with a cooling capacity up to 50 tons (600,000 BTU/hr) over the course of eight years (1980-1987) by scrutinizing insurance claims which were filed for the repair of air conditioning equipment. Many different types of refrigeration systems were examined, incorporating both reciprocating and centrifugal compressors. While some compressor technology has changed in the intervening fifteen years, their basic findings are still quite useful in considering the range of failures which occur in refrigeration systems.

Of the 15,760 failures examined, 12,518 had their specific cause of failure denoted on the claim. The authors found that these units generally failed when they were approximately 10 years old, and that such units had no major inspections or overhauls over that entire period of time. Furthermore, 11,349 of the failures were electrical (comprising motors, controls, and electrical apparatus), while 4,411 were mechanical (compressor bodies, system piping, or vessels). It is important to reëmphasize the fact that compressors were separated into their two different functional halves, being the mechanical section of the compressor, including the pistons, valves, and associated hardware, and the compressor motor, which drives the mechanical apparatus that performs the compression.

The authors specifically examined the causes of failure for hermetically sealed air conditioning and refrigeration units: 76.6% of the failures were electrical (motor windings, control equipment, and other associated issues), 18.9% were mechanical (compressor valves, springs, bearings, connecting rods, pistons, crankshafts, lubrication), and 4.5% of the failures were caused by malfunctions in the refrigerant circuit. A few particular notes were also made trends which were observed in the causes of compressor motor failure. Insulation deterioration on the motor windings due to age and/or service, as well as unbalanced voltage and single phase operation were some of the main causes of the failure; degradation in motor stator windings was by far the most prevalent cause of motor failure, accounting for 84% of failures in hermetic motors and 74% in the non-hermetic motors. The remaining causes of the failures were generally broken rotor bars, bearings, and motor control equipment. Of the motor control failures, 168 failures were directly attributed to short cycling, or the repeated starting and stopping of the motor many times in rapid succession.

A more detailed study of mechanical compressor failures for reciprocating freon-based

units showed that the bulk of the failures could be attributed to two main causes. The first of these causes is that of metal fatigue in the internal suction and discharge valves and springs, due to the hundreds of millions of operating cycles that these parts see over the average lifetime. Liquid slugging, or the unintentional injection of liquid refrigerant into the cylinder, was also the direct cause of 20% of the mechanical failures, due to the hydraulic forces from the attempt to compress the incompressible liquid refrigerant which acts on the valves, valve plates, pistons, and connecting rods. Under normal operating conditions, gaseous refrigerant is pulled into the cylinder during the intake cycle, but when liquid refrigerant enters, these hydraulic forces can cause broken valves and valve plates, as well as cascading damage to the remaining mechanical components of the compressor.

While the information collected in [54] is valuable, it does not quantify the incidence of faults which would allow the RTU to continue operating in a less efficient manner, nor does it attempt to classify failures on the basis of their repair cost. This is a significant shortcoming in their report, as it only identifies the components which ultimately failed, not the proximate cause of those failures. Though many different faults can occur in an RTU, a significant portion of them can cause the compressor to fail; the identification of the compressor as the component which failed most often does not help to determine the type or frequency of problems in the RTU system which caused that failure. The cost of repair is also an important figure-of-merit in examining failures, as failures which are expensive to repair should have priority when choosing which faults to include in an FDD system.

Braun and Breuker [11] attempted to compensate for these shortcomings by examining two different types of faults in package rooftop air conditioners: those which caused the air conditioner to run inefficiently, but did not cause the equipment to cease operation, and those in which the RTU could no longer operate mechanically or electrically. By analyzing a statistically representative subset of a database containing 6000 separate faults observed from 1989 to 1995, the authors found that, of the fault classifications which resulted in "no air conditioning," or faults in which the unit was running inefficiently but was still electrically and mechanically operational, 60% were caused by electrical problems (such as motors and control problems), while the remaining 40% were caused by mechanical faults. On the basis of cost, however, compressors represented the most significant portion of the total unit repair cost (24%), even though they break much less frequently.

In examining the compressor failures, the authors found that approximately 70% of the compressor faults were due to internal motor problems, such as shorted windings, open windings, or locked rotors. One interesting fact which they point out is that, although the immediate cause of compressor failure was usually attributed to motor problems, the proximate cause was often a mechanical fault which overloaded the motor. Furthermore, they reiterate one of the conclusions from [54], that the prevalent cause of this mechanical overloading condition was again liquid refrigerant in the compressor cylinder. This speaks directly to the difficulty of the fault diagnostic problem, as the diagnosis of the faults in the compressor motor is difficult to directly ascribe to the presence of liquid slugging.

