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Author

Najafi, Massieh

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Fault Detection and Diagnosis in Building HVAC Systems

By

Massieh Najafi

A dissertation submitted in partial satisfaction of the

requirements for the degree of

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in the

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of the

University of California, Berkeley

Committee in Charge:

Professor David M. Auslander, Chair

Professor Andrew Packard

Professor Peter Bartlett

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ABSTRACT**Fault Detection and Diagnosis in Building HVAC Systems****by****Massieh Najafi****Doctor of Philosophy in Mechanical Engineering****University of California, Berkeley****Professor David M. Auslander, Chair**

Building HVAC systems account for more than 30% of annual energy consumption in United States. However, it has become apparent that only in a small percentage of buildings do HVAC systems work efficiently or in accordance with design intent. Studies have shown that operational faults are one of the main reasons for the inefficient performance of these systems. It is estimated that an energy saving of 5 to 15 percent is achievable simply by fixing faults and optimizing building control systems.

In spite of good progress in recent years, methods to manage faults in building HVAC systems are still generally undeveloped; in particular, there is still a lack of reliable, affordable, and scalable solutions to manage faults in HVAC systems. Modeling limitations, measurement constraints, and the complexity of concurrent faults have made the diagnosis of these problems as much an art as a science. The challenge is how to evaluate system performance within the boundaries defined by such limitations.

This thesis focuses on a number of issues that, in our opinion, are crucial to the development of reliable and scalable diagnostic solutions for building HVAC systems. Diagnostic complexity due to modeling and measurement constraints, the pro-activeness of diagnostic mechanisms, bottom-up versus top-down diagnostic perspectives, diagnosis-ability, and the correlation between measurement constraints and diagnostic capability will be discussed in detail.

We will develop model-based and non-model-based diagnostic algorithms that have the capability of dealing with modeling and measurement constraints more effectively. We will show how the effect of measurement constraints can be traced to the information entropy of diagnostics assessments and how this can lead to a framework optimizing the architecture of sensor networks from the diagnostic perspective.

In another part of this study, we focus on proactive diagnostics. In the past, the topic of proactive fault diagnostics has not been given enough attention, even though the capability of conducting and supervising automated proactive testing is essential in terms of being able to replace manual troubleshooting with automated solutions. We will show how a proactive testing problem can be formulated as a decision making problem coupled with a Bayesian network diagnostic model.

The algorithms presented in this thesis have been implemented and tested in the Lawrence Berkeley National Laboratory (LBNL) using real and synthetic data.

DEDICATION

I dedicate this work to my wife Iman and my parents. No words will ever express how grateful I am to them.

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1. INTRODUCTION

The operation of building HVAC systems accounts for more than 30 percent of annual energy consumption in United States [1, 2]. However, it has become apparent that only in a small percentage of buildings do HVAC systems work efficiently or in accordance with the design intent [3, 4]. Studies have shown that operational faults are one of the main reasons for the inefficient performance of these systems. It is estimated that an energy saving of 5 to 15 percent is achievable simply by fixing faults and optimizing building control systems [5].

Current methods for detecting faults or performance creep in building HVAC systems are labor-intensive. Typically, building operators or engineers use intuition and various rules of thumb to identify the problem. In practice, the labor-intensiveness of these tasks is such that they are not routinely performed, and they may never be performed in most buildings. If the achievable 5 to 15 percent energy savings are to be met in practice, building energy management systems must be capable of detecting when a failure has occurred or when performance is creeping, and be able to determine the likely offending hardware or operating condition. Automated systems for fault detection are therefore essential if low-energy or net zero energy goals are to be met nationally.

The topic of automated fault detection and diagnosis (FDD) has been an active area for research and development in applications such as aerospace, process control, automotive, and manufacturing over the past four decades [6-17]. In building HVAC systems, FDD has received increasing attention over the last decade or so [18, 19]. A variety of diagnostic methods from first-principle-model-based approaches [20-23] to empirical-model-based approaches [24-34] and qualitative/rule-based approaches [35-42] have been developed by researchers to automatically detect and isolate faults in HVAC systems: air handling units [22, 40, 43-48], chillers [23, 49-53], heat pumps [54-55], and others.

In spite of good progress in recent years, methods to manage faults in building HVAC systems are still generally undeveloped; in particular, a lack of reliable, affordable, and scalable solutions to manage faults in HVAC systems still exists. A variety of reasons, from technical barriers to financial motivations and regulatory obstacles, account for the absence of widespread availability and deployment of FDD systems [19]. From a technical standpoint, which is the focus of this thesis, modeling limitations, measurement constraints, and diversity and multiplicity of faults have made the problem significantly more complex.

In this thesis, we focus on a number of issues that in our opinion are crucial to the development of reliable, affordable, and scalable solutions. Diagnostics complexity due to modeling and

measurement constraints, proactiveness of diagnostic mechanisms, transition from bottom-up to top-down automated diagnostics, and the correlation between measurement constraints and diagnostics capability are the subjects that we will discuss in detail, and will also suggest some systematic solutions.

1.1 Modeling limitations and measurement constraints

One of the main challenges in building HVAC diagnostics is modeling limitations. The principles of HVAC equipment are known well enough to create a suitable model structure. However, from a widespread availability and deployment perspective, the accuracy of these models can be improved up to certain levels. Beyond that, extensive effort is required to obtain high-quality *a priori* knowledge¹ that affects the scalability attribute. This limits the applicability of diagnostic solutions that depend on highly accurate or detailed models. Such models require an extensive amount of configuration data that may not be available or measurable in practice.

On the other hand, when the focus leans toward less accurate models, either by using simplified first-principle models or empirical models with some level of uncertainty, the new challenge then becomes how to differentiate inconsistencies (the difference between system outputs and model predictions) that arise from modeling errors and system faults.

One way to deal with such complexity is to change the diagnostic focus to behavioral patterns instead of residuals. In other words, instead of analyzing a system's performance by comparing the difference between the outputs and model predictions at one or a few operating points, diagnostics is achieved by evaluating the system behavior pattern over a window of operation. This strategy has been used in some diagnostic methods, especially qualitative and semi-quantitative approaches [1-4]. The key here is an inference mechanism to match the observed behavior from the system with a set of predefined or even new hypotheses in an environment affected by noise and uncertainty.

Fuzzy logic has turned out to be a popular choice for these types of problems. The inherent flexibility embedded in fuzzy sets and fuzzy rules make it a suitable solution for reasoning in domains affected by uncertainty and error. In building HVAC systems, fuzzy-based diagnostic mechanisms have been used in several studies [21, 56, 57, 58]. For example, in [57], Haves et al. have developed fuzzy-based diagnostic routines for fault detection and diagnosis of VAV air-handling units. In their proposed approach, fuzzy-based inference mechanisms compare system

¹ If the model is a detailed first-principle model, the *a priori* knowledge is mainly model parameters values and their variations. If the model is an empirical model, the *a priori* knowledge is usually high-quality training data of the system behavior in different modes.

outputs with the predictions of simplified models at various operating points to draw conclusions about the system health status.

However, fuzzy-based inference mechanisms have their own limitations. As the problem complexity grows (due to the system complexity, large number of disparate sensor data, and many possible faults, etc.), a prohibitive number of fuzzy sets and fuzzy rules are required for system diagnostics. Added to this is the issue of adjusting and tuning fuzzy sets either manually or through other approaches.

It is worth mentioning that another way of dealing with modeling limitations in HVAC diagnostics is rule-based diagnostics [20-34]. In this approach, the *a priori* knowledge is formulated through a set of if-then-else rules, and an inference mechanism searches through the rule-space to draw conclusions. Rule-based systems can be based on expert knowledge or first principles. The strength of rule-based systems is ease of development and the ability to reason under uncertainty. However, as it has been discussed in [18], as the problem complexity grows or when new rules are to be added, the simplicity of rule-based systems is lost quickly. Furthermore, sometimes the activation of the rules depends on threshold(s) that may highly depend on model uncertainties, measurement errors, or other issues. More discussion on this can be found at [40].

Another challenging issue in building HVAC diagnostics is measurement constraints. In building HVAC systems, sensor network architectures are not necessarily designed solely based on diagnostic purposes. Other factors such as controls, financial constraints, and practical limitations are also involved. As a result, it is common to have one or more components being monitored through only one sensor (or one set of sensors). In such a scenario, when the sensor output is contaminated, it could be due to the malfunctioning of any of the involved components, and it may not be a straightforward task to locate the affected one. In other words, the problem complexity expands from the diagnostics of one component to a network of components.

An example of this is the air-handling unit. As will be discussed in Chapter 2, in air-handling and rooftop units, there is usually no reliable measurement of the mixed air temperature due to the incomplete upstream mixing. This results in using the downstream supply-air temperature to infer the performance of both the mixing box and the heating/cooling coils (Figure 1.1). In other words, the functionality of three components is monitored through only one sensor.

In general, the complexity of diagnostic problems due to measurement constraints has not been addressed in a systematic fashion or in much detail. Most methods reported in the literature assume that either the required measurements are available, or a unique solution exists that is sufficiently described by existing measurements.

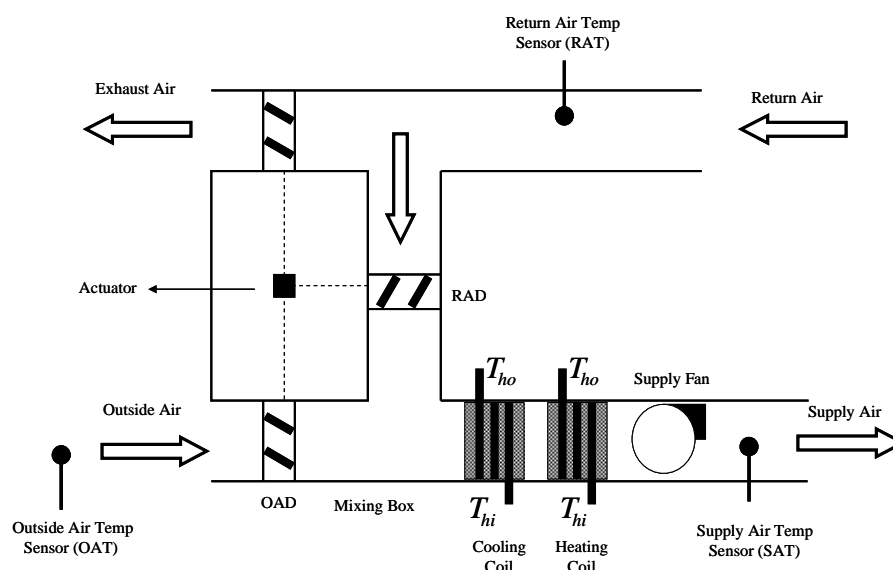


Figure 1.1: Air-handling unit schematic diagram

A part of our focus in this study is to develop diagnostic algorithms that can systematically deal with modeling and measurement constraints. In Chapter 2, we present a Bayesian network-based diagnostic mechanism that analyzes a system's performance by evaluating the behavioral patterns over a window of operation and comparing them with various hypotheses. Each hypothesis is indeed a predicted performance of the system (developed by simplified models) under the assumption of one or more faults. We will demonstrate how the framework can be systematically expanded as the problem complexity grows.

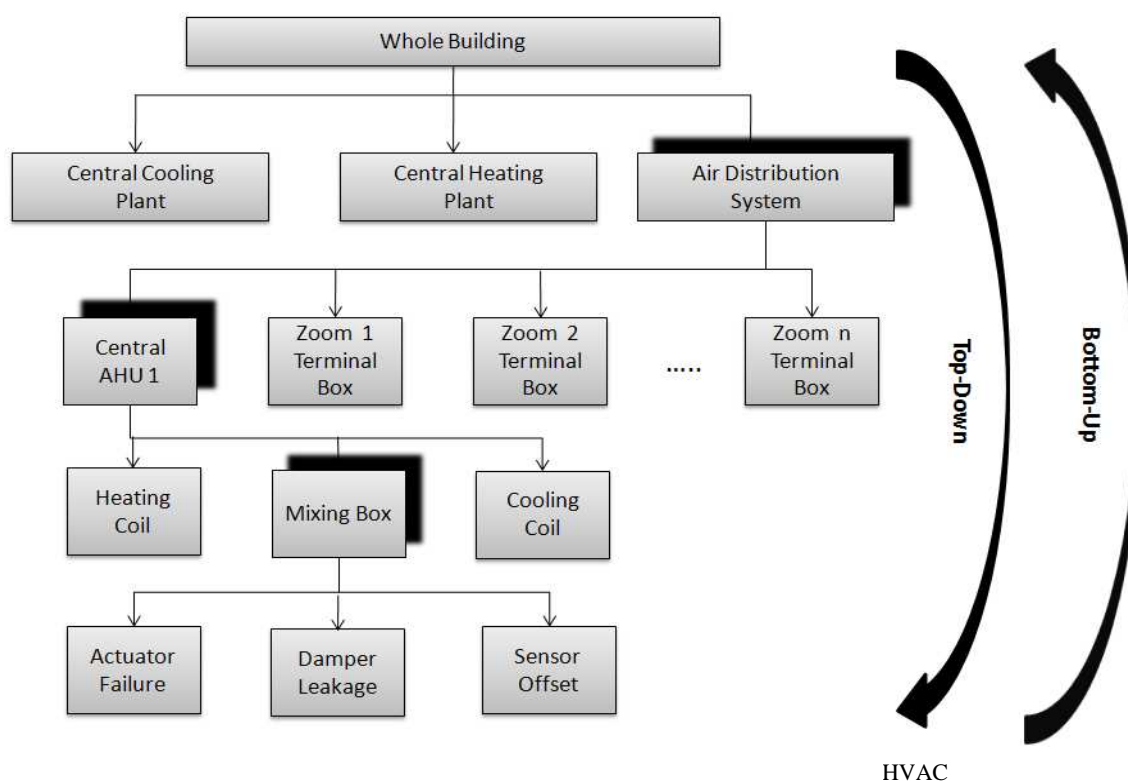
Another attribute of the proposed mechanism is its capability to deal with measurement constraints. As it will be shown in Chapter 2, the missing measurements can be formulated as hidden variables in the Bayesian model.

