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An overview of techniques for diagnosing and detecting faults in household air conditioning systems

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A B S T R A C T

For more than 20 years, research on air conditioning system fault detection and diagnosis, or FDD, has been ongoing. Most approaches, nevertheless, were created with commercial structures in mind. The residential market offers distinct opportunities and problems that should be taken into consideration apart from the commercial HVAC and industrial refrigeration systems, even though a large portion of this work is applicable to this sector. In this work, the most recent approaches to FDD for air conditioning systems are reviewed and assessed. Opportunities for development exist in the area of applying these techniques to the home market, and they include: Taking into account the fault diagnosis level that offers the best value in the home market, Reducing the number of sensors needed for FDD. This research also examines the newly-emerging subject of cloud-based thermostat data-based defect detection for residential air conditioning systems. Large-scale analyses of thermostat data have only lately been released by publishers, but experts anticipate significant growth in this field.

Keywords:

Fault detection and diagnosis Residential buildings,Split systems Smart homes Smart thermostats

1.Introduction

Reducing energy usage and maintenance costs are the two most widely acknowledged benefits linked with successfully identifying and diagnosing faults in air conditioning systems. But even with these advantages, the expense of implementing failure detection and diagnosis (FDD) techniques in the residential air conditioning industry has not been sufficiently offset. This study is mostly devoted to developing cutting edge FDD techniques for household air conditioning systems and finding ways to lower these techniques' costs. On the other hand, the goal of this introduction is to provide a more thorough grasp of the advantages that efficient FDD offers.

1.1.Motivation for fault diagnosis

The home occupant is the primary beneficiary of reducing energy consumption, and the homeowner is the primary beneficiary of reducing the maintenance costs. However, FDD provides other important benefits to both the occupant and owner. The occupant may benefit more from the reliable comfort that FDD can provide than from the reduced costs of electricity, and the homeowner may benefit more from the satisfaction of the occupants than the reduced costs of maintenance. Furthermore, the homeowner and occupant are only two of the entities in a large value chain for air conditioning. However, many other enti- ties benefit from FDD as well.

Fig. 1 provides a simple representation of the air conditioning value chain, as well as the benefits that FDD provides its various entities. Reduced air conditioning loads will lead to reduced peak demand, which will significantly reduce the demands on the electricity generation, transmission, and distribution entities. Effective FDD methods could also improve the commissioning process of air conditioning systems and provide service technicians with a means of verifying the effectiveness of their service.

By detecting faults before the home occupant notices the effects, occupants can also address them during the shoulder seasons, which would reduce the strain on the air conditioning service industry during the summer. Furthermore, it would reduce repair costs for the home- owner. Effective FDD methods could provide the manufacturer and dealer with feedback about the design and sales of systems, in order to identify where improvement may be made and which systems have a history of reliability. Finally, improving air conditioning operations provide significant benefits to the environment by reducing refrigerant leakage and carbon emissions at power plants.

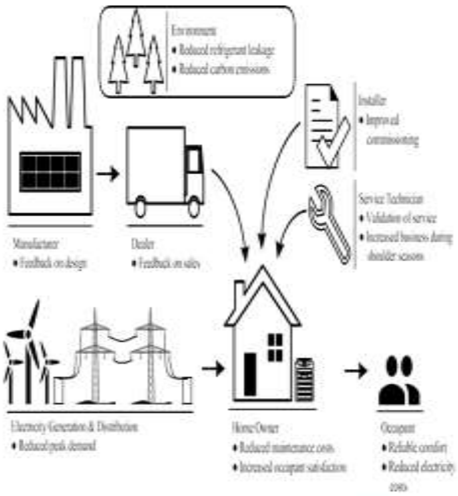

Fig. 1. EXamples of the benefits that automated FDD can provide throughout the air conditioning value chain

To achieve a widespread adaptation of FDD in the residential sector, one needs to understanding the benefit of this diagnosis throughout the value chain. Someone has to pay for higher costs of the FDD system, and multiple parties may share the costs if these benefits are realized. For example, electric-grid operators could provide an incentive in the form of a cash rebate for customers who install the FDD system. In addition, manufacturers could offer an FDD-enabled system to the dealer at a discounted price. The dealer, installer, and service company could also pay for access to the FDD data, in order to receive feedback about their services.

The following studies have highlighted the potential for significant improvement in the areas listed in Fig. 1:

• Reduced maintenance costs

As you can see in Ref. [1], service records showed that 65% of in- stalled residential systems required repairs, as well as 71% of installed commercial systems. For the compressor, a decreased performance leads to an increased workload. Therefore, the authors of [2] reported that compressor repairs are the most expensive repairs. Furthermore, according to a database of 6000 separate fault cases, compressor faults accounted for 24% of all repair costs.

• Reduced electricity costs

The authors of [3] reported that the operation of residential air conditioners operate at (at least) 17% below their rated efficiency. The authors of [4] reported that the prevalence of common faults included incorrect refrigerant charges, duct leakage, and low indoor air flow. In addition, the authors reported that an average of a 16% increase in efficiency could be achieved by simply addressing problems with charges and airflow.

• Improved commissioning

In more than 60% of residential air conditioners, the refrigerant charge is incorrect [3]. In addition, 47% of residential systems are oversized, with respect to the recommended sizing calculation [4].

• Reduced peak demand

Degraded efficiency increases peak demand levels, as well as the overall energy consumption. In Texas, peak demand levels in the summer are about 25% higher than peak levels in the winter [5], which is primarily due to air conditioning and chiller loads.

• Reduced carbon emissions and electricity costs

The FDD for air conditioning has a significant impact on overall energy consumption, in addition to the consumption of individual homes. Combined, air conditioning and space heating account for 30% of electricity expenditures, as well as 40% of total energy expenditures in the U.S. residential sector [6]. The residential sector accounts for 39% of U.S. electricity expenditures [6,7] and 20% of total U.S. energy expenditures [8]. Given that information, residential air conditioning and space heating account for 11.7% of U.S. electricity expenditures, as well as 8.0% of total energy expenditures in the U.S.

1.2. Previous reviews and surveys

The previous section established a broader understanding of the benefits that FDD may provide in the residential air conditioning market, and the following sections will introduce state-of-the-art tactics for this diagnosis in the residential sector. Over the past 20 years, the potential for significant energy savings and reduced maintenance costs has spurred a considerable amount of work aimed at diagnosing faults in HVAC systems. Several high-quality reviews have documented these efforts, and they provide an appropriate starting point for under- standing the broad scope of this work.