The authors also specify the main contributors to the costs for faults in the condenser, evaporator, and general air handling systems. In analyzing repairs to the condenser unit, defective fan motors accounted for 50% of the cost, while fouled coils represented 30% of the cost. In comparison, fouling represented 61% of the cost of repairing an evaporator unit, and coil damage represents 25% of the cost. One interesting sidenote is that only 18% of the evaporator fouling and 14% of the condenser fouling faults resulted in a loss of comfort. Other general costs required to fix miscellaneous electrical components were dominated by contactor failure, which represented 40% of the cost, followed by 27% for general damaged components, and 13% for wiring errors and short circuits.

Though much of the stated motivation in developing FDD methods for air-conditioning systems focuses on the effect on system owner and user, equipment manufacturers are also affected by the incidence of faults in equipment. As documented in [13, 34], the difficulty of properly identifying and diagnosing faults in field-installed equipment results in air-conditioning technicians generating a large number of misdiagnoses, either because the technician does not know that a given fault can be fixed in the field or because the failure is attributed to an incorrect cause. According to Copeland Corp., half of the compressors which are returned to the factory under warranty are victim of this tendency to misdiagnose; when these diagnoses are checked by factory technicians, no defect is found in nearly half of them. This is often referred to as the NDF (no defect found) problem, and is another strong motivation for the development of accurate and cost-effective FDD methods for air-conditioning systems.

1.2.3 FDD Methods for Air-Conditioners

While it is clear from §1.2.2 that the incidence of faults in HVAC equipment is sufficiently high to warrant the development and implementation of FDD systems, there are a number of other factors which can have important consequences for the design of such systems. First among these is the fact that many buildings are not owner-occupied. This fact makes the market for air-conditioning system very first-cost sensitive, as the owner has little incentive to provide more efficient and expensive equipment when less expensive equipment will suffice [33]. The air-conditioning industry has responded to this fact, producing little equipment which exceeds the federal standard; as of 2000, less then 10% of the packaged air-conditioners with a cooling capacity between 5.5 and 11.25 tons¹ exceeded the federal standard for energy consumption by 20%, 21% of the packaged air-conditioners with a cooling capacity between 11.25 and 20 tons exceeded the federal standard by the same amount [51].

When buildings are owner-occupied, higher-efficiency air-conditioners are more frequently used, but they are still adopted more slowly than might be expected (only 6.7% of residential air-conditioners exceed federal standards by 40%). A variety of reasons contribute to this phenomenon; for example, the air-conditioning system is often one of the last systems to be installed in a house, and cost overruns make less expensive air-conditioning units attractive, even despite knowledge of higher operating costs [61]. In addition, as the cost of energy per month is much lower than most other commercial expenses (such as salaries or manufacturing costs), little attention is often paid to the cost of operating an inefficient air-conditioning system unless energy prices are extremely high [33].

Motivated both by the need reliability in air-conditioning equipment and the potential for increased interest in high-efficiency units, there has been a surge over the last 10 years in the investigation and development of FDD methods for air-conditioning units. Much of this work has focused on using temperature and pressure measurements in order to evaluate the relative health of the unit as well as forecasting any incipient problems which have yet to degrade the performance seriously, as can be seen by surveying the published literature on such systems, some of which is treated in detail in [15].

¹1 refrigeration ton = 12,000 BTU/hr = 3.52 kW

A number of papers have been published that address the problem of casting FDD methods into the general framework for FDD systems discussed in 1.1. Haves, et al [26] presents a particularly thorough perpective on some of the challenges inherent in constructing these methods. The authors of [21, 44] also discuss the variety of different approaches for implementing FDD methods on air-conditioners, and also address concerns and potential strategies for achieving higher market penetration with such systems. Stylianou [55] also discusses ways that these FDD methods might be integrated into building energy management systems. Thybo, et al [57] also provide some interesting perspectives on implementing FDD methods in air-conditioning units after their research in developing FDD methods for refrigerated display cases for supermarkets. Some important considerations identified in designing an FDD method include the method's scalability for different types of equipment, reducing the number of sensors in the system due to their cost and added complexity, and minimizing the procedures required for a technician to commission the FDD system. The authors also emphasize the fact that FDD methods are generally more effective when incorporated into the system during the design stage. A set of important faults is identified via a survey in [64], which determined that many of these faults occur because of improper design and commissioning. The authors of this paper also surmise that fault detection in air-conditioners is increasingly difficult because the high complexity of the systems can obscure the effects of the faults and the large number of components can make it difficult locate the source of a fault.