In Chapter 4, we present another diagnostic approach, a model-free approach, for rooftop units. The approach evaluates rooftop unit performance by analyzing the correlation among parameters and matching them with various predefined patterns without using any model. We will demonstrate the effectiveness of the method by testing it with data coming from different retail stores.

1.2 Bottom-up versus top-down diagnostics

Fault detection and diagnostics in building HVAC systems can be approached from two perspectives: bottom-up and top-down perspectives [59]. In the bottom-up approach, lower-level performance measures of HVAC systems (Figure 1.2)² are used to isolate the problem and propagate its effect on building performance. Conversely, in the top-down approach, higher-level performance measures are used to reason about possible lower-level causes of degradation to the higher-level measures.

Bottom-up diagnostic routines are usually initiated by complaints from the occupants. When occupants complain about a hot, cold, or uncomfortable environment, a diagnostic routine on the area related to the complaint is begun to trace the problem and locate the malfunctioning device. In contrast, top-down diagnostic processes, which are also known as whole building diagnostics, are normally motivated by a concern for efficient building operation. When, for example, building energy usage increases unexpectedly, a top-down diagnostic process is performed to locate the inefficient division/section and trace the problematic device or cause.



² Figure 1.2 is borrowed from [59].

In recent years, there has been growing interest in top-down diagnostic approaches [60-64]. Part of this is due to growing concerns about building efficiency. Another reason is measurement flexibility. Top-down diagnostic processes are usually based on monitoring the energy consumed by the building and/or subsystems (e.g., cooling/heating systems, fans, lights, etc.), which is measured indirectly by monitoring the amount of electricity or gas provided to the building (or subsystem). This is an easier way of measuring energy usage than the direct way of measuring state parameters such as temperature, pressure, or other indicators to calculate the energy usage.

From an automated diagnostics perspective, a wide range of research studies has been performed for the automation of bottom-up diagnostic processes [18, 19]. However, for top-down diagnostics, the story is different: building-level diagnostic processes are still performed manually, in which building experts analyze the performance graphs, looking for predefined signatures to detect and isolate abnormalities [59, 60, 61]. In more advanced cases, a building model (developed by DOE2, Energy Plus, etc.) is used as a rough reference as well [63, 64].

When diagnostics is to be achieved at the building level, the problem complexity extends to a new horizon. At the component level, there is a small set of faults to deal with, while at the building level, a massive number of faults need to be managed. Added to this is the complexity of concurrent faults, which expands the set of abnormal scenarios exponentially. Another issue is fault detectability. All building HVAC faults are not necessarily detectable through high-level measures. The impact of some faults may not be differentiated from modeling and measurement errors. For example, it is very unlikely to be able to detect the effect of a damper leakage or stuck damper fault on the total energy used by a four-story building. The challenge is that there is no systematic framework to differentiate between detectable and non-detectable faults. In other words, there is no standard routine for evaluating available measures to determine which faults should be included and which ones should be removed from the diagnostic process.

These challenges are the main barriers to the automation of building HVAC diagnostics from a top-down perspective. The extensive number of faults and the complexity of fault detectability limit the applicability of conventional diagnostic approaches. In this study, we approach the problem in a different way. We extend the Bayesian network diagnostic model, presented in Chapter 2, to whole building-level diagnostics and employ numerical routines to manage the problem complexity. In Chapter 5, we demonstrate how the proposed diagnostic solution can effectively analyze building performance from a top-down perspective and how the limitation of fault detectability influences diagnostic results.

1.3 Proactive fault diagnostics

Most research studies on fault detection and diagnosis in building HVAC systems have focused only on one side of the problem: analyzing system outputs for diagnostics purposes. Fewer studies have addressed the other side of the problem: manipulating system inputs for better diagnostics. In other words, the question of how diagnostic mechanisms can supervise system inputs for diagnostic purposes is still open. If the aim of automated diagnostics is to replace manual troubleshooting with automated tools, FDD mechanisms should be capable of supervising system inputs for comprehensive or targeted tests, especially when it comes to commissioning and functional testing. The feedback control loop may never generate enough excitation of the system inputs to explore broadly enough for a complete diagnostic analysis. The ability to supervise and manage automated diagnostic tests would extend diagnostic tool capabilities into a new horizon.

Conventional approaches for proactive testing are mainly based on predefined tests [21, 57, 58, 65-68]. Researchers and engineers with a sufficient understanding of system dynamics design test sets or test sequences as the standard for comprehensive or targeted diagnostic assessment. This concept has been pursued in HVAC systems as well [57, 58, 67, 68]. For example, in [67, 68], Katimamula et al. have developed decision-tree-type test procedures to proactively analyze the functionality of hot water and cold water valves in air-handling units. In another studies [57], Haves et al have developed test procedures to analyze the functionality of mixing box, fan, and heating/cooling coils in air-handling units.

One drawback of predefined test-based approaches is the lack of flexibility and adaptability. Usually, these tests are structured to check the existence of one (or more) fault(s) at each step (or subset of steps). For example, in order to check for an outside air damper leakage fault in a mixing box, the damper is commanded to a fully closed position to see whether the discharge and return air temperatures are equal. However, due to the uncertainties arising from modeling limitations, measurement constraints, etc., the diagnostic mechanism may not be able to conclusively confirm a fault status based on one or two measurements. As a result, at the end of the test cycle, a substantial level of uncertainty may still remain in the diagnostic assessment.

In addition, when these tests are to be performed in an orderly fashion, which is true in most applications, there is not that much space for adaptability. In other words, there is no systematic routine to adjust and modify test sequences based on the diagnostic assessment at each step. These limitations apply to both Haves' and Kapipamula's frameworks.

Another part of this study is to develop systematic frameworks for proactive diagnostics. We think of a proactive testing problem as an optimization problem in which an optimum path from the current state (the current diagnostic assessment) to the final state (a diagnostic assessment

with minimum uncertainty) needs to be found. In Chapter 3, we show how such an optimization problem can be formulated as a decision-making problem, coupled with a Bayesian network-based diagnostic mechanism.

1.4 Quantification of measurement constraints' impact on diagnostics capability

As mentioned previously, measurement constraints can expand the complexity of building HVAC diagnostic problems significantly. An important question to ask is how the relationship between measurement constraints and diagnostic capability can be quantified systematically. Solving this problem will open new horizons in building HVAC diagnostics. It can be used as a framework to analyze the effect of new measurements on diagnostic strength, which consequently leads to better design and optimization of sensor network architectures.

The first step is determining how to quantify diagnostic improvement. In other words, the question is, How can one diagnostic assessment be quantitatively compared to another one? In Chapter 6, we will show that the information entropy associated with diagnostic assessments can be used a metric system to compare different diagnostic results. A diagnostic assessment is said to be improved if the associated information entropy is reduced. We will then show that the impact of measurement constraints can be linked to the expected value of the information entropy of diagnostic assessment. We will demonstrate how, through this proposed framework, we can justify and select additional or new measurements for diagnostic purposes.

2. BAYESIAN NETWORK BASED DIAGNOSTIC FRAMEWORK

2.1 Bayesian Network Based Diagnostic Mechanism

In the proposed approach, we think of system output as a random variable conditionally dependent on the system input and the fault mode (Figure 2.1). A system fault is interpreted as external input affecting the mapping function from the input to the output. Such an interpretation helps us to systematically deal with existing uncertainties in system output arising from modeling and measurement errors, as they can be quantified into the variance of the output random variable. The variance estimation can be achieved analytically or statistically.

We assume to know the system input when we measure the output. The aim of diagnostics is to find the fault condition that results in performance similar to what has been observed. In other words, the proposed diagnostic algorithm seeks a fault condition that generates the closest output pattern.

To solve the problem, we formulate it as a Bayesian network model. Briefly, a Bayesian network (BN) is a directed graph in which each node is annotated with qualitative probability information. The full specification is as follows:

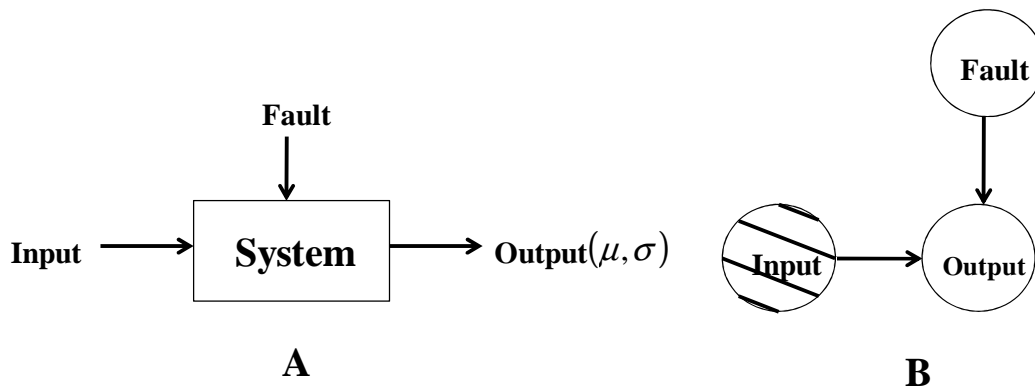


Figure 2.1 A: Diagnostic framework, B: Dual Bayesian Model

- 1- A set of random variables makes up the nodes in the network. Variables may be discrete or continuous.
- 2- A set of directed links or arrows connects pairs of nodes. If there is an arrow from node A to node B, A is said to be the parent of B (Figure 1). In a properly constructed network, the intuitive meaning of an arrow is usually that A has a direct influence on B.
- 3- Each node X_i has a conditional probability distribution $P(X_i|parents(X_i))$ that quantifies the effect of the parents on the node.
- 4- The graph has no directed cycles.

The topology of the network –the set of nodes and links—specifies the conditional independent relationships that occur in the domain. Given its parents, each node is conditionally independent of all its non-descendants. For example, in Figure 2.2, D is conditionally independent of A given B. The combination of the topology and the conditional distributions suffices to specify (implicitly) the full joint distribution for all variables.

Using the chain rule in probability, a joint distribution can always be broken down into a product of conditional probabilities. For example, for A, B, C, and D, $P(A, B, C, D)$ can always be represented as:

$$P(A, B, C, D) = P(A)P(B|A)P(C|A, B)P(D|A, B, C) \quad (2.1)$$

The conditional independence assumptions expressed by a BN allow a compact representation of the joint distribution. For example, in Figure 1, knowing that A and D are conditionally independent given B, the joint probability distribution can be simplified to:

$$P(A, B, C, D) = P(A)P(B|A)P(C)P(D|B, C) \quad (2.2)$$

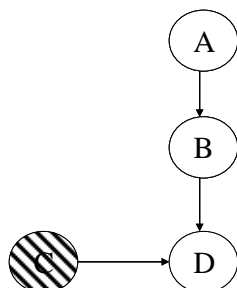


Figure 2.2

In general, in Bayesian networks with X_1, X_2, \dots, X_n as random variables, the joint probability can be simplified as:

$$P(X_1, X_2, \dots, X_n) = \prod_i P(X_i | \text{parents}(X_i)) \quad (2.3)$$

The proposed Bayesian diagnostic model contains three nodes (Figure 2.1). The input node represents the system inputs; the output node represents the system outputs; and the fault node represents system faults and their combinations.