This section will introduce several of the most helpful reviews. These reviews are presented in an order that allows the scope to gradually narrow from general FDD methods (without a specific application) to methods that are specific to vapor-compression air conditioners. The present work is aimed at further narrowing the scope to specifically focus on the residential sector.

General FDD methods are reviewed in parts [9–11]. This three-part review classifies FDD methods according to whether they use a priori knowledge of the process. Generally, quantitative and qualitative model-based methods are a priori, and process history-based methods are not. The authors readily acknowledged that this distinction can be confusing because almost all physics-based models require process data for identifying parameters (e.g., tuning a gray-boX model), and many data-driven models are quantitative (e.g., polynomial regression and neural networks).

In addition to this classification, the authors of [9] presented a general mathematical framework, which highlighted a full FDD algorithm that includes several steps. Furthermore, they analyzed raw measurements to generate useful features, which were used to diagnose specific faults. Generally, this three-part review is a helpful way to understand the general FDD approach. However, the review did not provide details about specific applications.

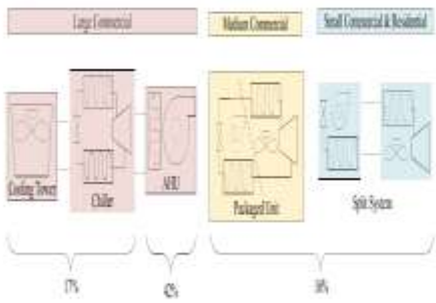

Fig. 1. An approximate breakdown of FDD literature for building systems, according to system type [14]. Other categories (25%) include overall building, water heaters, refrigerators, and lighting.

The authors of [12,13] reviewed FDD methods for building systems. The first part of this review provided a useful background for FDD methods, and it used the specific application of buildings as a motivation. The second part provided a comprehensive list of FDD publications for chillers , air conditioners, and air-handling units (AHUs).

The authors of [14] provided an update to the review found in Refs. [12,13] by including a comprehensive list of publications since 2004. This updated review broke down the ways that various methods are distributed throughout the body of literature. The authors reported that 45% of publications used exclusively black boX modelling methods, and 42% of publications specifically dealt with AHUs; see Fig. 2. This two- part review [12,13] and the update [14] are helpful for understanding how FDD work is distributed across various HVAC system. These three pieces also convey the general methods for diagnosing buildings ac- cording to FDD standards. However, by considering FDD work for all building systems, these reviews did not provide substantial detail about methods specific to air conditioners.

Fourteen FDD products that are currently available were compared in Ref. [15]. The authors classified the products according to several categories, including the intended market, the sensors used, the de tectable faults, and the methods and algorithms. They reported that FDD is being used in nearly all larger commercial buildings. They also concluded that these FDD products analyze the data of the building- automation system, rather than providing additional sensor information. The majority of methods and algorithms are rule-based, but some process history-based techniques are emerging. The rule-based methods typically incorporate expert systems or decision trees, as well as some physical understanding of the underlying processes. While this review allows the reader to understand the commercialized state of FDD for building systems, the majority of the methods have focused on large buildings using chillers and AHUs. These authors highlighted the need for designing commercial products for small buildings. The author of [16] provided a tutorial-style review of FDD methods that were specifically intended for vapor compression systems. This discussion described the important faults in vapor compression systems, the use of performance-monitoring for fault detection, the process of steady-state detection, and classifiers of fault detection and diagnosis. One of the greatest challenges identified was the balance between the cost of the sensors and the simplicity of the algorithm. While temperature sensors are cheap, analyzing the temperature measurements to generate useful features is complex. The authors also touched on the history and progress of commercially available products. At the time[16] was published, commercially available FDD tools for vapor compression equipment were generally comprised of tools that could be installed during routine maintenance, rather than tools designed for continual monitoring.

1.3 OVERVIEW

The previous section introduced several review papers that are relevant to the field of FDD for air conditioning. The authors of [9–11] reviewed general FDD methods. The authors of [12–14] reviewed FDD methods for building systems, and the authors of [15] reviewed commercially available FDD products for large buildings. The authors of[16] reviewed FDD methods that are specifically intended for vapor compression systems. The present review focuses on FDD for residential air conditioning systems. Section 2 reviews the typical process for performing FDD for vapor compression systems (with an emphasis on air conditioners). It then evaluates several methods that are specific to air conditioning, in terms of the sensor requirements and faults that are diagnosed. Section 3 reviews the emerging field of fault detection by using smart thermostat data. In conclusion, Section 4 discusses several opportunities for the following:

(a) Traditional FDD methods that utilize installed sensors.

(b) Ways to improve the fault-detection capabilities using thermostat data.

As highlighted in Fig. 2, most FDD methods have been developed for large commercial HVAC systems. Furthermore, even among the 16% developed for smaller air conditioning systems, the majority are focused on packaged rooftop units. While FDD methods for rooftop units are not optimized for the residential market, they are still applicable to smaller residential split systems. In addition, they play an important part in the development of air conditioning FDD. Therefore, Section

2 includes methods for both packaged and split systems, and Table 2 (at the end of Section 2) distinguishes between the methods applied to packaged and split systems.

2. Detection and diagnosis of air conditioning faults

2.1. Common soft faults in air conditioners

The vast majority of the FDD work related to air conditioners has been focused on soft faults, as opposed to hard faults. Soft faults result in degraded performances without sacrificing occupant comfort, whereas hard faults result in uncomfortable occupant conditions [2]. For the purposes of FDD, the distinction between hard and soft faults is that hard faults may be detected by analyzing the indoor conditions, whereas some insight to the system operation is necessary for detecting soft faults. The research community has had a greater interest in soft faults for two reasons:

They are more difficult to detect.

They will often remain intact for an extended time because they are not detected by the occupant.

Table 1 provides a list of both air-side and refrigerant-side soft faults

Table 1

Examples of soft, mechanical faults in air conditioning systems.