Many signal-based FDD methods have been developed for air-conditioning systems. One popular approach involves identifying a set of relationships between measurements of steady-state quantities (typically temperatures and pressures) which are indicative of particular faults. Such methods are typically referred to as rule-based methods, as the relationships between variables are expressed in the form of rules derived from physical knowledge of the system. notes on the training of the system.

how many measurements do they need?

Jim Braun and his graduate students at Purdue University have been using and refining this rule-based approach for FDD methods since 1995, and have experimentally demonstrated a system which can diagnose six common faults: loss of volumetric efficiency of the compressor, fouled evaporator coils and filters, fouled condenser coils and filters, liquid line restriction, incorrect refrigerant charge, and the presence of noncondensible materials in the refrigerant loop. This system was originally developed for air-conditioners with fixed orifice expansion (FOX) devices [12, 43], and was also investigated in systems with TXVs [14]. Improvements to this FDD method resulted in the ability to successfully detect and diagnose multiple simultaneous faults [37, 38, 40, 41], and this method was experimentally demonstrated to identify faults and increase the operating efficiency of airconditioners at a number of locations in California [36,39]. The detector used to ensure that the air-conditioner is operating in steady-state was subsequently studied in [30] where it was proposed that the two standard measurements which are used to determine steadystate (the evaporator superheat T_{sh} and condenser subcooling T_{sc}) were not sufficient to determine the steady-state in all tests, and that all of the variables should be analyzed before steady-state operation can be declared.

Other research also incorporates similar rule-based approaches. An object-oriented FDD method is developed in [24], which uses rule-based methods to evaluate the performance of the air-conditioning unit, and also evaluate the performance of the sensors by implementing redundancy checks on the sensors. Rule-based FDD methods are also used in [31] to identify faults in a variable speed vapor compression system, and a similar system is also evaluated in [22], albeit with a larger number of measurements.

A variety of black-box system-modeling FDD methods have also been tested. These methods do not require any physical knowledge of the air-conditioning system, but instead use training data to help the model characterize the non-faulty behavior of the system. The authors of [?] develop a method which combines polynomial regression and locally-weighted regression techniques with statistical machine learning techniques to identify faults in the air-conditioning system, and test this method on detecting incorrect refrigerant charge in an experimental unit. Genetic algorithms are used in [1] to identify faults in boilers, while the performance of rule-based methods is experimentally compared with the performance of a method which uses fuzzy models and classifiers to detect faults in a three zone HVAC system in [9]. A similar fuzzy-modeling approach is also taken in [65], along with the use of vibration analysis to identify faults in pumps and motors. Rule-based knowledge is also used with artificial neural networks in [23] to identify fouling in an air-handling unit.

Grey-box system-modeling techniques, in which information about the physical processes governing the system are incorporated into the model, have also been extensively used. While these methods typically also require some level of initial training to distinguish faulty behavior from nonfaulty behavior, much of this training only requires the specification of thresholds, and does not require the full characterization of the fieldinstalled equipment. Physical models of the system are formulated in [63], which uses recursive least squares to identify the model parameters from training data, while physical models are also used in tandem with nonlinear observers and threshold-checking methods to detect condenser fan failure and capillary tube blockage in [60]. State-space models of an air-handling unit are integrated into a Kalman filter to identify and update the model parameters in [59], and airflow and sensor faults are experimentally identified based upon features in the residual waveforms generated by the Kalman filter. A state machine-like approach is also used in [?] to identify when valves and actuators get into faulty states, as when they are stuck open.

Hybrid grey-box approaches, in which machine learning techniques are used to identify parameters of physical model, have also been used extensively. Neural network and bond-graph techniques are used to identify parameters of a physical model of a refrigeration system in [57,58], allowing faults to be diagnosed via fixed and trending thresholds. This method also integrates the fault detection system with a controller for the equipment, to mitigate the effect of the faults. The challenging problem of distinguishing the slowly changing characteristics of the air-conditioning system from soft faults is discussed in [27], in which radial basis functions and direct-search algorithms are used to identify the physical parameters of a system and identify the presence of fouling and valve leakage faults in an air-handling unit.

The identification of sensor faults, as distinct from system faults, is addressed in [62] by analyzing discrepancies between sensor readings which are related through a model. The model outputs are compared with the sensor outputs, and genetic algorithms are used to determine the existence of sensor faults in the air-conditioning unit.