The mapping function from the input to the output node is indeed a simplified model of the system that the fault node affects. The fault node's impact can be realized in different ways: There could be a different mapping function for each fault mode, or the output may be a set of basis functions generated at the input node and linearly combined with coefficients defined by the fault node.

The undefined parts of the mapping function should be addressed in the training phase. This process may include (but is not limited to) the following: the variance of the output node variable(s), and the coefficients of linearly combined basis functions. If the distribution of the output node random variable is Gaussian (or more generally from an exponential family of distributions), it is straightforward to estimate the output node variance and coefficients of linearly combined basis functions.³

The posterior probability of the fault node is interpreted as the diagnostic belief or, in other words, the fault condition (hypothesis) that resembles the system output. Using the Bayesian network inference mechanism, this probability can be calculated as:

$$P(f_i | I, O) = \frac{P(f_i)P(O|f_i, I)}{\sum_i P(f_i)P(O|f_i, I)} \quad (2.4)$$

where f is the fault list, $f = \{f_1, f_2, \dots, f_n\}$, I is the input(s), and O is the output(s). $P(f_i)$ is the prior distribution of the fault node.⁴ As an example, we can apply the proposed diagnostic framework to an HVAC device, an air-handling unit.

³ This is a parameter estimation problem for generalized linear models. In [reference], it is shown that the problem can be formulated as a convex optimization problem.

⁴ f can be estimated statistically or as a quick solution it can be assumed to be uniformly distributed. In this chapter, we assume it is uniformly distributed.

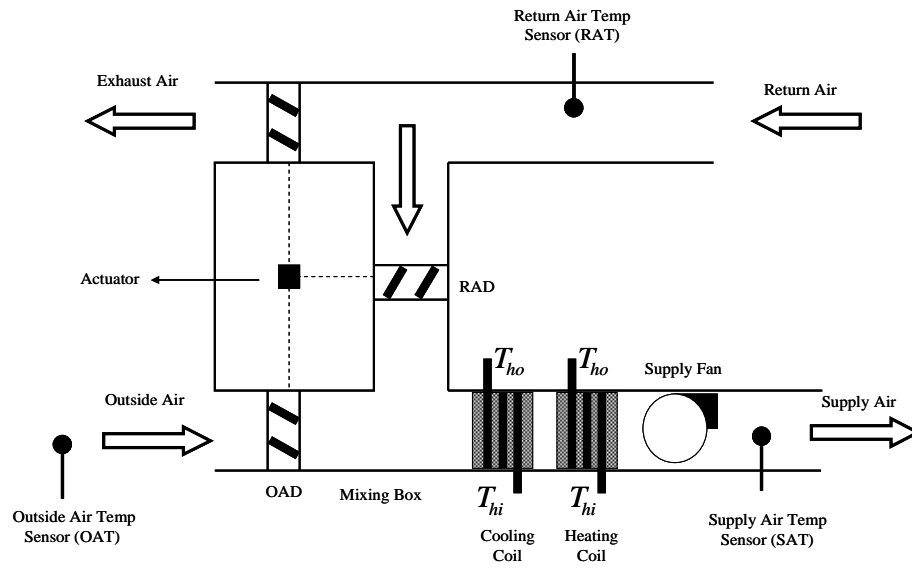


Figure 2.3: Air handling unit schematic diagram

The air-handling unit is known as the most common source of heating, cooling, and ventilation in medium and large commercial buildings. It consists of a mixing box, one or two fans, and heating/cooling coils (Figure 2.3).⁵ The mixing box controls the mixing process between the return and outside air streams, while the heating and cooling coils control the temperature and humidity of the air supplied to the occupied space. In a typical air-handling unit, there are usually three temperature sensors, measuring outside air temperature (OAT), return air temperature (RAT), and supply air temperature (SAT).⁶ It may also contain an air-flow sensor to measure the supply air rate.

The problem of air-handling unit diagnostics illustrates a classic example of the complexity of diagnostics due to modeling and measurement constraints. These devices are usually designed and customized for each application, making it impractical to develop highly accurate models for diagnostic purposes. On the other hand, in practice, AHU's do not contain enough sensors to fully monitor system health status directly. In this example, we focus on mixing box functionality.

As mentioned, the mixing box performs the role of mixing the air coming out from the building (Return Air) with the outside air, based on the ratio defined by the controller. The ratio is specified to minimize the energy required to heat up or cool down the supply air, and also to

⁵ It may contain both or either

⁶ There may also be a temperature sensor between the mixing box and heating/cooling coils to measure the mixed air temperature (MAT). However, due to incomplete upstream mixing, the readings from this sensor are usually unreliable.

satisfy the standard of fresh air required for occupants. Mixing box malfunction is a common fault in air handling units. Mixing box abnormalities could result from a damper being stuck, leakage of the outside or return air dampers, reversed action of the actuator, or sensor offset.

Mixing box performance is usually analyzed by a dimensionless parameter, Outside Air Fraction (OAF), which is the ratio of the difference between the mixed air temperature (MAT) and the return air temperature (RAT) over the difference between the outside air temperature (OAT) and the return air temperature (RAT).

$$OAF = \frac{T_{mat} - T_{rat}}{T_{out} - T_{rat}} \quad (2.5)$$

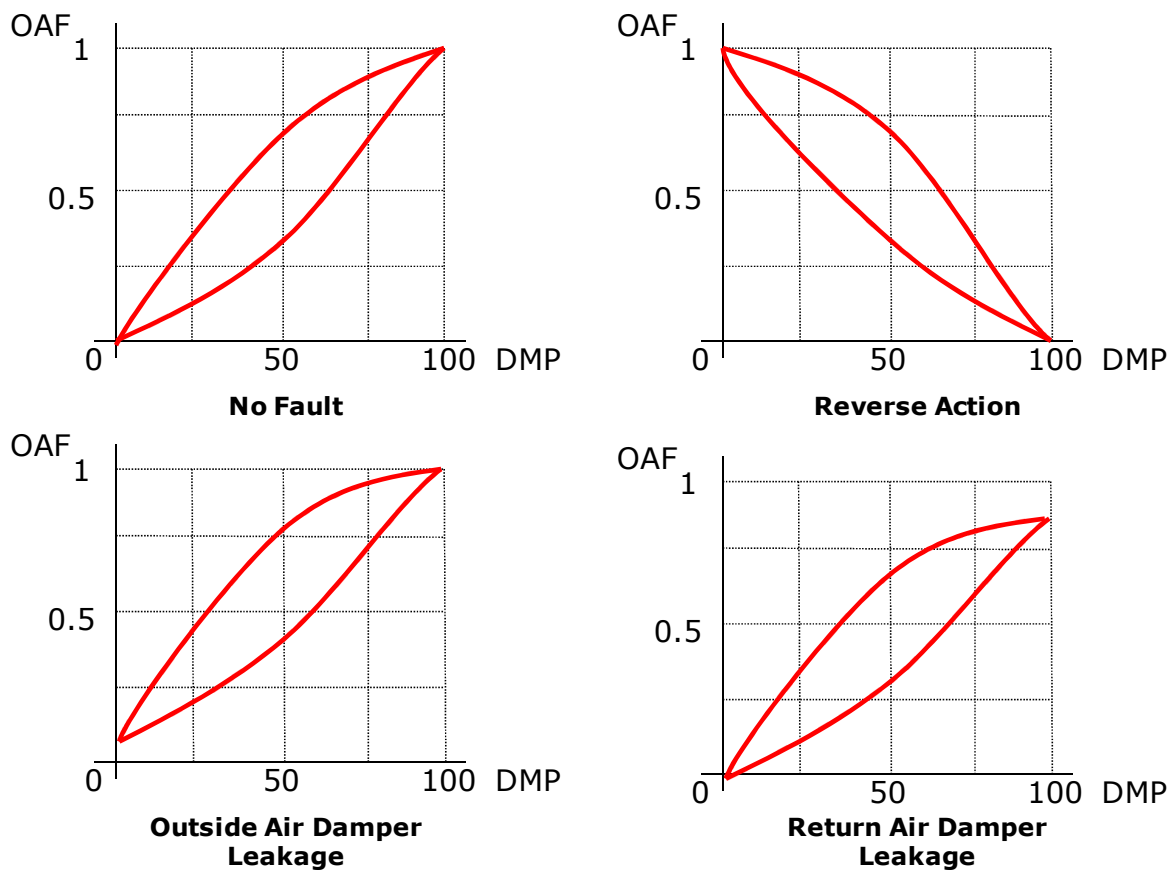


Figure 2.4: Variations of the outside air fraction (OAF) versus the outside air damper position (DMP) in a mixing box. The upper-left graph shows the behavior in normal operation, while the others illustrate different fault modes. The envelope defines the model uncertainty involved. In other words, the output (OAF) can reside anywhere inside the envelope. The wide range of uncertainty is due to parameters not easily measurable in practice (fluid resistance, air velocity, thermal resistance, etc).

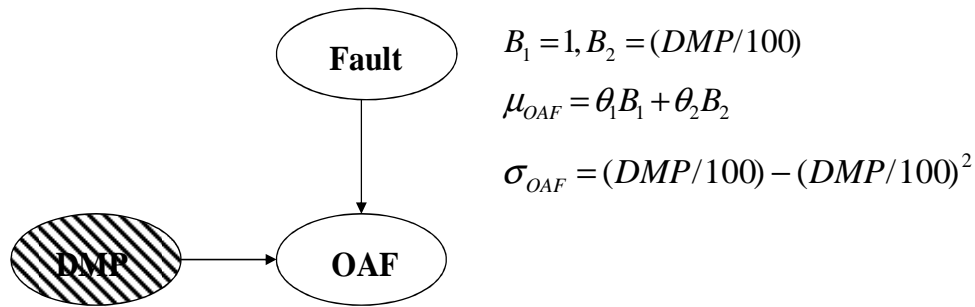


Figure 2.5: Fault diagnostic mechanism for mixing box. A set of basis functions (B_1 & B_2) is generated from the damper position, and then linearly combined with a set of coefficients (θ_1 & θ_2) – defined by the fault node – to estimate the OAF.

OAF is an indication of the influence of the outside air temperature on the mixed air temperature. It ideally reads one when the outside air damper is fully open, and zero when the damper is closed. Figure 2.4 shows the variations of OAF versus damper position (control signal) during various operating conditions.

The designed diagnostic mechanism for a mixing box is shown in Figure 2.5. A set of basis functions, B_1 and B_2 , is generated from the damper position, and then linearly combined with a set of coefficients (θ_1 and θ_2) – defined by the fault node – to estimate the OAF. Once the OAF has been estimated, the mixed air temperature (MAT) can be obtained from Equation 2.2.

The diagnostic mechanism was tested by data attained from Iowa Energy Center, an experimental facility for research, education, and demonstration [76]. During the experiment, the coils were shut off to be able to use the readings of the supply air temperature sensor instead of mixed air temperature. A diagnostic result is shown in Figures 2.6 and 2.7.

Note how in Figure 2.7, the diagnostic belief improves as more data is observed. It seems that there is a Return Air Damper Leakage (RADL) fault in the system. However, as the RADL fault cannot be isolated until the damper opens 100% (due to the nature of the fault), the diagnostic mechanism waits until it sees the system response at that state, and then finalizes its evaluation.

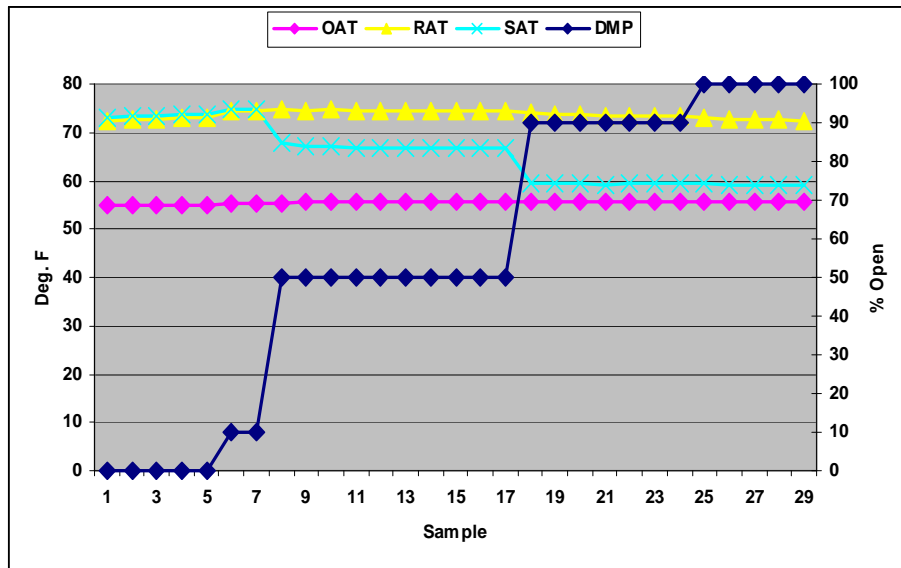


Figure 2.6: Mixing box performance. OAT: Outside Air Temperature, RAT: Return Air Temperature, SAT: Supply Air Temperature, DMP: Damper. The data comes from a test run on one of the air handing units at Iowa Energy Center. The diagnostic result is shown in Figure 2.7.