Air-Side	Refrigerant-Side
Low Evaporator Airflow	Liquid Line Restriction
- Clogged air filter	– Clogged filter/drier
- Fouled evaporator	– Malfunctioning expansion device
- Closed supply registers	Overcharge[a]
- Damaged ductwork	Non-condensables[a]
- Degraded blower	Undercharge
- Improperly installed blower[a]	– Leaking refrigerant
- Improper sized duct[a]	– Improper service[a]
- Leaking duct[a]	Compressor Valve Leak
Low Condenser Airflow	Fouled Evaporator[b]
- Fouled condenser	Fouled Condenser[b]
- Degraded fan	
- Improperly installed fan[a]	

[a] Common service faults.

[b] For fault diagnosis, refrigerant-side foulng is nearly identical to low air-flow.

that are commonly studied in the literature. Note that the faults listed in Table 1 are all mechanical faults. However, many service calls for air conditioning are due to the failure of an electric component, such as a failed contactor, a wiring short, or a failed motor [2]. However, these electrical faults typically result in a hard fault, and they are immediately noted and reported by the occupant. The vast majority of soft faults are related to mechanical systems (such as compressors, heat exchangers, and duct work).While the list of faults in Table 1 is far from comprehensive, it contains the most commonly studied faults. A portion of the air conditioning faults listed here are studied in Refs. [17–27]. Other potential soft faults (e.g., a malfunctioning expansion device, a vapor line re- striction, or a malfunctioning pressure switch) are not as commonly studied as those listed in Table 1. In addition, installing sensors for the purpose of FDD introduces an entirely new set of potential soft faults: sensor bias and drift. These sensor faults have been commonly studied in commercial AHUs. In Section 4.1, they are discussed as an area of research that must be adapted to air conditioning systems. A portion of the faults listed in Table 1 are considered service faults because they can only be introduced during the installation of the system or during the service [28]. For example, the presence of non-condensables or an overcharged system indicates that a technician in- correctly charged this system. However, an undercharged system may be due to a leak in the system (i.e., an operational fault) or an improper charge procedure (i.e., a service fault).

2.2. Quantifying the effect that faults have on operation

The faults listed in Table 1 will affect the system in two important ways: performance and operation. The effect that the faults have on system performance will be quantified by system parameters (such as capacity and efficiency). The effect on performance provides motivation for FDD, and it may be used to identify the faults that are most detrimental, as well as the efforts that should be prioritized by FDD. Typically, studies that quantify this effect on performance take one of these approaches: Several studies have analyzed service records or actively collected data during routine maintenance [1,2,4]. This approach has the additional benefit of providing insights about the prevalence of faults in the field. Section 1.1 cited these studies as ways to provide motivations for air conditioning FDD. Unfortunately, these field surveys are primarily focused on indoor airflow and refrigerant charge. Therefore, they do not provide insight about other potential faults, such as liquid line restrictions, compressor wear, and con- denser fouling.

• Other studies artificially impose faults in a controlled laboratory experiment [2,29–33] or impose faults in simulation [34,35].In both cases, the goal is to understand the impact that faults have on performance. While these studies don't provide insight about the prevalence of faults, they do include a broader range of faults. For example [30], presents a comprehensive study of the impact that is determined through laboratory experiments at various operating conditions. This impact includes various levels of (1) compressor leakages, (2) outdoor airflow faults, (3) indoor airflow faults, (4) liquid line restrictions, (5) refrigerant charge, and (6) non-condensable gas faults have on performance parameters. It includes the (1) latent cooling capacity, (2) sensitive heat ratio, (3) refrigerant mass flow, (4) condenser heat transfer, (5) evaporator heat transfer, and (6) compressor work.

In addition to the performance degradation, air conditioning faults can impact the system operation. This effect can be quantified by operating parameters, such as the air and refrigerant temperatures throughout the vapor compression cycle. For example, reducing the evaporator airflow will decrease the evaporator air-exit temperature, and reducing the refrigerant charge will decrease the level of sub- cooling. While faults may be detected by monitoring the system performance, quantifying the effects on the operation is critical to diagnosing faults. A large portion of the research in air conditioning FDD has been dedicated to understanding the expected effect that faults could have on the system operation. However, these effects evolve with air conditioning technology. As air conditioning systems have transitioned from fiXed- orifice to variable-orifice expansion devices, several studies observed that the operating parameters be-come less sensitive to faulty behavior [19,24]. The authors of [36] observed that a similar reduction in sensitivity occurs when a variable speed compressor is used on a commercial chiller unit. As technology continues to develop, there will be an ongoing need to understand the impact that faults have on operating parameters. The general FDD process described in the next section includes selecting appropriate measurements and transforming them into features that may be used to classify the operation as fault-free or faulty, then diagnosing the faulty operation.

2.3. The FDD process

Any given FDD system is likely to combine several methods. The mathematical framework presented in Ref. [9] describes this combined FDD:

(1) Features must be generated from raw measurements.

(2) Decisions must be based on these features.

(3) A fault must be diagnosed based on these decisions.

On its own, feature generation may involve a combination of qualitative rules, physics-based models, and data-driven models. After features are generated, entirely different methods may be used to detect and diagnose faults. Previous reviews have designated FDD systems as either being process history-based or quantitative model-based. However, most FDD systems realistically consist of several different methods.

This review will describe the general process that is commonly used for air conditioning FDD. This process consists of:

(1)Selecting features that use the available measurements (and choosing the correct measurements).

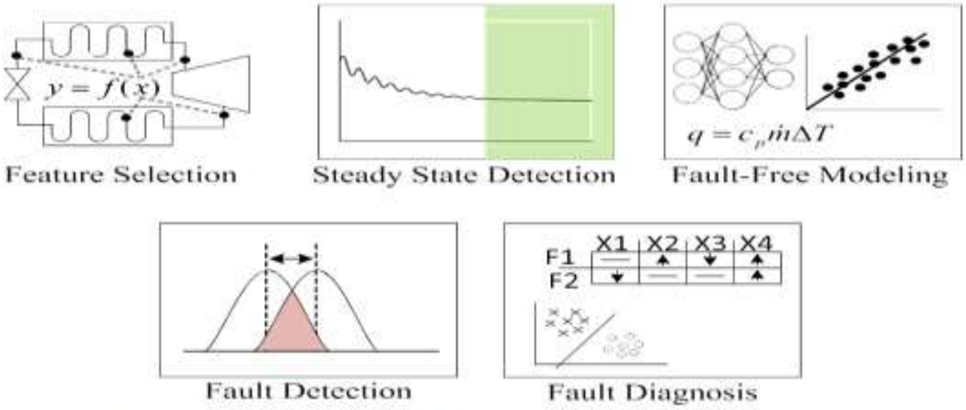

Fig. 3. An overview of common FDD processes for air conditioning systems.