Research into non-temperature sensor based FDD methods is another ongoing area of research. A preliminary system is developed in [20] which detected changes in the system due to a variety of faults from measurements of the motor current, but this system was

not developed into afull FDD system which could diagnose separate faults. FDD methods based solely upon electrical measurements are also tested in [2, 3] for the purposes of identifying a variety of types of faults, such as incorrect refrigerant charge and fan imbalance. Copeland Corporation has also developed a FDD system for compressors based upon measurements of electrical power, named the ComfortAlert system [13]. This system is designed to identify basic compressor faults, such as long run time, short cycling, system pressure trip, locked rotor, open circuit, or low control voltage. This system has also been demonstrated to be effective and has been marketed and distributed since 2002. Other relevant literature regarding the detection of motor faults includes work published in [7,8,46,48], among numerous others.

1.3 Electrically-based FDD techniques

Previous work in developing FDD systems sets the bar high for making new contributions to FDD systems in packaged and unitary air-conditioning units. Existing systems have detection thresholds which are sufficiently low that they can detect faults before a 5% drop in either the capacity or coefficient of performance (COP). As these systems have also been developed with an eye toward commercial implementation, FDD systems like that developed at Purdue University are projected to cost as little as \$250-300/unit [39].

One notable characteristic of many of the FDD methods discussed in §1.2.3 is that they rely upon a relatively extensive network of sensors. Many of the methods have five or more temperature sensors, as well as pressure sensors, mass-flow sensors, and relative humidity sensors. While these mechanical sensors can provide valuable information about the state of an air-conditioning system, their use in a FDD method must be considered in the context of their cost and rate of failure. For example, mass flow sensors are typically very expensive, with prices exceeding a few hundred dollars per unit. Other sensors, such as temperature sensors, are prone to bias if they are not properly mounted to the measured surface, or if a radiation shield is not installed properly. Much like air conditioners, it is clear that sensors are vulnerable not only to hard faults, but also to soft faults, such as sensor bias due to environmental or unforeseen manufacturing defects. Though the ability of the FDD system to successfully identify faults certainly may outweigh the sensor

reliability concerns, the effects of both cost and reliability must be considered in the design of FDD methods for air-conditioners.

Another interesting observation which might be made of most of the extant FDD methods is that many of the common faults identified in the surveys of §1.2.2 are not identified by the FDD methods. In the case of many of the electrical faults, a variety of methods have already been developed by the community of engineers who study motor faults which could be easily adapted to the case of identifying faults in the compressor or fan motors. Other faults simply are simply not conducive to the types of measurements made by the majority of the FDD systems. For example, even though liquid slugging is identified by all three fault surveys as a primary cause of damage in compressors, no published FDD method includes a means for identifying this fault. This is probably due to the fact that a substantial amount of sensitive mechanical instrumentation must be installed in order to detect this phenomenon [42, 52, 53].

Mechanical diagnostic techniques based upon the output of electrical sensors represent an interesting and potentially viable alternative fault detection approach for air-conditioning systems which addresses both of the above concerns. In effect, these methods measure the currents and the voltages at the terminals of the electromechanical device, and then identify faulty mechanical behavior on the basis of these observations. These techniques are fundamentally rooted in the first law of thermodynamics: in many situations, the electrical power flowing into an electromechanical device is directly to the mechanical power flowing out of it, so that changes in the mechanical load of the motor which are related to fault behavior can be observed in corresponding changes in the electrical power flowing into the motor. FDD methods using this approach either use a signal-based approach, in which *a priori* knowledge is used to relate mechanical faults to particular features observed in the sensor output, or a model-based approach, in which the observed inputs and outputs of the system are used to characterize the behavior of the system and determine the existence of any faults.

This electrically-based approach to fault detection, suggested by [2,3] has a variety of benefits, not the least of which is the fact that electrical diagnostics, such as broken rotor bars and shorted windings, can be performed without using any additional sensors (unlike the FDD methods which rely upon mechanical measurements.) The electrical information can also be used to measure the energy consumption of the air-conditioning system for end-use load information purposes. Perhaps the greatest benefit, however, is that electrical sensors are generally easier to install, less expensive, and more reliable than the equivalent mechanical sensors. This is due in part to the fact that electrical sensors do not need to be in close physical proximity to the unit to function well, allowing them to be placed indoors or in a similarly protected location, while at least part of the physical air-conditioning apparatus (the condensing unit) usually resides outside. These features have not gone unnoticed by industry, as the ComfortAlert product manufactured by Copeland Corp relies upon electrical measurements to perform its diagnostic procedures.