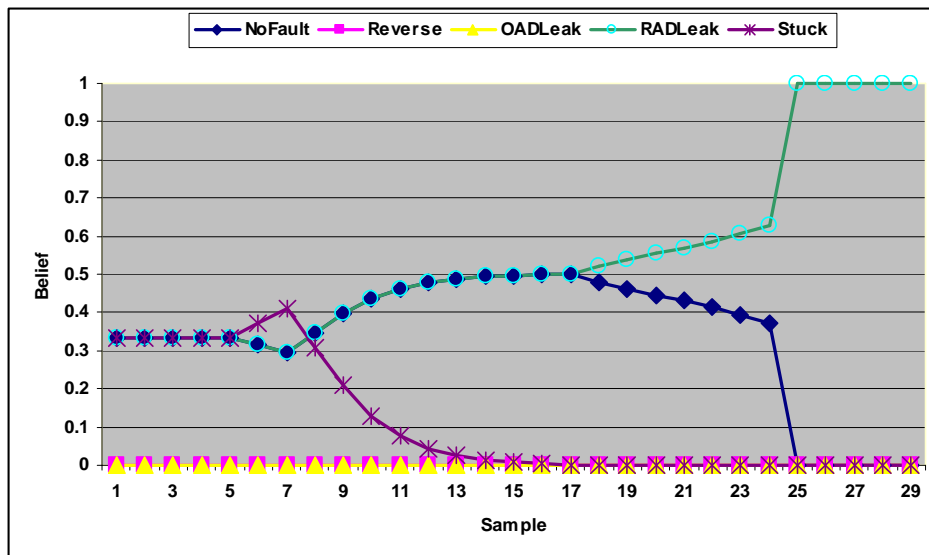


Figure 2.7: Diagnostic results. Note how belief about the system health status improves as more data are observed. It seems that there is a Return Air Damper Leakage (RADL) fault in the system. However, as the RADL fault cannot be isolated until the damper goes to 100% open (due to the nature of the fault), one can see the diagnostic mechanism waits until it sees the system response at that state, and then finalizes its evaluation.

2.2 Diagnostics of Mixture of Components

As discussed earlier, the architecture of a sensor network may extend the complexity of a diagnostic problem. The diagnostic mechanism may be restricted to monitoring the performance of two or more components through only one sensor (or one set of sensors). In such a scenario, when the sensor output is contaminated, it could be due to the malfunction of any of the involved components, and locating the one affected may not be straightforward. An example of this issue can be found in AHU diagnostics. In air handling units, the readings of the mixed air temperature sensor, if they exist, are not reliable due to incomplete upstream mixing. This scenario means that the supply air temperature sensor must be used to infer the functionality of both mixing box and heating/cooling coils.

An intuitive solution is to analyze the functionality of each component, while the effects of others are neutralized (shutting down or taking to certain states). For example, in the case of the mixing box, the coils can be turned off while mixing box performance is analyzed. However, this procedure may not be compatible with normal operation unless the system is in free cooling mode.

Our proposed approach is to extend the designed Bayesian model to a mixture model of components, an example of which is shown in Figure 2.8. In this figure, each node is itself a Bayesian model of the related component. The interaction among components is defined based on the system architecture and other specifications. A component input may contain all or part of the adjacent component outputs, and similarly, its output may construct all or part of the next component inputs. Here, the input nodes are not necessarily deterministic, and the output nodes may not be fully observed.

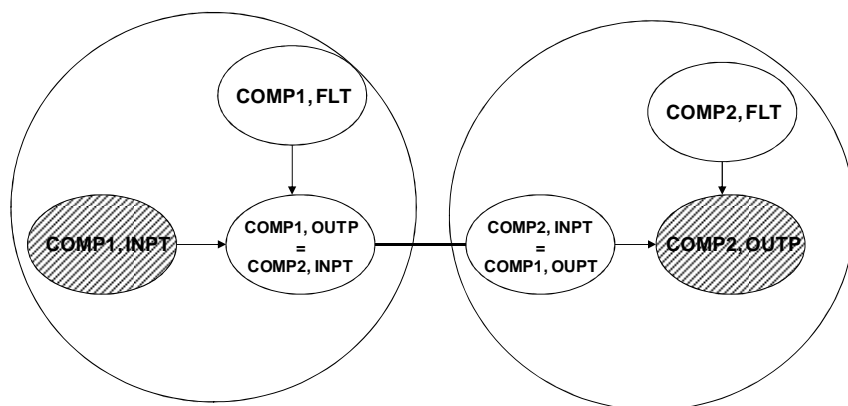


Figure 2.8: A mixture model example with two components: the output of the first component constructs the input of the second one

When a component of a mixture model malfunctions, the relation between the input and output nodes is contaminated. From a larger perspective, this contamination leads to a change in the system behavior pattern, because each component affects the ones adjacent to it. To detect and isolate such abnormalities, the system behavior pattern is again compared with various hypotheses; each hypothesis is based on the assumption that one or more components are in fault modes. Due to measurement constraints, if an input or output node is partially observed, the unobserved random variable will be considered a hidden variable and will be summed out over all its possible values. For instance, in Figure 2.7, if it is assumed that the output of the first component (also the input of the second component) is hidden, the posterior probability of the fault nodes can be calculated by:

$$P(f_{c_1,i}, f_{c_2,i} | I_{c_1}, O_{c_2}) = \frac{\sum_{O_{c_1}} P(f_{c_1,i}) P(f_{c_2,i}) P(O_{c_1,k} | f_{c_1,i}, I_{c_1}) P(O_{c_2} | f_{c_2,j}, O_{c_1,k})}{\sum_{f_{c_1}} \sum_{f_{c_2}} \sum_{O_{c_1}} P(f_{c_1,i}) P(f_{c_2,i}) P(O_{c_1,k} | f_{c_1,i}, I_{c_1}) P(O_{c_2} | f_{c_2,j}, O_{c_1,k})} \quad (2.3)$$

where $f_{c_1} = \{f_{c_1,1}, f_{c_1,2}, \dots, f_{c_1,n}\}$ is the fault list of the first component; $f_{c_2} = \{f_{c_2,1}, f_{c_2,2}, \dots, f_{c_2,n}\}$ is the fault list of the second component; I_{c_1} is the input of the first component; O_{c_2} is the output of the second component; and $O_{c_1} = I_{c_2} = \{O_{c_1,1}, O_{c_1,2}, \dots, O_{c_1,n}\}$ is the output of the first component.

As an example, we can apply the mixture model framework to the diagnostics problem of an air-handling unit consisting of a mixing box and heating coil.

As mentioned earlier, the heating coil heats up the air going into the building. It is a finned tube heat exchanger with hot water on the hot side and air on the cold side, and it usually contains one or a few sets of tubes that are mounted perpendicularly to the flow of air passing through the coil. The heat transfer rate is controlled by manipulating the hot water valve to vary the water flow rate through the coil. The most common faults in a heating coil system (the coil and the valve) are as follows: fouling of the heat exchange surface, valve leakage, valve sticking, and valve reverse action. The heating coil simplified-first-principle model used in this study is based on the Holme's effectiveness-NTU method [71]. Briefly, the model is (Figure 2.9):

$$T_{co} = \varepsilon(T_{hi} - T_{ci}) + T_{ci} \quad (2.4)$$

$$\varepsilon = \frac{1 - \exp(-NTU * \alpha)}{1 - \alpha * \exp(-NTU * (1 - \alpha))} \quad (2.5)$$

$$\alpha = \frac{C_{min}}{C_{max}}, C_{min} = \min(C_h, C_c), C_{max} = \max(C_h, C_c) \quad (2.6)$$

C_h is hot fluid capacity rate; C_c is cold fluid capacity rate.

$$NTU = \frac{UA}{C_m}, U = \frac{1}{r_t}, r_t = r_a * v_a^{-0.8} + r_m + r_w * v_w^{-0.8} \quad (2.7)$$

v_w and v_a are water and air velocity. r_m , r_w , and r_a are metal, water, and thermal resistance.

The diagnostic mixture model of an air-handling unit with a mixing box and heating coil is shown in Figure 2.10. As is apparent in the figure, the mixed air temperature (MAT) which is the output of the first component (mixing box) and one of the second component (heating coil) inputs is assumed to be hidden (unobserved). The inputs of the heating coil are mixed air temperature (MAT), supply air CFM,⁷ entering hot water temperature (TWin), the valve command (VLV); and the output is the supply air temperature (SAT). The diagnostic results are shown in Figures 2.11 and 2.12.

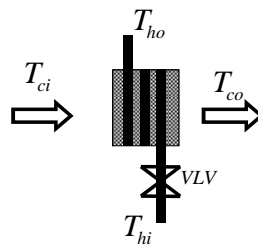


Figure 2.9

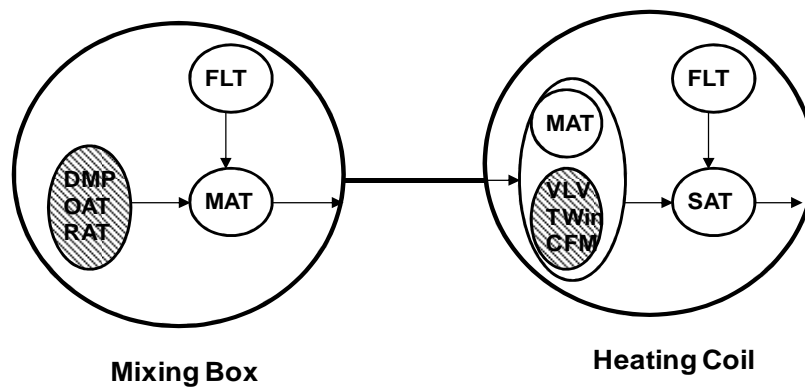


Figure 2.10: The mixture model of an air-handling unit with a mixing box and a heating coil

⁷ CFM is short for cubic feet per minute, measurement of air volume flow rate

It is important to note that this systematic way of dealing with measurement constraints does not come without a price. There will be some level of degradation in the diagnosis performance, a fact that needs to be understood in advance. Comparing Figures 2.7 and 2.12, one notices that, in the mixture model's case, the diagnostic mechanism takes more time to reach a solid conclusion about the system's health status. This difference represents the cost of the missing a sensor. In this application, it has arisen as slower diagnostic analysis; in other applications, it may appear in the confidence level of the diagnostic result.

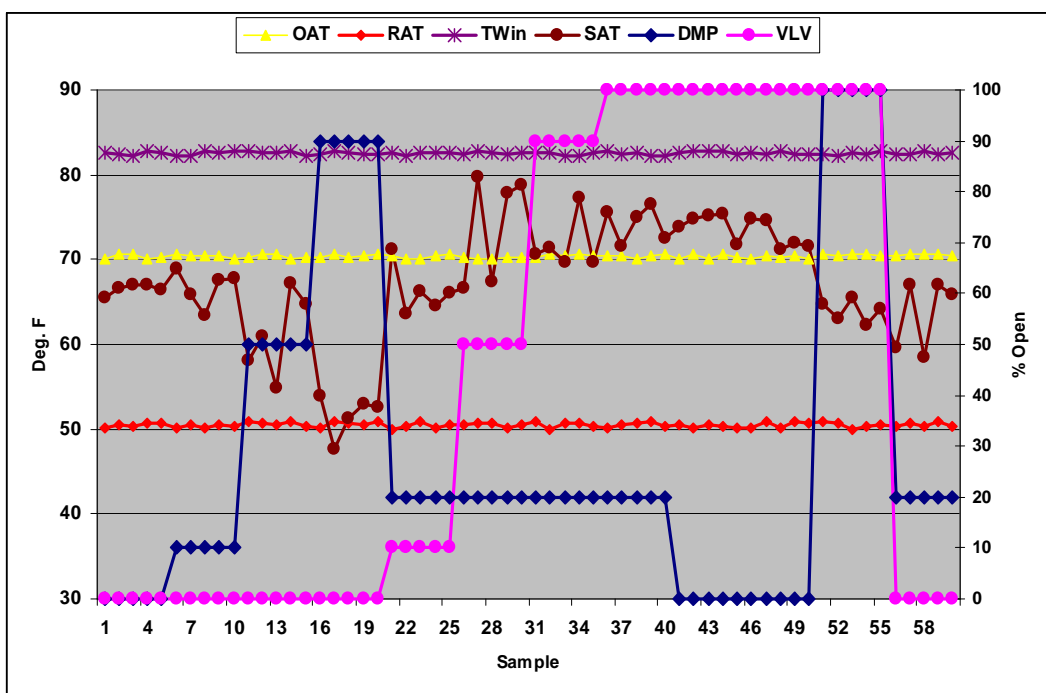


Figure 2.11: OAT: Outside Air Temperature, RAT: Return Air Temperature, TWin: Hot Water Temperature entering the coil, SAT: Supply Air Temperature, DMP: Damper Position, VLV: Valve Position.