(2)Detecting steady-state operations and filtering the data accordingly.

(3)Modeling the steady-state fault-free behavior of the system at the current operating conditions.

(4)Classifying the current operations as faulty or not.

(5) Diagnosing the fault

Fig. 3 visually illustrates this process with simple representations of the way these steps are often performed.

2.3.1. Feature selection

Features include the variables that are analyzed for detecting and diagnosing faults. They may be directly measured, or they may be de- rived from measurements and models. For example, the refrigerant superheat is derived from measurements of the temperature and pressure of the refrigerant exiting the evaporator. While superheat is a useful feature that is relatively straightforward for estimates that in- volve temperature sensors, many useful features are difficult and ex- pensive to obtain.

One option involves a direct measurement of a desired feature. For example, the refrigerant charge would be easy to analyze by directly measuring the total refrigerant mass. However, this approach isn't practical, and considerable effort has been devoted to estimating refrigerant charge by using other measurements.

In most FDD methods, a variable such as superheat is not used directly as a feature. Instead, the difference between the estimated superheat and the modeled fault-free superheat is used. This difference is known as a residual.

Determining a residual requires both an estimate during current operating conditions and an estimate during fault-free operating conditions. This latter estimate is typically determined by using a fault-free steady-state model. Therefore, Section 2.3.2 reviews the process of steady-state detection, and Section 2.3.3 Reviews the fault-free modeling methods.

The authors of [17] proposed one of the earliest air conditioning FDD methods. The set of features chosen in Ref. [17] has influenced much of the research since it was written, and these seven features include residuals for:

(1)The evaporating temperature (Tevap)

(2)Suction line superheat (Tsh)

(3)The condensing temperature (Tcond)

(4)Liquid line sub-cooling (Tsc)

(5)The compressor discharge temperature (Tdis)

(6)The air-temperature rise across the condenser (ΔTca)

(7)The air-temperature drop across the evaporator (ΔTea)

The method proposed in Ref. [17] was further evaluated in Ref. [18], and these 7 features were used for the evaluation. In addition, these features were used in Refs. [20,37]. The authors of [21] referred to these features (with the addition of the temperature difference across the liquid-line filter/drier Tll) as system state variables, and [21] de- rived other meaningful features from these system-state variables. The features that were ultimately chosen in Ref. [21] were designed to decouple the various faults, in order for each feature to correspond to a specific fault.

The Sensitivity Ratio Method proposed in Ref. [19] is an attempt to further reduce the number of features [19]. used four residual ratios as features. For example, one of the features is the ratio of the evaporating- temperature residual to the condensing-temperature residual. The Simple Rule-Based Method proposed in Ref. [19] used feature selection to avoid the need for a fault-free model. This method was compiled by choosing measurements that are sensitive to faults, but insensitive to operating conditions (e.g., return air and ambient air conditions). The authors of [19] presented these four features. While the premise of the methods in Ref. [19] seems promising, the methods were not further developed, and the state-of-the-art tactic shifted to the decoupling methods in Refs. [21,28].The authors of [21,28] presented a physics-based FDD method that focused on choosing features that decouple faults to enable a diagnosis of multiple simultaneous faults. For example [21], directly used refrigerant mass as a feature by deriving a gray-boX model of the refrigerant in the system. This gray-boX model was dubbed a virtual sensor, and it was further developed in Ref. [38]. The decoupling physics-based features have been more successful than earlier methods, and this success is partially due to the simple FDD classifiers enabled by this decoupling method.

There is a strong contrast between the original seven features presented in Ref. [17] and the physics-based virtual sensors presented in Ref. [21]. Essentially, the virtual sensors require more information about the system (e.g. estimated pressure losses and a model of the compressor), but the resulting classifiers are simple and intuitive. This contrast will become more evident as the associated FDD classifiers are described.

The potential features are largely limited by the available sensor measurements. Therefore, sensor selection is an important precursor to feature selection. Up until this point, the methods described intuitively placed sensors with an understanding of underlying thermodynamics. The authors of [39] used a genetic algorithm to balance the number of sensors with the diagnostic capability.

This work on sensor selection was a follow-up to work that had already been presented in Refs. [40,41]. While these researchers used many sensors, this earlier research focused on the detection and diag- nosis classifiers, rather than on feature selection. Given assumptions about the sensor costs, the genetic algorithm-based optimization in Ref.
[39] reduced the number of required sensors from 48 down to 8, while retaining the accuracy reported in Refs. [40,41]. Even though the optimization method may be of value, the reported case study is some- what trivial. The sensor set was reduced from 48 to 8, but most pro- posed air conditioning FDD methods already propose between 7 and 10 sensors.

Diagnosing a variety of faults requires many features and sensors, which drives up the price of an FDD system. The author of [42] re- cognized the need for low-cost FDD methods for smaller buildings, and he also proposed a basic FDD system to meet this need. The proposed solution is to use two temperature measurements and noninvasive load monitoring (NILM) to monitor performance (i.e., efficiency and capacity) and run some rudimentary diagnostics.

NILM was first proposed in Refs. [43,44] for the purpose of analyzing the operations of various household appliances from a single sensor, and [22,45–48] have furthered these methods for air conditioners. This set of NILM-based methods proposed the diagnosis of specific faults (e.g., refrigerant charge, liquid line restrictions, and compressor leakage) by analyzing the transients at a high sampling rate (i.e., 120 Hz). In contrast, the NILM-based method in Ref. [42] is significantly less sophisticated.

2.3.3 Steady-state detection

The majority of FDD methods include models developed for steady- state operation. The thermodynamics of vapor compression develop on a much faster timescale than overall building dynamics. Therefore, the system may be considered in a pseudo-steady state when the para- meters have settled to the point that the remaining transient behavior is due to drifting in the external driving factors. In order to use a steady- state model, the data must be processed with a steady-state filter. Generally, there are two types of steady-state filters: slope-based and variance-based.

The authors of [49] proposed a steady-state detector called the Exponentially Weighted Variance Method. Essentially, this method computes the running variance and exponentially weights the values; the more recent values have a larger impact on the overall weighted variance. This steady-state detector may be tuned by adjusting the exponential weighting and the threshold that determines when a steady state has been reached. While the original application for this method was AHUs, it was adopted for rooftop air conditioning systems in Refs. [18,19].