Another appealing characteristic of electrically-based FDD methods is that diagnostics can conceivably be performed on an aggregated electrical signal which contains electrical power information for multiple loads. Generally referred to as non-intrusive load monitoring (NILM) [19,32,35,47,49,50], this technique is useful because it can further reduce the number of sensors needed to identify the operation of loads and perform control and diagnostic operations for those loads, since multiple loads can be monitored simultaneously. There are limits to the number of loads which can be effectively monitored with a NILM, as well as the types of diagnostics which can be successfully implemented, due to bandwidth and noise limitations; nevertheless, the synergy between electrically-based FDD methods and potential NILM applications makes the development of such FDD methods that much more attractive.

Naturally, this alternative approach to fault detection and diagnostics also has its limitations. One such limitation is apparent in the use of electrical measurements to detect changes in a motor's mechanical load; the motor is being used for the dual purposes of both a transducer and an energy conversion device. While motors are typically designed to be good energy conversion systems, they are not usually intended to be used as transducers, so that variations in the motor's operating characteristics, while not problematic for their role as energy conversion systems, make it much harder to develop reliable fault detection methods. In some cases, there are mechanical faults which have no observable effect on the electrical variables because of effects like noise or scaling problems, such as arise for loads coupled through gearboxes. Electrically-based methods can also require substantial computational support, although the decreasing cost of computation and the prevalence of similar requirements among other FDD methods for air-conditioners suggest that this is less of a barrier than might otherwise be perceived. The final disadvantage of this approach is caused by the fact that the wide variety of mechanical changes, which can be measured via temperatures, pressures, forces, and so forth, are being mapped into the relatively small number of electrical variables, i.e. currents and voltages. This mapping can make fault isolation more difficult, since different types of mechanical faults sometimes have identical effects on the electrical variables.

The observation that different mechanical faults may not be individually distinguishable because they have identical effects on the electrical variables has a direct impact on the design of the FDD method. It is therefore incumbent upon the FDD method designer to carefully model the physical behavior underlying the different mechanical faults, so that distinguishing characteristics of each fault might be identified and utilized for fault isolation. The high bandwidth of electrical sensors is of considerable assistance in this process, as it makes it possible to identify fault signatures which contain relatively high-frequency behavior. Fault signatures which have timescales ranging from fractions of a second to many hours can therefore be used in these electrically-based FDD techniques; faults can thus be isolated not only by looking for different types of behavior on the same interval of time in the signal or model, but also by analyzing the input data on a number of very different timescales. Such an approach differs markedly from that used by many other FDD methods, which rely upon steady-state features of the measured variables partly because of the low bandwidth of many mechanical sensors, e.g. thermocouples.

1.4 Research Overview

The main objective of this research is the development of electrically-based FDD methods for a set of common faults in air-conditioners. Though most extant FDD methods for air-conditioners rely upon mechanical sensors, the opportunity to identify a range of mechanical faults with a small number of reliable eletrical sensors is quite compelling, as is the fact that such a FDD system would be able to identify both electrical and mechanical faults with a single sensor array. Moreover, the relatively low cost for the sensors and processing system makes such an approach attractive in the cost-sensitive air-conditioning market. This research represents a continuation and dramatic expansion of the early efforts initiated by Peter Armstrong and published in [2–4], which suggested the potential inherent in these approaches. Three particularly common and problematic classes of faults will be studied in this research: airflow faults, liquid slugging, and refrigerant leaks. Each of these faults is investigated theoretically and experimentally, and this document will address both the fundamental characteristics of these faults as well as the many experimental considerations which arose in inducing and detecting these faults in commerciallyavailable equipment.

With regards to the structure of the remainder of this document, the airflow diagnostic methods will be discussed first in Chapter ?? due to the fact that many of the issues which surround the simulation and parameter estimation of induction machine models are treated extensively in this chapter. The liquid slugging FDD methods, which also rely upon the induction machine model of Chapter ?? will then be addressed in Chapter ??. Chapter ?? will address the diagnostic techniques used to identify the presence of refrigerant leaks in an air-conditioning system with electrical measurements and two temperature measurements, and then the range of FDD methods developed over the course of this research will be reviewed and placed in the larger context of potential air-conditioning FDD systems in Chapter ??. Each of these chapters will begin by motivating the development of FDD methods for the particular fault of interest and reviewing the previous work done in identifying these faults. The theoretical background used to develop the electricallybased approach to identifying these faults will then be discussed; this will be followed by a survey of the experimental apparatus used to simulate and develop the particular diagnostic techniques. Finally, the experimental results for the class of faults studied will be presented and discussed at the end of each chapter.