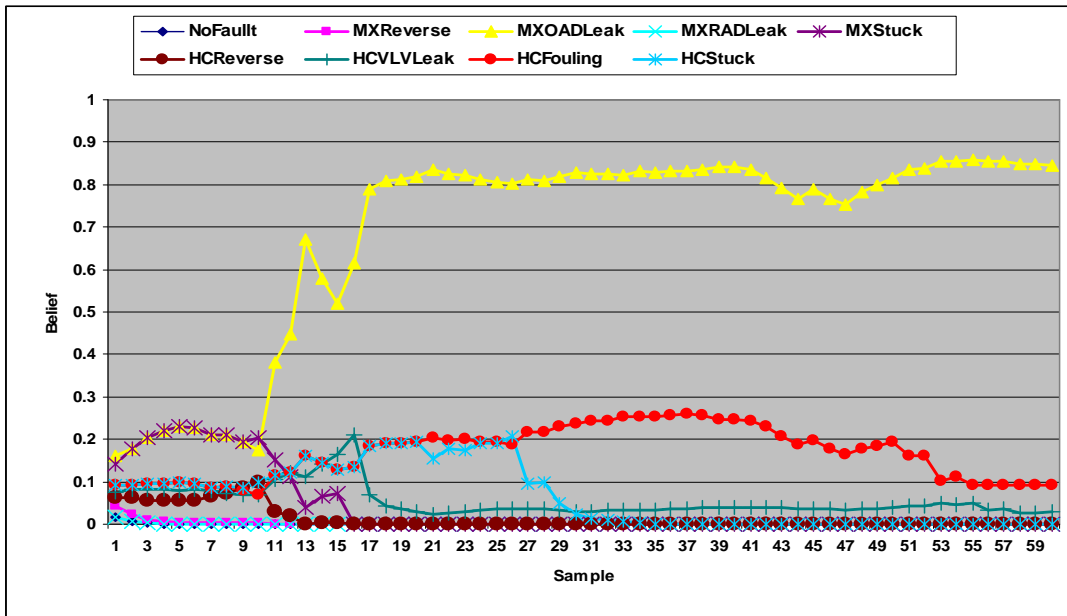


Figure 2.12: Diagnostic Results, MX and HC are short for mixing box and heating coil, respectively. Note how the belief about the system health status improves gradually as more data are observed, especially in the case of the heating coil fouling. It seems that there is an outside air damper fault in the system.

3. PROACTIVE FAULT DIAGNOSTICS

3.1 Introduction

As mentioned in Chapter 1, most research studies in fault diagnostics for building HVAC systems—or even in fault diagnostics in general—have focused on one side of the problem: analyzing system outputs for diagnostics purposes. Fewer studies have addressed the other side of the problem: manipulating system inputs for better diagnostics. In other words, the question of how diagnostic mechanisms can supervise system inputs for diagnostic purposes is still open. If the aim of automated diagnostics is to replace manual troubleshooting with automated tools, FDD mechanisms should be capable of supervising system inputs for comprehensive or targeted tests, especially when it comes to commissioning and functional testing. The feedback control loop may never generate enough excitation of system inputs to explore broadly enough for a complete diagnostic analysis. The ability to supervise and manage automated diagnostic tests would extend diagnostic tool capabilities into a new horizon.

Proactive fault diagnostics is the process of proactively manipulating system inputs to perform a diagnostic test. It consists of a diagnostic part and a proactive testing part. The proactive testing part manipulates/directs the Input, and the diagnostics part analyzes the output to assess the system's health status. The aim of proactive testing is to control adjustable parameters—for example, damper position, fan speed, and so on—to facilitate and complete the diagnostic process.

Ideally, a proactive testing mechanism should perform in an adaptive manner. It first should analyze the current diagnostic assessment results from previous tests⁸ and then proceed to the next step. Its direction should be in alignment with diagnostics capability, taking into account the strengths and weaknesses of the diagnostic mechanism. If there is an unclear understanding of the system's behavior in some areas, it should be factored systematically into the test design process. The proactive testing mechanism should also be flexible with practical limitations. For example, if operating conditions do not allow exploring some areas—for example, the damper cannot be at the fully closed position—the tests should be adjusted accordingly. Directions of the proactive testing mechanism should be based on maximally improving the diagnostic assessment.

We think of a proactive testing problem as a dynamic optimization problem in which an optimal path from the current stage (the current diagnostic assessment) to the final stage (a diagnostic assessment with minimum uncertainty) needs to be found. The optimal path is indeed a sequence

⁸ Previous tests or daily operation.

of tests and should lie within the boundaries defined by limitations such as operating conditions, diagnostic capability, and so on.

We formulate such an optimization problem as a decision-making problem coupled the Bayesian network diagnostic mechanism introduced in Chapter 2. The proposed framework decides on a test based on its potential effect on the information entropy of the diagnostic assessment.

3.2 Proactive Fault Diagnostic Mechanism

A schematic diagram of the proposed proactive diagnostic mechanism is shown in Figure 3.1. It is an extension of the diagnostic framework introduced in Chapter 1. The next input node is a decision node, which represents the next input value that ought to be determined by the proactive testing mechanism. The next output node represents the system output (system response) to the next input. It is a random variable, conditionally dependent on the next input node and the fault node.

The utility node contains the utility function quantifying the preference of diagnostic results. It computes the closeness of a diagnostic assessment to an ideal one, an assessment with minimum uncertainty. Indeed, the utility function is the information entropy of the fault node random variable.

In information theory, information entropy is a measure of the uncertainty associated with a random variable; the bigger the uncertainty, the bigger the information entropy. Information entropy quantifies information contained in a random variable, message, and so on. For a random variable, X , with n outcomes $\{x_1, x_2, \dots, x_n\}$, the information entropy is defined as:

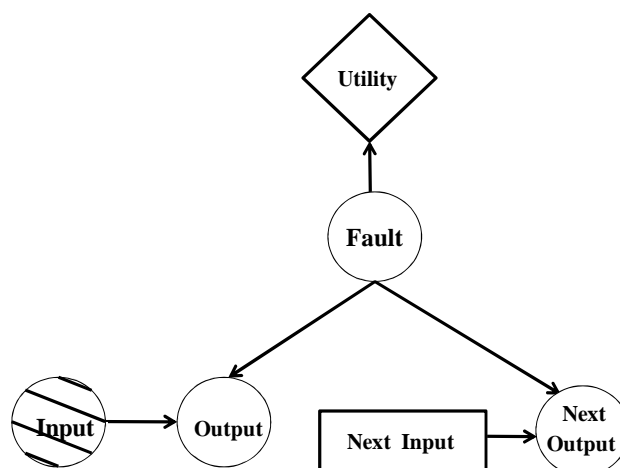


Figure 3.1: A schematic diagram of proactive testing mechanism.

$$H(x) = - \sum_{i=1}^n P(x_i) \log_b P(x_i) \quad (3.1)$$

Where $P(x)$ is the probability mass function of the outcome x , and b is the base of the logarithm. Common values of b are 2, e , and 10. For example, if we assume that the probability distribution of x_1, x_2, \dots, x_n is uniform, $p(x_i) = \frac{1}{n}$, the information entropy will be:

$$H(x) = \sum_{i=1}^n \frac{1}{n} \log \left(\frac{1}{n} \right) = - \log \left(\frac{1}{n} \right)$$

Conversely, if we assume that somehow it has become apparent that x_3 is true and others are false, $P(x_3) = 1$ & $P(x_i) = 0 \quad \forall i \neq 3$, the information entropy will be:

$$H(x) = \log(1) = 0$$

In general, the bigger the uncertainty associated with a random variable, the bigger its information entropy.

At each step, after calculating the diagnostic assessment (the posterior probability of the fault node in Figure 3.1, $P(f|I, O)$) based on previous tests, the proactive testing mechanism should find the next best input (next test) that can maximally improve the assessment. In other words, it looks for an input value that can maximally reduce the information entropy of the fault node. The challenge is that for each potential input, the mechanism does not know in advance what the system output would be to estimate its impact on the information entropy; therefore, instead of focusing on the actual value of the diagnostic assessment, it calculates the expected value.

For any potential input (I_n), there would be a set of possible outputs ($O_{n_i}(I_n) \quad i = 1 \dots m$). Each output leads to a different diagnostic assessment and, consequently a different utility function outcome:

$$U(f|I, O, I_n, O_{n_i}) = - \sum_{j=1}^n (P(f_j) \log_e P(f_j) | I, O, I_n, O_{n_i}) \quad (3.2)$$

The expected value of the utility function is calculated by averaging over all possible outputs ($O_{n_i}(I_n)$):

$$E\{U(f|I, O, I_n)\} = \sum_{i=1}^n U(f|I, O, I_n, O_{n_i}) P(O_{n_i}|I, O, I_n) \quad (3.3)$$

Using the Bayesian network interface algorithm, $P(O_{n_i}|I, O, I_n)$ can be calculated by:

$$P(O_{n_i}|I, O, I_n) = \frac{\sum_{j=1}^n P(f_j)P(O|f_j, I)P(O_{n_i}|f_j, I_n)}{\sum_{i=1}^n \sum_{j=1}^n P(f_j)P(O|f_j, I)P(O_{n_i}|f_j, I_n)} \quad (3.4)$$

Now, the next best input is the one that leads to the minimum expected value of the utility function (minimum expected value of the information entropy):

$$\text{Best Next Input} = \arg \min_{I_n} \{E\{U(f|I, O, I_n)\}\} \quad (3.5)$$

At each step, the mechanism first updates the posterior distribution of the fault node (the diagnostic assessment) and, consequently, the utility function based on the observed data. Then, to find the next best input that maximally improves the diagnostic assessment, it estimates the expected value of the utility function for each potential input using Equations 3.2, 3.3, and 3.4. The input that maximally reduces the expected information entropy is chosen as next best input. The system input then is changed to the calculated best next input to measure the system output. After updating the diagnostic assessment and the associated information entropy, the process starts over again to find another input to further improve the diagnostic assessment. If operating conditions do not allow exploring some inputs, they will be removed from the potential set, and the mechanism will be forced to choose its candidate from the remaining set.

Note that at each iteration, the mechanism, in fact, searches through an n-dimensional space—the dimension of the system input—to find the best next input values. In other words, the computational load is related to the system input dimension. If the input dimension is high, finding the optimum inputs may take substantial time. One way to deal with computational load in high-dimension scenarios could be optimizing for each dimension while other dimension values are fixed. Further research study and development may be required.

3.3 Proactive Testing of Air Handling Unit

In this section, we apply the proposed mechanism to proactively diagnose air handling unit components. As the first example, let us revisit the mixing box diagnostics problem in Chapter 2. From a proactive testing perspective, the aim is to control the damper position (the input) for a comprehensive diagnostic test. As before, the input node contains the outside air damper position, DMP , outside air temperature, T_{out} , and return air temperature, T_{rat} , the output node contains outside air fraction, OAF , and the fault node contains different combination of mixing box faults. The mixing box model is also the same model used in Chapter 2.

An example of proactive testing results is shown in Figure 3.2. The upper left graph shows the directions of the Proactive Testing Mechanism.⁹ The upper right graph shows the system response, and the lower graph shows the diagnostic results. Note how the proactive testing mechanism directs the system to the areas (around 0% and 100% position), where there is less uncertainty about the system behavior and more potential to improve the health status assessment. As you see, the assessment improves substantially when the system responses around 0% and 100% positions are observed.