The exponentially weighted variance method was found to be very similar to the simple method for moving-window variances in Ref. [20]. The authors combined these variance-based methods with a method for moving-window slope, in order to improve the reliability of the filter. Placing a threshold on the slope of a measured value in a moving window will detect when a measured value is oscillating around a constant mean. However, placing a threshold on the variance within a moving window will detect when these oscillations fade. The authors of [39] used a similar approach; the exponentially weighted variance method is combined with a moving-window time derivative.

The proposed steady-state filters require that the past variance or slope must fall below a threshold. The selected window-size (i.e., the forgetting factor in exponentially weighted filters) and the threshold are important tuning parameters. The authors of [37] described methods for systematically selecting these parameters. They determined these thresholds by applying the 3σ rule to steady-state data from a large sample of experiments, and the window size was determined by applying the transient data from these experiments.

In order to detect a steady state, one must consider the features (i.e., the measurements) and the type of filter involved. The features used in this determination are known as *steady-state indicators.* Additional steady-state indicators increase the required computation, but fewer steady-state indicators may lead to the false detection of a steady state. The authors of [18] observed that the discharge temperature is the slowest of system states. Therefore, they only used this measurement as a steady-state indicator. However, they only used the liquid-line sub-cooling as a steady-state indicator in Ref. [19].The authors of [37] found that superheat and subcooling suffice as steady-state indicators. However, if the indoor temperature is changing, the superheat and subcooling may misidentify steady-state conditions. In this situation, the indicators are the evaporating temperature and the air-temperature drop across the evaporator. For robustness, the authors of [37] recommended using all features as indicators, and all features were similarly used as steady-state indicators in Ref. [50].

The experiments used in Refs. [18,37] indicate that it takes about seven to ten minutes to obtain and detect a steady state. When the cooling load is low, a cycling air conditioner may not run for more than five minutes before shutting off. Thus, the steady state won't be ana- lyzed during low-load conditions. However, applying FDD during low- load conditions is important for analyzing an air conditioning system during shoulder seasons. These seasons included the time period before comfort is affected in the summer and times when maintenance costs are low. Therefore, in order to obtain steady-state data, the system must either run longer than would normally be necessary, or the transients must be analyzed, instead of the steady state.

2.3.3. Modeling without errors

Commonly utilized residuals as features necessitate a model of the system functioning faultlessly and in steady state. In order to forecast system states, these models typically receive operating conditions (such as the return air and ambient air temperatures). The temperature of the air entering the condenser and the temperature and humidity of the air entering the evaporator are two external factors that many people frequently believe have no effect on a fault-free air conditioner [17].

The authors of [18] investigated the use of both lookup tables and low-order polynomial regression models for estimating fault-free values. The scientists discovered that although lookup tables can depict extremely nonlinear relationships when used with training data, they offered no advantages over low-order polynomial models. Using low-order polynomial models has the advantage that reasonable extrapolation can be done to some extent. In contrast, [18] contrasted neural networks and polynomial models using lookup tables [24,51, 52]. Enhancing steady-state models for FDD in packaged air conditioning systems was the main goal of the authors of [51]. Additionally, they contrasted four approaches to black-boX modeling: back-propagation neural networks, radial-basis functions, polynomial regression, and general regression neural networks (GRNN). According to the authors' findings, a hybrid approach works best when

- A GRNN is used for interpolation.
- A low-order polynomial model is used for extrapolation.

The authors of [20] also used this hybrid model. In addition, the authors of [24,52] explored both low-order polynomial models and back-propagation neural networks. Similarly, they concluded that third-order polynomial models are better suited to be fault-free models than the neural networks (due to a lack of significant nonlinearity).

The authors of [24] also included an interesting discussion about the challenges of using models in the field. One specific challenge of residential systems involves the variation between installations of se- parate indoor and outdoor units. The installation of these separate units results in significant variation in the length of refrigerant tubing. The authors of [53] presented a self-training model to overcome the chal- lenge of implementing models on a field-installed system. Specifically, they intended for this model to be developed after it is installed. This goal is accomplished by slowly developing the model as different op- erating conditions become available. To make an initial evaluation after installation, preliminary fault-free models are used with relaxed thresholds. If installation errors are not detected, the models will be further developed. These models continue to be developed as more data becomes available. When the operating conditions cover the desired range, the final fault-free models are developed, and the self-training ceases.

In this review, the models presented in Ref. [53] are the only so- lution presented for developing models on field-installed systems. The majority of methods use an extensive set of laboratory experiments to characterize the fault-free behavior. However, these experimental results are not available for all systems. Even when they are available, these models may not capture the variation in split-system installations. Installed systems will probably need to be benchmarked during the commissioning process. Methods such as the ones proposed in Ref. [53] should be further developed to customize the model for a specific installation.

2.3.4. Classifiers for fault detection

FDD can start when the features have been created using models and measurements. A classifier is a tool used in fault diagnosis or detection. Although they are frequently done independently, diagnosis and detection classifiers can occasionally be done in a single step.

For instance, FDD was carried out by the authors of [24] using a single classifier. FDD is carried out concurrently if features are dissociated such that each feature corresponds to a distinct fault. Stated differently, the concept of [21,28] is that diagnosing the defect associated with a detached feature is equivalent to detecting a fault using that feature.

The most popular classifier for defect detection uses straightforward feature thresholds. The researcher has found a flaw if a feature rises or falls below the threshold. The Sensitivity Ratio Method, the Simple-Rule-Based Method from Reference [19], and the decoupling techniques from Reference [21] are among the techniques that employ this kind of classifier. Nonetheless, a number of stricter classifiers have been proposed. A Bayes classifier was presented in Ref. [17] for determining when one of the residuals has a significant value according to a given statistical confidence. However, this method required the full covariance matrix under both current and fault-free operations. When implementing this method [18], simply assumed the same diagonal covariance matriX for both current and fault-free operations. This simplification detracts from the rigor involved in the original presentation.