Bibliography

- P.P. Angelov, R.A. Buswell, V.I. Hanby, and J.A. Wright. A methodology for modeling HVAC components using evolving fuzzy rules. In 26th Annual Conference of the IEEE Industrial Electronics Society, volume 1, pages 247–252, Nagoya, 28 October 2000.
- [2] P. R. Armstrong. *Model Identification with Application to Building Control and Fault Detection*. PhD thesis, Massachusetts Institute of Technology, September 2004.
- [3] P.R. Armstrong, C.R. Laughman, S.B. Leeb, and L.K. Norford. Fault detection based on motor start transients and shaft harmonics measured at the RTU electrical service. In *International Refrigerigation and Air Conditioning Conference at Purdue*, number R137, pages 1–10, 12 July 2004.
- [4] P.R. Armstrong, C.R. Laughman, S.B. Leeb, and L.K. Norford. Detection of rooftop cooling unit faults based on electrical measurements. *HVAC+R Research Journal*, 12(1):151–175, January 2006.
- [5] ASHRAE. ASHRAE Handbook: HVAC Systems and Equipment. ASHRAE, Atlanta, GA, 2004.
- [6] A. Bejan. Advanced Engineering Thermodynamics. Wiley-Interscience, second edition, 1997.
- [7] M.E.H. Benbouzid and G.B. Kliman. What stator current processing-based technique to use for induction motor rotor faults diagnosis? *IEEE Transactions on Energy Conversion*, 18(2):238–244, June 2003.

- [8] M.E.H. Benbouzid, M. Veiera, and C. Theys. Induction motors' faults detection and localization using stator current advanced signal processing techniques. *IEEE Transactions on Power Electronics*, 14(1):14–22, January 1999.
- [9] M. Benouarets, A.L. Dexter, R.S. Fargus, P. Haves, T.I. Salsbury, and J.A. Wright. Model-based approaches to fault detection and diagnosis in air-conditioning systems. In *Proceedings of the Fourth International Conference on System Simulation in Buildings*, pages 529–547, Liege, Belgium, 1995.
- [10] J.E. Braun. Automated fault detection and diagnostics for vapor compression cooling equipment. ASME Journal of Solar Energy Engineering, 125:266–274, August 2003.
- [11] M.S. Breuker and J.E. Braun. Common faults and their impacts for rooftop air conditioners. *International Journal of HVAC+R Research*, 4(3):303–318, June 1998.
- [12] M.S. Breuker and J.E. Braun. Evaluating the performance of a fault detection and diagnostic system for vapor compression equipment. *International Journal of HVAC+R Research*, 4(4):401–425, October 1998.
- [13] B. Checket-Hanks. Compressor problem: 'No Defect Found'. Air Conditioning, Heating, and Refrigeration News, pages 10,12, 19 May 2003.
- [14] B. Chen and J.E. Braun. Simple rule-based methods for fault detection and diagnostics applied to packaged air conditioners. ASHRAE Transactions, 107(1):847–857, 2001.
- [15] M.C. Comstock and J.E. Braun. Literature Review for Application of Fault Detection and Diagnostic Methods to Vapor Compression Cooling Equipment. Technical Report HL 99-19, Report #4036-2, Purdue University, December 1999. Sponsored by ASHRAE Deliverable for Research Project 1043-RP.
- [16] G. Cooper. Air-Conditioning America: Engineers and the Controlled Environment, 1900-1960. Johns Hopkins University Press, 1998.
- [17] R.W. Cox. Minimally intrusive strategies for fault detection and energy monitoring. PhD thesis, Massachusetts Institute of Technology, September 2006.