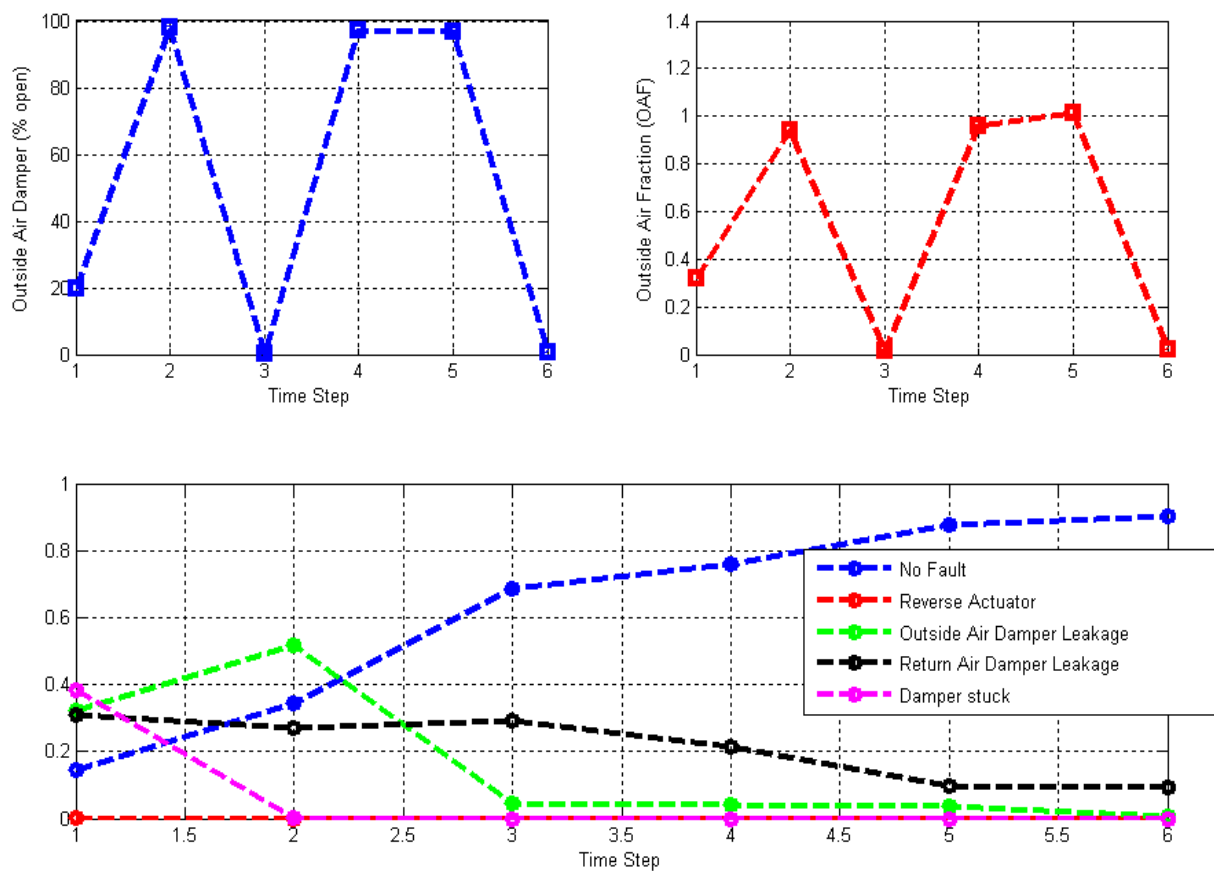


Figure 3.2: Proactive testing of mixing box. The upper left graph shows the directions of the Proactive Testing Mechanism (PTM). The first sample comes from the normal operation. PTM becomes effective from the second sample. The upper right graph shows the system response, and the lower graph shows the diagnostic results. Note how PTM directs the system to the areas (around 0% and 100% position) where there is less uncertainty about the system behavior and more potential to improve the health status assessment. As you see, the assessment improves substantially when the system responses around 0% and 100% positions are observed.

⁹ The first sample comes from the normal operation. The proactive testing mechanism becomes effective from the second sample.

As the second example, we focus on heating coil diagnostics. Again, from proactive diagnostics perspective, we aim to manipulate the valve to conduct a complete diagnostic test. Applying the proposed framework, the input node would contain valve position, VLV , temperature of the water entering the coil, T_{wat_in} , temperature of the entering air, T_{air_in} , air flow rate, CFM , and the output node would be the supply air temperature, T_{air_out} . The fault node contains different combinations of heating coil faults. The heating coil model is the same NTU based model introduced in Chapter 2. A proactive testing result is shown in Figure 3.3. You can see how the mechanism directs the system from one area to another once it gets clear about the targeted faults.

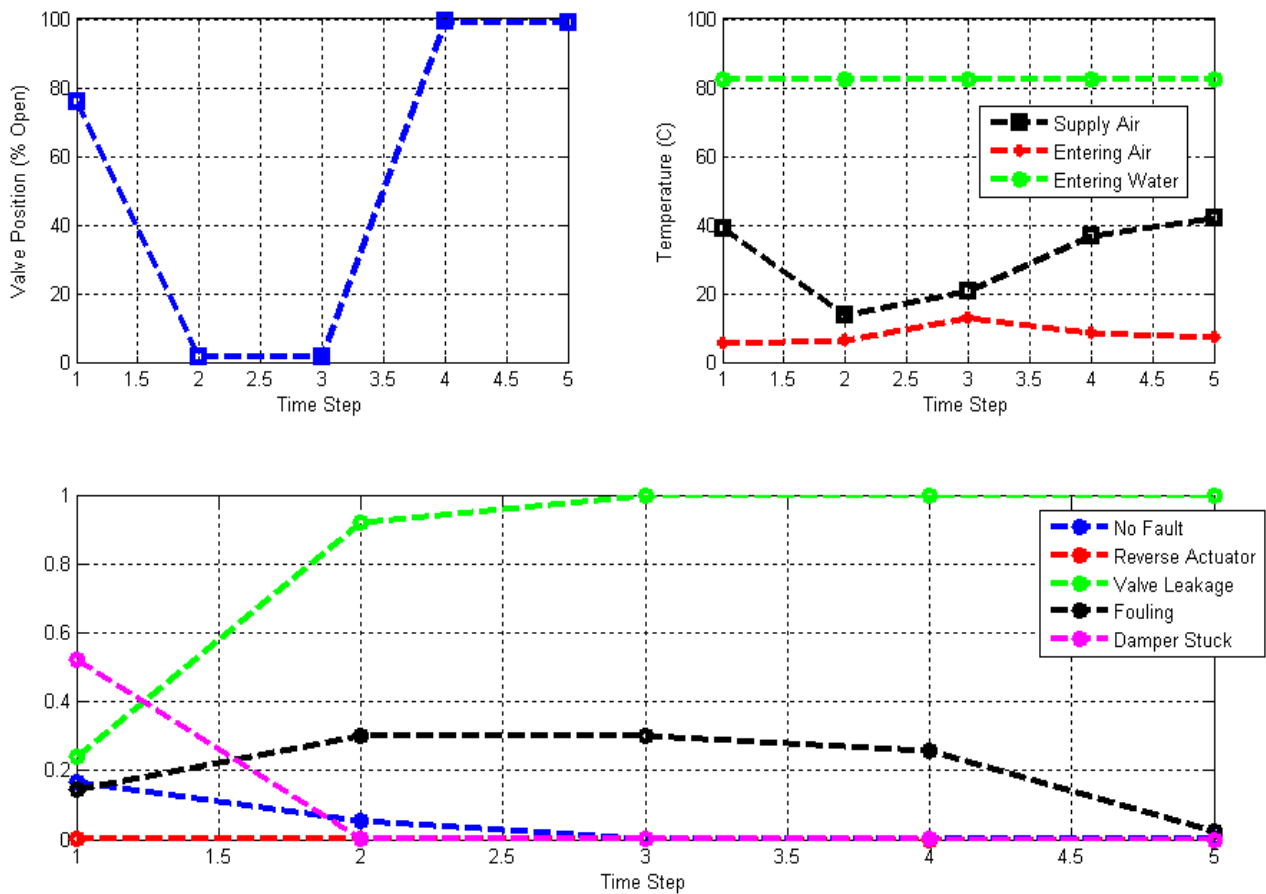


Figure 3.3: Proactive testing of heating coil. The upper left graph is the valve position defined by the proactive testing mechanism (PTM). The first sample comes from the normal operation. PTM becomes effective from the second sample. The upper right graph shows the measurements at each step. The supply air temperature varies as the valve position changes. The variations of entering air temperature and entering water temperature are from external sources. The diagnostic results are shown in the lower graph. Due to the possibility of multiple faults, the beliefs (the posterior probability of faults) are not necessarily summed up to one.

4. A STATISTICAL PATTERN ANALYSIS APPROACH FOR ROOFTOP UNIT DIAGNOSTICS

4.1 Introduction

Rooftop units (RTU) are the most common source of heating, cooling, and ventilation in small and medium-sized commercial buildings, including retail stores, supermarkets, and restaurants. The U.S. Department of Energy estimates that rooftop and unitary air-conditioning equipment accounts for 62% of the 1.66 Quads of annual energy consumption used for cooling of the current building stock of commercial buildings in the United States [1].

Rooftop unit malfunction is known to be one of the main reasons for inefficient operation in buildings. A fault induced during installation or developed over time can go undetected for a long period, resulting in high energy costs, shortened equipment life, and adverse impact on occupant comfort and health.

Functionally, a rooftop unit is an air handling unit (AHU) with built-in sources of heating and cooling (Figure 4.1). It usually contains a fan, two dampers, a gas-fired heating coil, and/or a direct expansion (DX) cooling coil. Usually, there are several stages of cooling and/or heating. Each stage can be thought of as an independent source of cooling or heating. When it is turned on, a certain amount of cool or heat is generated. The stages are activated sequentially by the controller to meet the load.

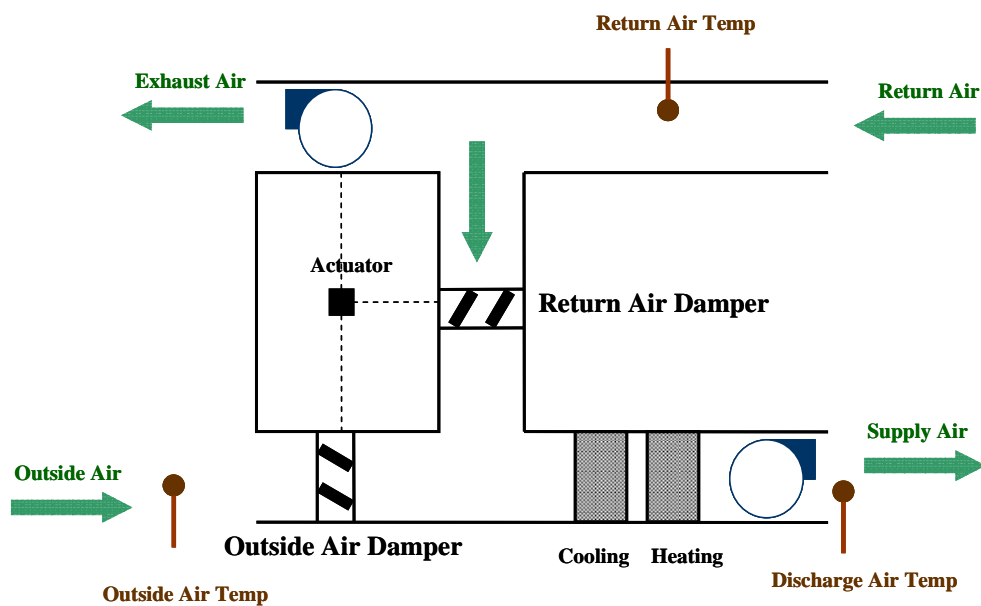


Figure 4.1: Rooftop unit schematic diagram

Most limitations of AHU diagnostics apply to RTU diagnostics as well. For example, with both problems, there is no reliable measurement of the mixed air temperature (MAT), or no measurement of the supply air flow rate, which limits the estimation of fan efficiency and coil duty.

In this chapter, we present a statistical approach for rooftop unit diagnostics. The proposed solution does not depend on a detailed model and can deal systematically with measurement constraints. Another attribute is steady state condition flexibility. Usually, diagnostic mechanisms based on simplified models have the limitation of using measurement obtained in steady state condition because the models are limited to simulating the static behavior of the system. A typical strategy is to wait until parameter variations are small enough to mimic steady state condition. However, steady-state conditions may not happen frequently either because of cycling during routine operation, high frequency disturbances, or control loop oscillation. The proposed diagnostic approach has the advantage of not requiring steady state condition. By analyzing the correlation among parameters and comparing them with various hypotheses, the diagnostic framework locates the pattern that best matches the data and evaluates the performance.

4.2 Proactive Testing of Air Handling Unit

We evaluate rooftop unit functionality in two steps:

- i) Cooling/heating system diagnostics
- ii) Mixing box diagnostics

4.2.1 Cooling/Heating System Diagnostics

A common fault in rooftop unit is malfunction of the heating/cooling system in which one or more stages are broken (non-functional). An intuitive approach to detect and isolate the faulty heating/cooling stage is to monitor the variations of the discharge air temperature. When DAT does not respond accordingly as a cooling or heating stage is turned on (or off), it is an indication of the coil malfunction. However, in practice, tracking coil effect in DAT variations may not be straightforward. Usually, there is a delay between a control command and DAT response which complicates the situation, particularly when coils are turned on and off frequently to maintain the DAT set-point. One way to tackle the problem is to analyze the

linear correlation between heating/cooling commands and DAT variations.¹⁰ The correlation function can tell us if there is any relation between the causes (heating/cooling commands) and the effects (DAT variations).