To overcome this simplification, the authors of [20] proposed the Normalized Distance Fault Detection Classifier. Essentially, this detection classifier generalized the 3σ rule of thumb for higher dimensions. At this point, the unknown covariance matriX for the current operations is no longer necessary. The generalized likelihood ratio test (GLRT) was used as a detection classifier in Refs. [39–41]. Like other likelihood tests, the GLRT is used to determine how likely it is for the null hypothesis to be rejected. In this application, the GLRT is used to detect the abrupt introduction of a fault. Therefore, the null hypothesis states that operations have not changed. The GLRT requires that the nominal operating distribution should be known. As a result, the authors of [39–41] assumed that the mean and variance were known before the change point. While this assumption is not practical, rigorous methods for change point detection are certainly valuable for fault detection. However, the change point detection methods must account for uncertainty in the nominal operating distribution.

2.3.5. Classifiers for fault diagnostics

Rule-based and machine learning approaches will be the two general methods for diagnosing air conditioning faults that are examined. Using a qualitative rule-based approach, the user classifies the present operations by applying statistical approaches to identify the feature patterns for a group of errors. Using training data, a machine learning approach generates the patterns automatically.

The comprehensive review provided in Ref. [13] credited the authors of [54] for laying a foundation for future diagnostic work in qualitative rule-based approaches. The determination of [54] was that a given feature would increase, decrease, or remain unchanged under a given fault condition. These authors then generated a score to reflect the probability with which the current conditions match the fault conditions.

The authors of [17] applied these rule-based methods to packaged air-conditioners. Similar to the accompanying detection classifier, the rule-based diagnosis classifier in Ref. [17] also required the full probability distributions for both fault-free and current operations. The authors of [18,20] found this solution to be impractical, so the authors of [18] simplified this method by using the same diagonal covariance matriX for both fault-free and current operations. The Distance Ratio Fault Diagnosis Classifier presented in Ref. [20] circumvented the need for a covariance matriX. In this classifier, the authors designate a point for each fault type in the feature space. They then calculate the distance from the current operating point to each fault point. A fault is diagnosed when the ratio of the shortest distance to the next shortest distance falls below a preset threshold.

The fault diagnosis classifier presented in Ref. [24] is similar to that of [17]. However, the authors of [24] accounted for the possibility that some features won't change (i.e., increase or decrease) during certain fault conditions. This acknowledgment was necessary because the rules presented by Ref. [17] were developed for a packaged air conditioner with a fiXed-orifice expansion device.

A variable expansion device (e.g., a TXV) essentially introduces an internal control loop. In it, the refrigerant flow into the evaporator is controlled by its response to the superheat. This internal control loop results in a more fault-tolerant system, and it makes it more difficult to perform a fault diagnosis. With a TXV, many of the features do not increase or decrease with certain faults. For the rules in Ref. [17], each feature increased or decreased according to each fault that was con- sidered. However [24], included many situations in which there is no change. The authors of [24] observed that a system becomes even more fault-tolerant with the use of a variable speed compressor. Similar to Ref. [18], the authors of [24] simplified the statistics-based diagnosis classifier by ignoring cross-correlation.

While the diagnosis classifiers described to this point used rule- based methods supported by statistics, the authors of [40,41] explored several machine-learning methods for fault diagnosis. Rather than ob- serving patterns in the features under various fault conditions, the au- thors trained algorithms using the experimental data of a chiller under various operating and fault conditions [55]. The explored methods are Principle Component Analysis (PCA), Partial Least Squares (PLS), and Support Vector Machines (SVM). Among these methods, SVMs showed the best performance.The authors of [56] proposed a fault diagnosis classifier by using clustering methods. Traditional clustering methods can only handle faults of discrete magnitudes. (In other words, the severity of the fault must remain constant.) However, the authors of [56] proposed a vector- clustering technique to overcome this limitation and account for gra- dual faults. Essentially, this method clusters data according to the way the features are developing over time.

Although every fault-diagnosis classifier discussed here has been effectively applied in lab settings, none of them have been put to use on an operational field system. Refs. [21,28] and [25,57] present and utilize decoupling techniques that have been applied to field-operating systems. These techniques execute FDD concurrently since every feature is associated with a distinct defect.

2.3.6. Analysis based on transients

Feature selection, fault-free modeling, steady-state detection, and FDD classifiers are all part of the described FDD process. Every technique that has been discussed so far has been based on a steady-state analysis.

Table 2

An evaluation of several FDD methods for air conditioning systems. The emphasis is placed on the type of system used for development and validation, the source of data used for validation, the number sensor used, and the types of faults diagnosed.

Paper	Packaged/Split	Validation	Sensors					Diagnosed faults						
			T	RH	P	V	I	UC	OC	LR	CL	CF	EF	NC
[illegible]	packaged	lab data	8	1				√		√	√	√	√	
[illegible]	packaged	lab data	7	1				√	√	√	√	√	√	√
[illegible]	packaged	lab data	7					√	√	√	√	√	√	√
[illegible]	packaged	lab data	8	1				√		√	√	√	√	
[illegible]	both	field data	10	1	2			√	√	√	√	√	√	√
[illegible]	packaged	lab data				1	1	√	√		√	√	√	
[illegible]	unspecified	unspecified	8					√	√					
[illegible]	split	lab data	8	1				√	√	√	√	√	√	
[illegible]	packaged	field data	8					√	√	√		√		
[illegible]	split	lab data	7		2			√	√	√		√	√	
[illegible]	packaged	lab data	4	2									√	

a T = temperature, RH = humidity or wet-bulb temperature, P = pressure, V = voltage, and I = current.

b UC = undercharge, OC = overcharge, LR = liquid-line restriction, CL = compressor valve leakage, CF = condenser airflow/fouling, EF = evaporator airflow/fouling and NC = non-condensables.

c Some initial testing was performed in Ref. [17] but the method was tested more fully in Ref. [18] by using the data they obtained in Ref. [1].

d Sensitivity Ratio Method.

e Developed using their own laboratory testbed.

f Simple Rule-Based Method.

g The testing was performed using data from Ref. [18].

h Initial testing was performed with data from Ref. [18]. [57] then tests the decoupling method by introducing faults on a unit operating in the field. Finally, the method was applied to field data, but it didn't use a validation by extracting this field data.

i Testing was specifically performed for this project by using a testbed at another lab.

j The paper is unspecific: "The experimental data was collected from several devices of the same class, installed in different locations" [illegible].

k Tested by introducing artificial faults in a packaged unit that operated in the field.

l Developed using their own laboratory testbed as well as their own existing laboratory data. A single field test was performed to test ease of use.