- [18] M. Cunniffe, R.W. James, and A. Dunn. An analysis of fault occurrence in refrigeration plant and the effect on current practice. *Australian Refrigeration, Air Conditioning, and Heating*, 40(7):36–43, July 1986.
- [19] T. DeNucci, R.W. Cox, S.B. Leeb, J. Paris, T.J. McCoy, C.R. Laughman, and W.C. Greene. Diagnostic indicators for shipboard systems using non-intrusive load monitoring. In *IEEE Electric Ship Technologies Symposium*, Philadelphia, PA, July 2005.
- [20] D. Dragomir-Daescu, A.A. Al-khalidy, M. Osama, and G.B. Kliman. Damage detection in refrigerator compressors using vibration and current signatures. In SDEMPED 2003 – Symposium on Diagnostics for Electric Machines, Power Electronics, and Drives, pages 355–360, Atlanta, GA, 24 August 2003.
- [21] Michael Y. Feng, Kurt W. Roth, Detlef Westphalen, and James Brodrick. Packaged rooftop units: automated fault detection and diagnostics. *ASHRAE Journal*, 47(4):68– 72, April 2005.
- [22] H.T. Grimmelius, J.K. Woud, and G. Been. On-line failure diagnosis for compression refrigeration plants. *International Journal of Refrigeration*, 18(1):31–41, 1995.
- [23] A.K. Halm-Owoo and K.O. Suen. Applications of fault detection and diagnostic techniques for refrigeration and air conditioning: a review of basic principles. *Proceedings* of the Institution of Mechanical Engineers Part E - Journal of Process Mechanical Engineering, 216(3):121–132, August 2003.
- [24] C.Y. Han, Y. Xiao, and C.J. Ruther. Fault detection and diagnosis of HVAC systems. ASHRAE Transactions, 105(1):568–578, 1999.
- [25] A. Hasan. The occurrence of faults in heating and air conditioning equipment. *The Heating & Ventilating Engineering and Journal of Air Conditioning*, 47(561):447–455, April 1974.
- [26] P. Haves. Fault modelling in component-based HVAC simulation. In *Building Simulation '97; Fifth International IBPSA Conference*, volume 1, pages 119–127, 8 September 1997.

- [27] P. Haves, T.I. Salsbury, and J.A. Wright. Condition monitoring in HVAC subsystems using first principles models. *ASHRAE Transactions*, 102(1):519–527, 1996.
- [28] R. Isermann. Process fault detection based on modeling and estimation methods a survey. *Automatica*, 20(4):387–404, July 1984.
- [29] R. Isermann. Fault-Diagnosis Systems: An Introduction from Fault Detection to Fault Tolerance. Springer, 2006.
- [30] M. Kim, S.H. Yoon, P.A. Domanski, and W.V. Payne. Design of a steady-state detector for fault detection and diagnosis of a residential air conditioner. *International Journal* of Refrigeration, 31:790–799, 2008.
- [31] Minsung Kim and Min Soo Kim. Performance investigation of a variable speed vapor compression system for fault detection and diagnosis. *International Journal of Refrigeration*, 28:481–488, 2005.
- [32] C.R. Laughman, K.D. Lee, R.W. Cox, S.R. Shaw, S.B. Leeb, L.K. Norford, and P.R. Armstrong. Power signature analysis. *IEEE Power and Energy Magazine*, 1(2):56–63, March 2003.
- [33] T.M. Lawrence, J.D. Mullen, D.S. Noonan, and J. Enck. Overcoming barriers to efficiency. ASHRAE Journal, 47:S40–S47, September 2005.
- [34] S. Lee. Don't bury the compressor before it's dead. Air Conditioning, Heating, and Refrigeration News, pages 01,10, 4 April 2005.
- [35] S.B. Leeb, S.R. Shaw, and J.L. Kirtley. Transient event detection in spectral envelope estimates for nonintrusive load monitoring. *IEEE Transactions in Power Delivery*, 10(3):1200–1210, July 1995.
- [36] H. Li and J.E. Braun. On-line models for use in automated fault detection and diagnosis for HVAC&R equipment. In *Proceedings of the 2002 ACEEE Conference*, 7.147-7.158, Monterey, CA, 2002.
- [37] H. Li and J.E. Braun. An improved method for fault detection and diagnosis applied to air conditioners. ASHRAE Transactions, 109(2):683–692, 2003.

- [38] H. Li and J.E. Braun. Application of automated fault detection and diagnostics for rooftop air conditioners in california. In *Proceedings of the 2004 ACEEE Conference*, pages 3.190–3.201, Monterey, CA, 2004.
- [39] H. Li and J.E. Braun. An economic evaluation of automated fault detection and diagnosis for rooftop air conditioners. In *Proceedings of the International Refrigeration and Air Conditioning Conference at Purdue*, R145, pages 1–10, 12 July 2004.
- [40] H. Li and J.E. Braun. A methodology for diagnosing multiple-simultaneous faults in rooftop air conditioners. In *Proceedings of the International Refrigeration and Air Conditioning Conference at Purdue*, R131, pages 1–10, 12 July 2004.
- [41] Haorong Li. *A Decoupling-Based Unified Fault Detection and Diagnosis Approach for Packaged Air Conditioners*. PhD thesis, Purdue University, August 2004.
- [42] Z. Liu and W. Soedel. An investigation of compressor slugging problems. In 1994 International Compressor Engineering Conference at Purdue, volume 2, pages 433–440, July 1994.
- [43] T. M. Rossi and J.E. Braun. A statistical, rule-based fault detection and diagnostic method for vapor compression air conditioners. *International Journal of HVAC+R Research*, 3(1):19–37, January 1997.
- [44] K. Roth, D. Westphalen, and J. Brodrick. Residential central ac fault detection and diagnostics. ASHRAE Journal, 48(5):96–97, May 2006.
- [45] A. Salkin. Shivering for luxury. *The New York Times*, 26 June 2005.
- [46] R.R. Schoen and T.G. Habetler. Effects of time-varying loads on rotor fault detection in induction machines. *IEEE Transactions on Industry Applications*, 31(4):900–906, July 1995.
- [47] S.R. Shaw, C.B. Abler, R.F. Lepard, D. Luo, S.B. Leeb, and L.K. Norford. Instrumentation for high performance nonintrusive electrical load monitoring. *Transactions of the ASME Journal of Solar Energy Engineering*, 120(3):224–229, August 1998.