For each stage of heating and cooling, we assign a binary variable:

$C_1, C_2, C_3, \dots, H_1, H_2, H_3, \dots$

$$C_i(t) = \begin{cases} 1 & \text{Cooling Stage } i \text{ is on} \\ 0 & \text{Cooling Stage } i \text{ is off} \end{cases} \quad H_i(t) = \begin{cases} -1 & \text{Heating Stage } i \text{ is on} \\ 0 & \text{Heating Stage } i \text{ is off} \end{cases}$$

the cooling/heating sum (CHS) is then defined as:

$$CHS(t) = C_1(t) + C_2(t) + \dots + H_1(t) + H_2(t) + \dots \quad (4.1)$$

When there is no fault, CHS and DAT should be strongly correlated. The correlation can be verified by analyzing the cross-correlation and cross-spectrum functions. For two series x_t and y_t , the cross-correlation function:

$$\gamma_{xy}(h) = E[(x_{t+h} - \mu_x)(y_t - \mu_y)] \quad (4.2)$$

where E is the abbreviation for the expected value, μ_x and μ_y are the mean values of x_t and y_t respectively. The cross-spectrum, which is the Fourier transform of the cross-correlation, is:

$$f_{xy}(\omega) = \sum_{h=-\infty}^{\infty} \gamma_{xy}(h) e^{-2\pi i \omega h} \quad -1/2 < \omega < 1/2 \quad (4.3)$$

The cross-spectrum is a complex-valued function. The squared-coherence function, ρ , is then defined as:

$$\rho_{y.x}^2(\omega) = \frac{|f_{yx}(\omega)|^2}{f_{xx}(\omega)f_{yy}(\omega)} \quad (4.4)$$

¹⁰ Although the relation between heating/cooling systems and DAT variations is not completely linear, it is a reasonable assumption for diagnostic purposes; the heat balance between the air stream and the coil can be specified by [reference]:

$$q = hA(T_{coil} - T_{air})$$

where h depends on the air velocity and A is the effective surface area. If T_{coil} , h , and A are assumed to be constant, the relation between the air temperature (T_{air}) and q is linear. Now, if we assume that when a heating/cooling stage is turned on or off, certain amount of heat/cool (q) is provided or taken, we can say that relation between T_{air} and heating/cooling command(s) is linear.

where $f_{xx}(\omega)$ and $f_{yy}(\omega)$ are the individual spectra of x_t and y_t . Although cross-correlation and cross-spectrum functions are used to analyze the correlation among random processes, they can also be used for the analysis of linear relations among deterministic variables, which is the case for our problem. More details about cross-correlation and cross-spectrum functions can be found in [75].

For example, in Figure 4.2, we show the performance of a rooftop unit located in a retail store in Texas. The plot shows 24 hr operation, excluding the unoccupied period, on a hot summer day. In Figure 4.3, the corresponding CHS, coherency, and phase functions are shown. Note that DAT and CHS are highly correlated at low frequencies. As there is usually a 2-3 minute delay between two consecutive heating/cooling commands, the CHS dominant frequencies are low-band (lower frequencies).

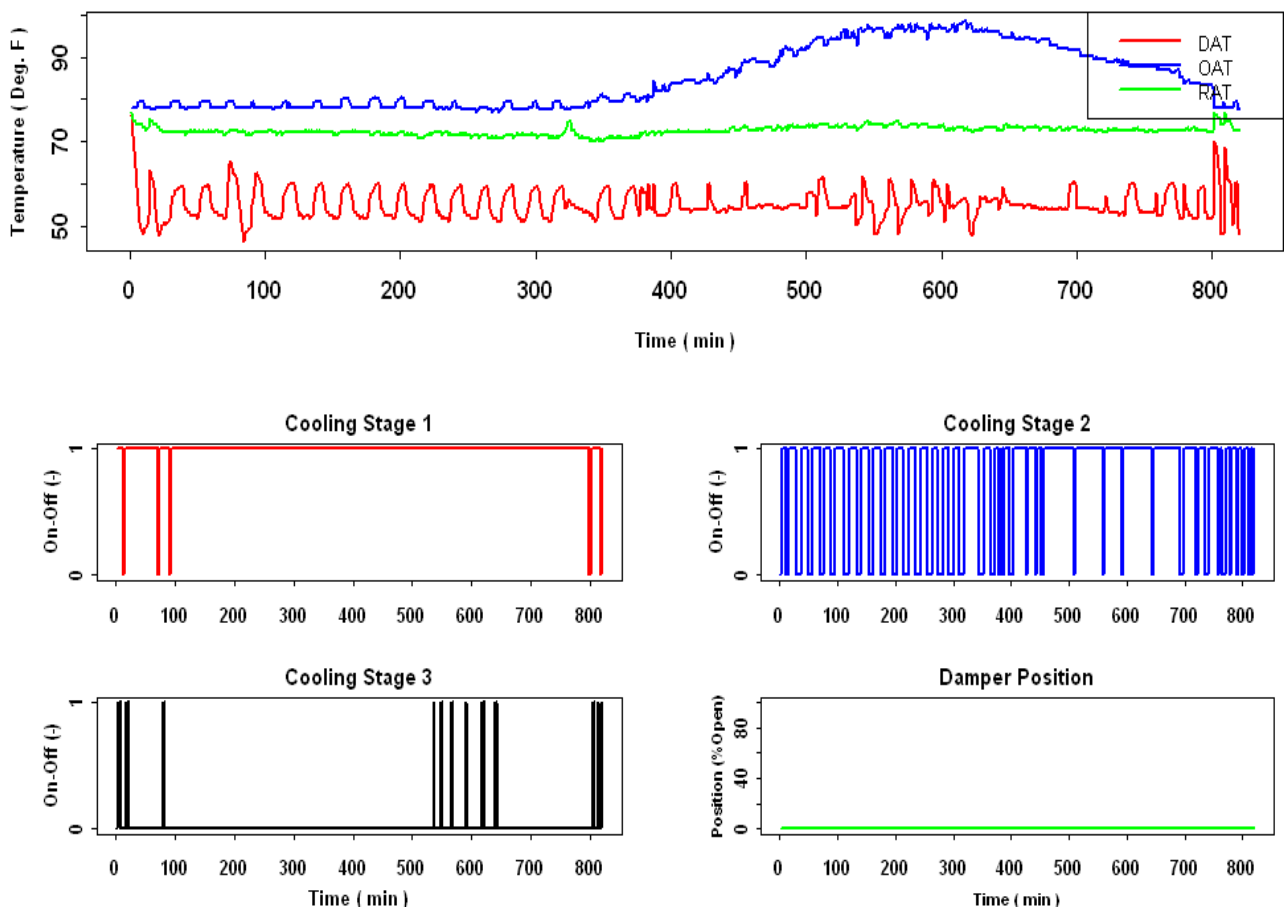


Figure 4.2: A rooftop unit performance located in a retail store in Texas. Data contains 24 hr operation excluding unoccupied periods with a sampling rate of 1 min. It was collected in the summer of 2008. The RTU has three cooling stages and three heating stages.

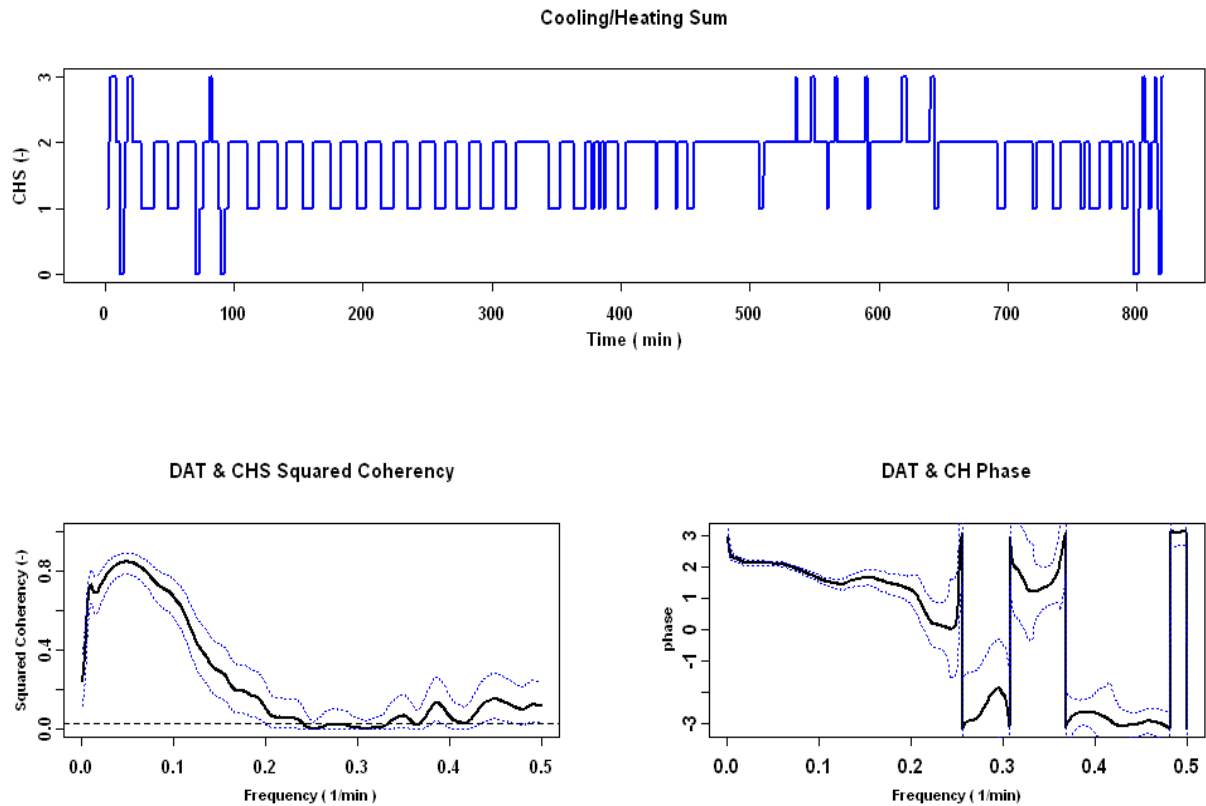


Figure 4.3: The cooling/heating sum (CHS), coherency, and phase between the DAT and CHS of the RTU in Figure 4.2. The blue dash lines in the coherency and phase graphs are the confidence intervals. The flat line in the coherency graph shows the approximate value that must be exceeded by the squared coherency to confirm that the coherency is non-zero at the specified frequency ($\rho_{y,x}^2(\omega) \neq 0$). A second-order difference operator was applied to make the data stationary before calculating the coherency and phase.

When there is a faulty stage of heating or cooling, the CHS/DAT correlation degrades. In order to isolate the faulty stage, the coherency between DAT and a number of CHSs are compared. Each CHS is constructed based on the assumption that one or more cooling/heating stages is non-functional. When a stage is assumed to be non-functional, its associated $C_i(t)$ or $H_i(t)$ is set to zero. The CHS that has the strongest correlation with DAT is chosen as the closest match, and the corresponding assumption is concluded to be the operational status of the heating/cooling systems.

For example, in Figure 4.4, three different CHSs and the corresponding coherency graphs of the RTU in Figure 4.2 are shown.¹¹ Note that the no-fault case has the highest correlation, as expected.

¹¹ Due to space limitations, only a few scenarios are shown.