However, several researchers have found advantages in analyzing transient periods.The authors of [22] used noninvasive load monitoring (NILM) to analyze the transient compressor and fan power and diagnose improper refrigerant charge, condenser fouling, and liquid-line restriction. The use of transients enabled the diagnosis of many common faults through the use of just one sensor. Also, these methods were capable of diag- nosing faults such as slugging and a flooded start. The authors proposed that using the NILM sensor with temperature sensors could improve the confidence of FDD.While the majority of decoupling methods presented in Ref. [21] rely on steady-state operations, the authors used the transient liquid- line temperatures to determine the liquid-line pressure drop, and they isolated a clogged filter/drier fault. The authors observed that the liquid line consists of a two-phase flow during the startup transients. There- fore, the subcooling will be near zero. While the liquid line contains a two-phase flow, the refrigerant pressure on either side of the filter/drier is directly related to the refrigerant temperature. Subsequently, the pressure drop across the filter/drier may be determined by using the temperatures. The authors of [58] also promoted the use of transient-based fault detection for vapor compression system faults. The authors noted that dynamic methods could detect fan failures quicker than static methods, and that dynamic methods were essential for detecting a very slow refrigerant leak early on (especially if a receiver is present). The challenge involved with implementing the proposed methods is that they require an accurate model of the transient behavior. This is a challenge because a transient model is more difficult to obtain that a steady-state model.Most of the transient-based methods have not progressed to field implementations. As with other proposed methods, they work well using laboratory data. However, a field implementation is required to validate the performance. As an exception, the authors of [21] implemented their liquid-line restriction indicator on a field-installed unit owned by the research lab and on other field-installed rooftop units

2.4. Evaluation of methods

To some degree, FDD methods are always evaluated when they are presented. Generally, this evaluation includes an evaluation of the method's accuracy (e.g., the rate of false positives and false negatives). They may also evaluate a method's sensitivity to faults. For example, the authors of [18] reported the level of fault severity that first gen- erated an alarm, as well as the level of severity required to consistently generate an alarm. The authors of [18] emphasized the utility of these evaluation methods as a general tool for all FDD methods. Similarly, the authors of [59,60] developed a method for evaluating any proposed FDD method. These authors rated an FDD method against the diag- nostic capabilities of a routine maintenance visit. The authors found that methods which include some level of fault assessment (i.e., de- termining if service is cost-effective) are most valuable.

When FDD methods are presented, they almost always work well.However, it is important to consider the method used to evaluate them when ascertaining their potential in the field. Almost all methods were developed by using data collected during careful laboratory experi- ments that involved artificially introduced faults (e.g., obstructing a portion of the heat exchanger). Research groups either perform ex- periments to generate their own data, or they use the data previously published by another group. After the initial development, some methods were tested with data collected from units operating in the field [25,57]. During many of these tests, faults were artificially in- troduced to these field units, similar to the ways they would be in- troduced in a laboratory.The present review provides a simple evaluation of FDD methodsthat were specifically proposed by air conditioning systems. These methods are evaluated according to:

(1) How they were validated.

(2) How many sensors are required.

(3) Which faults may be diagnosed.

Table 2 summarizes this evaluation, and it highlights how few of the methods have been applied to field units. In fact, the only tests using data collected from a field unit involved the decoupling method de- scribed in Ref. [21] and a later variant of it [25].

The Simple Rule-based Method from Ref. [19] is the only method listed that does not use a fault-free model; instead, it aims to combine raw measurements that will create features that are not sensitive to operating conditions. Notably, all of the methods—aside from the NILM-based transient method from Ref. [22] and the virtual airflow sensor from Ref. [27]—use between seven and ten temperature measurements. Several methods use the evaporative air inlet relative humidity as a driving factor for generating fault-free models. Diagnostic techniques for non-condensable defects are scarce. Even the techniques described in Ref. [19] need the assistance of a technician in order to differentiate overcharge problems from non-condensables. In this case, the technician would have to compare the expected refrigerant saturation pressure at the recorded temperature with the evaporator pressure. Although the decoupling techniques described in Ref. [21] are similar to the technician's test suggested in Ref. [19], they do differentiate between non-condensables and overcharge issues. The saturation pressure connected to the condenser temperature is measured and contrasted with the discharge pressure.The evaluation in Table 2 provides an overview of the state of FDD for air conditioning systems. This evaluation shows that most FDD systems focus on the same group of faults and have similar sensor re- quirements. This evaluation also highlights that most methods have been tested in a lab, but few have been implemented in a field-oper- ating system. Reducing and simplifying the set of sensors required for FDD will be an important part of increasing the cost-effectiveness of these methods. However, this practice will probably require the diag- nostic capabilities to be somewhat reduced.

3.Fault detection using thermostat data

Up until this point, all of the described FDD methods require sensors to be installed throughout the system, in order to gain insight into the operation of the vapor compression cycle. Larger commercial systems (e.g., chillers and AHUs) come installed with many of the required sensors for FDD− because this information is used for the control of the system. However, these sensors are not typically included in a residential system.
The thermostat in a residential setting is used

to measure the temperature inside the conditioned room. On the other hand, the availability of domestic thermostat measures has significantly risen with the introduction of smart and linked thermostats. Fault detection could be done with the use of this data.

Smart thermostat data typically consists of the following: the system state (e.g., heating, cooling, or off); the indoor temperature and relative humidity; and an estimate of the exterior temperature that is derived from an outside source (e.g., the National Oceanic and Atmospheric Administration). Since smart thermostat datasets sufficiently capture indoor circumstances, they are ideally suited for hard defect identification.

Recall that hard faults occur when the system is not able to maintain occupant comfort. Therefore, a hard fault may have occurred when the system is unable to maintain the setpoint. Nevertheless, many factors are not captured by the thermostat data that will have a significant effect on the cooling or heating load (e.g., occupancy, fenestration, and plug loads). Therefore, uncomfortable conditions may be due to abnormally high loads, rather than a system fault. The detection of soft faults using thermostat data is also possible because thermostat data provides some insight into the system operation (in the form of the system status).