- [48] S.R. Shaw and S.B. Leeb. Identification of induction motor parameters from transient stator current measurements. *IEEE Transactions on Industrial Electronics*, 46(1):139–149, February 1999.
- [49] S.R. Shaw, S.B. Leeb, L.K. Norford, and R.W. Cox. Nonintrusive load monitoring and diagnostics in power systems. *IEEE Transactions on Instrumentation and Measurement*, 57(7):1445–1454, July 2008.
- [50] S.R. Shaw, L.K. Norford, D. Luo, and S.B. Leeb. Detection and diagnosis of HVAC faults via electrical load monitoring. *International Journal of HVAC+R Research*, 8(1):13– 40, January 2002.
- [51] J. Shugars, P. Coleman, C. Payne, and L.V.W. McGrory. Bridging the efficiency gap: commercial packaged rooftop air conditioners. In *2000 ACEEE Summer Study*, 2000.
- [52] R. Singh, J.J. Nieter, and G. Prater Jr. An investigation of the compressor slugging phenomenon. *ASHRAE Transactions*, 92(4):250–258, 1986.
- [53] R. Singh, G. Prater Jr, and J.J. Nieter. Prediction of slugging-induced cylinder overpressure. In 1986 International Compressor Engineering Conference at Purdue, volume 2, pages 444–459, August 1986.
- [54] D.E. Stouppe and T.Y.S. Lau. Air conditioning and refrigeration equipment failures. *National Engineer*, 93:14–17, 1989.
- [55] M. Stylianou. A response for performance degradation in rooftop units. Technical Report TR 1999-19, CEDRL - Natural Resources Canada, 1615 Lionel-Boulet, Varennes, Quebec, Canada, J3X 1S6, 1999.
- [56] TASC Technical Staff. Applied Optimal Estimation. MIT Press, 1974.
- [57] C. Thybo and R. Izadi-Zamanabadi. Development of fault detection and diagnosis schemes for industrial refrigeration systems - lessons learned. In *Proceedings of the* 2004 IEEE International Conference on Control Applications, pages 1248–1253, 2 September 2004.

- [58] C. Thybo, R. Izadi-Zamanabadi, and H. Niemann. Toward high performance in industrial refrigeration systems. In *Proceedings of the 2002 IEEE International Conference* on Control Applications, pages 915–920, Glasgow, Scotland, U.K., 18 September 2002.
- [59] P.B. Usoro, I.C. Schick, and S. Negahdaripour. An innovation-based methodology for HVAC system fault detection. *Journal of Dynamic Systems, Measurement, and Control*, 107(4):284–289, December 1985.
- [60] J. Wagner and R. Shoureshi. Failure detection diagnostics for thermofluid systems. *Journal of Dynamic Systems, Measurement, and Control,* 114(4):699–706, December 1992.
- [61] M.L. Wald. New math for summer: the cost of chill. The New York Times, 23 June 2005.
- [62] Shengwei Wang and Jin-Bo Wang. Robust sensor fault diagnosis and validation in HVAC systems. *Transactions of the Institute of Measurement and Control*, 24(3):231–262, 2002.
- [63] J. Wen and T.F. Smith. Development and validation of online parameter estimation for HVAC systems. *Journal of Solar Energy Engineering*, 125:324–330, August 2003.
- [64] H. Yoshida, H. Yuzawa, T. Iwami, and M. Suzuki. Typical faults of air-conditioning systems and fault detection by ARX model and extended Kalman filter. ASHRAE Transactions, 102(1):557–564, 1996.
- [65] M. Yoshimura and N. Ito. Effective diagnosis methods for air-conditioning equipment in telecommunications buildings. In 11th Annual Telecommunications Energy Conference, pages 21.1/1–21.1/7, Florence, 15 October 1989.