Analyzing the runtime may indicate that a system's performance has degraded to the point that it runs longer or harder than it previously did. Thermostat-based fault detection is still a relatively new field of research. It has been partially hindered by the lack of publicly available smart thermostat data. Studies using relatively small datasets and simulations have proposed methods for improving smart thermostat control [61] and identifying inefficient home construction [62]; in- efficient occupant behavior [63,64]; and air conditioning system faults [65]. However, Ecobee's Donate Your Data program has made larger- scale data analysis available to many researchers. Analysis results for have only been published recently [66,67]. The authors of [66,67] analyze the aggregate behavior of the available data, while [66] is focused on user behavior and [67] is focused on runtime. Therefore, these initial studies do not attempt to identify faulty behavior in specific homes. Among all of these studies [65], is the closest in line with detecting soft faults in air conditioning systems. The authors proposed recursive least squares (RLS) models to describe the thermostat behavior and propose that a fault may be detected when the model parameters change. However, the authors of [65] developed this model-based method using simulations. Therefore, the method may not easily generalize to real thermostat data. Indeed, when analyzing the thermostat data for 7000 homes, the authors of [67] noted that there is large variation in system runtime from one home to the next, even at constant ambient conditions. This finding indicates that other important factors are not captured in the thermostat data. Cloud-based thermostat data provides a much-needed opportunity to bring fault detection for air conditioning to the residential sector. However, the process involved in performing reliable FDD may remain an open research problem. Large-scale analysis results have only recently become available, and this field of research will see considerable growth over the next decade.

4. Conclusion

The FDD approaches for home air conditioning systems have been evaluated in this review. Due to the little amount of work especially produced for home air conditioners, it has included numerous technologies used for commercial systems. Details have been provided regarding the standard FDD process for air conditioning, which includes feature selection, steady-state detection, fault-free modeling, and detection and diagnosis classifiers. Additionally, the methods have been assessed based on the types of sensors needed, the faults identified, and the degree of validation applied (e.g., lab data or field data). Most state-of-the-art fault diagnosis and diagnosis (FDD) techniques require seven to ten temperature sensors, and the faults they identify are fairly standard and include liquid-line restriction, undercharge and overcharge, compressor valve leakage, and condenser and evaporator airflow faults. The only reviewed method that was assessed using a field-installed system was the physics-based gray boX method, which was proposed in Ref. [21] and modified in Ref. [25]. Section 3 assessed the state of fault detection techniques for residential air conditioning systems utilizing simply thermostat data, while Section 2 reviewed the more conventional FDD literature mentioned above. Although there hasn't been much open-source data in this area historically, extensive evaluations of data from smart thermostats have lately been published. As a result, significant expansion in this field is anticipated. There are numerous ways to use thermostat data and installed sensor data to improve FDD in domestic air conditioning. Throughout the vapor compression cycle, sensors are installed to offer comprehensive information on which choices can be employed to diagnose specific defects.

Many thousands of systems already have their thermostat data public. When used appropriately, this data may offer limited fault diagnostics as well as effective issue detection capabilities. A small sample of the research opportunities in these domains are outlined in the following sections:

4.1. Opportunities for FDD using installed sensors

The cost of the proposed sensor package is the main obstacle to implementing FDD methods in a residential system. These opportunities focus on reducing this cost.

4.1.1. Using FDD techniques related to AHUs

AHUs have been the focus of a significant amount of FDD work for building systems, as mentioned in Section 1.2. Consequently, a number of study areas have been investigated for AHUs. They haven't, however, been sufficiently developed for air conditioning systems. Proactive diagnostics and sensor problem detection are two instances. A continuous or drifting bias and a total failure in the sensors required for FDD are examples of sensor defects. The following techniques have been suggested for detecting sensor faults: wavelet analysis [72,74], neural networks [75,76], joint angle analysis [73], and principal component analysis [68–72]. Effective sensor FDD in air conditioning systems would boost the system's dependability when inexpensive sensors were employed.

A set of techniques known as "proactive diagnostics" involve controlling a system in an unconventional manner in order to obtain diagnostic information that would not be feasible during regular operation [77–79]. Proactive diagnostics, however, might enhance these techniques' capabilities to diagnose air-side sensors and actuator faults in the air-handling portion of a rooftop unit. State-of-the-art air conditioning methods for FDD are all designed to be implemented during normal operation. However, proactive diagnostics may improve the capabilities of these methods.

4.1.2. Selecting the ideal degree of defect diagnosis

It is true that fault diagnosis presents a more challenging issue than fault detection. The majority of the suggested FDD techniques that were assessed employed a large number of sensors in order to accurately and separately diagnose every defect. It would seem sense to assume that if fewer fault diagnoses were made, fewer sensors would be needed. For instance, a pressure sensor is required for diagnosis between overcharge and non-condensables [19, 21], although these sensors might not be required if these defects are not identified one at a time. A balance between the FDD system's capabilities and its sensor package cost determines the ideal level of fault diagnosis.

4.1.3. Making the necessary sensor set simpler

A major simplification of the necessary sensor package is needed before FDD sensors can be sold to homeowners. This simplification entails lowering the total number of sensors, taking into mind the kind of sensors that are employed, and taking into account the locations where these sensors must be placed. Because the evaporator and condenser are separated by a significant distance in the domestic air conditioning market (due to the usage of split systems), this presents a special difficulty for FDD systems. The interior and outdoor units must have sensors placed in order to use state-of-the-art techniques. However, if the sensors were restricted to one unit, the cost would be significantly lower. Optimizing the defect diagnosis capabilities will also involve simplifying the necessary sensor set, as previously mentioned.

4.2. Thermostat data-based fault detection opportunities

The main difficulty in using thermostat data is the absence of numerous significant variables from the dataset. The prospects that follow center on making the most of the data that may be obtained from thermostat data analysis.

4.2.1. Growing the pool of information

The most basic type of thermostat data merely contains the system status and indoor temperature. An estimate of the outside temperature is frequently added to this dataset, although there might be other beneficial ways to add information. Researchers may be able to reduce modeling errors by using smart thermostat data if they have access to additional climate parameters (like solar irradiation), home parameters (like square footage and construction date), and system parameters (like nominal cooling capacity).

4.2.2. Comparing how various systems operate

The functioning of a single system is the primary emphasis of conventional FDD techniques. But now that cloud-based thermostat data has been available, a completely other strategy is feasible. The operation of numerous different homes may now be compared to one another, and the least efficient homes (in comparison to the others) can be found using an outlier detection technique.Through the use of anomaly-detection techniques, researchers were able to gain insight into individual homes by utilizing data from numerous residences. An expanded dataset would significantly increase the utility of this kind of technique. Comparable homes can be compared based on location and square footage.

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