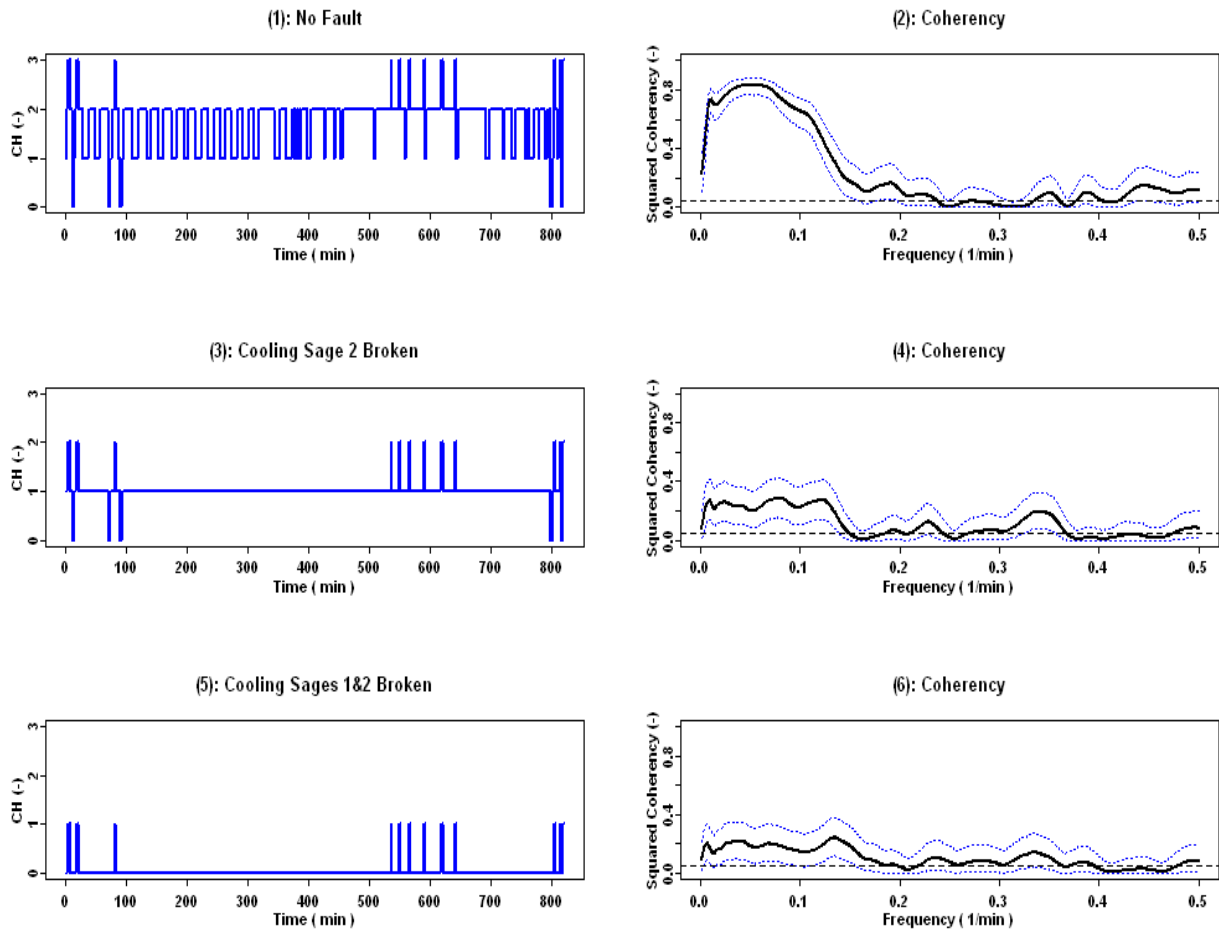


Figure 4.4: A number of CHSs and the corresponding coherencies based on different hypotheses for the RTU shown in Figure 4.2. It is clear that the no-fault case has the strongest correlation. Because of space limitations, only a few possible CHSs are shown.

As another example, Figure 4.5 shows the performance of another RTU located in a different retail store in California. Visual inspection indicates that DAT does not respond accordingly as the cooling stage 1 is activated. This suggests that the cooling stage 1 might be faulty. In Figure 4.6, various CHSs and the corresponding coherency graphs are shown. It is clear that the case related to a non-functional cooling stage 1 has the highest correlation.

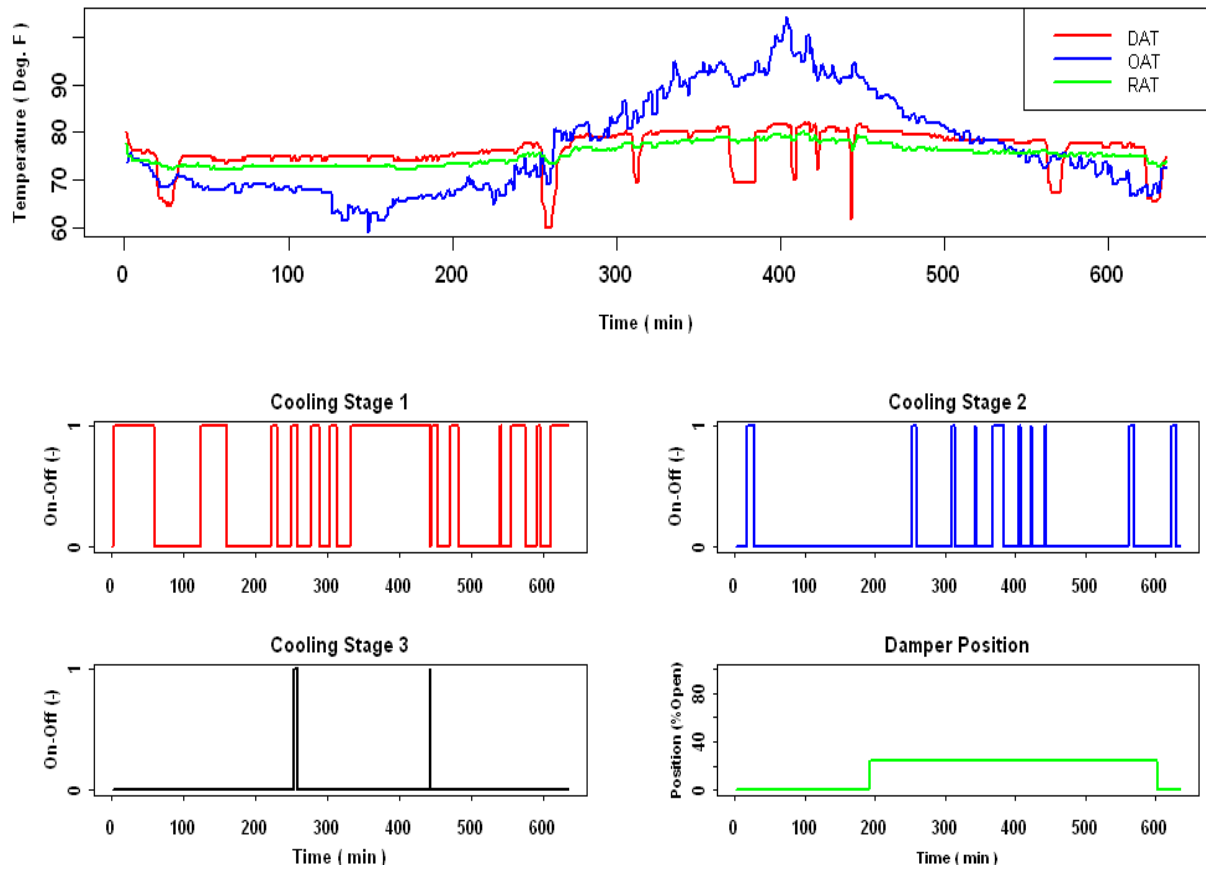


Figure 4.5: Rooftop unit performance located in a retail store in California. Data contains 24 hr operation, including unoccupied periods, with a sampling rate of 1 min. It was collected in the summer of 2008. The RTU has three cooling stages and three heating stages.

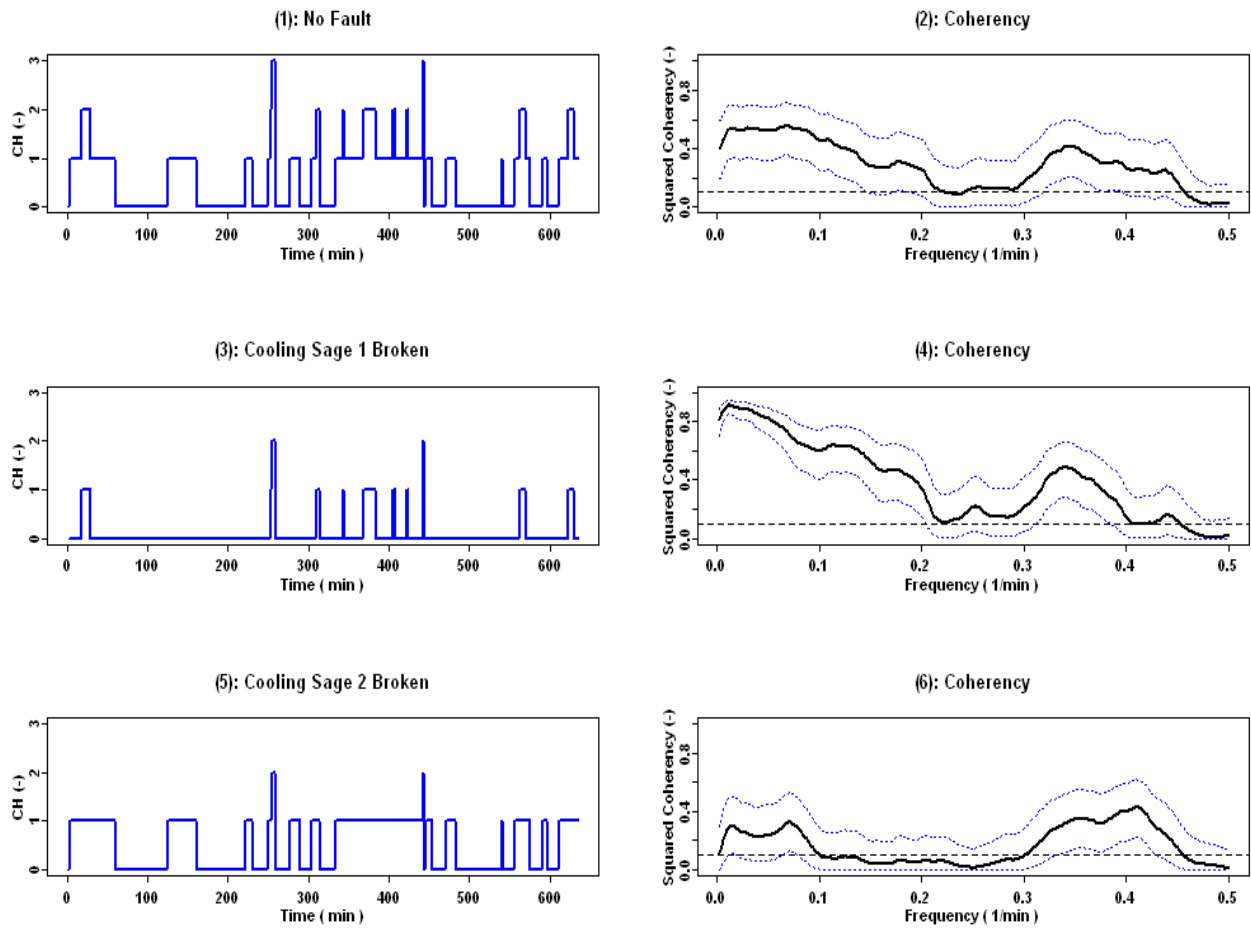


Figure 4.6: A number of CHSs and the corresponding coherencies based on various hypotheses for the RTU shown in Figure 4.5. It is clear that cooling stage 1 broken case has the strongest correlation. Because of space limitations, only a few possible CHSs are shown.

4.2.2 Mixing box diagnostics

As mentioned earlier, the main challenge in mixing box diagnostics is to deal with the lack of a mixed air temperature measurement (Figure 4.1); the main measured variable that is directly affected by the mixing box functionality is the discharge air temperature which is also affected by the coil behavior. The challenge is how to differentiate between coils and mixing box effects. An intuitive approach is to analyze mixing box performance while the coils are off. This may not be compatible with normal operation unless the system is in free cooling mode.

Our proposed approach is to remove the coil effect from DAT variations first, and then use the filtered DAT to analyze mixing box performance. The filtering coil effect can be achieved by finding $\{\beta_t\}$, which minimizes the following mean squared error function:¹²

$$MSE = E \left(DAT_t - \sum_{r=-\infty}^{\infty} \beta_t CHS_{t-r} \right)^2 \quad (4.5)$$

The Fourier transform of $\{\beta_t\}$ can be estimated as [74]:

$$\hat{\beta}(w_k) = \frac{\hat{f}_{DAT,CHS}(w_k)}{\hat{f}_{CHS,CHS}(w_k)} \quad (4.6)$$

$\{\beta_t\}$ can then be found by the inverse Fourier transform of $\hat{\beta}(w_k)$. The estimated β_t for the RTU in Figure 4.5 is shown in Figure 4.7. A possible model for β_t is:

$$\sum_{r=-\infty}^{\infty} \beta_t CHS_{t-r} = -1.1CHS_{t-3} - 1.43CHS_{t-2} - 0.98CHS_{t-1} - 3.12CHS_t + 1.29CHS_{t+1} + 0.70CHS_{t+2} + 0.86CHS_{t+4} \quad (4.7)$$

Now, the filtered DAT, an estimation of MAT, is:

$$MAT_t = DAT_t - \sum_{r=-\infty}^{\infty} \beta_t CHS_{t-r} \quad (4.8)$$

¹² Here, we again assume a linear relation between heating/cooling command and DAT variations.

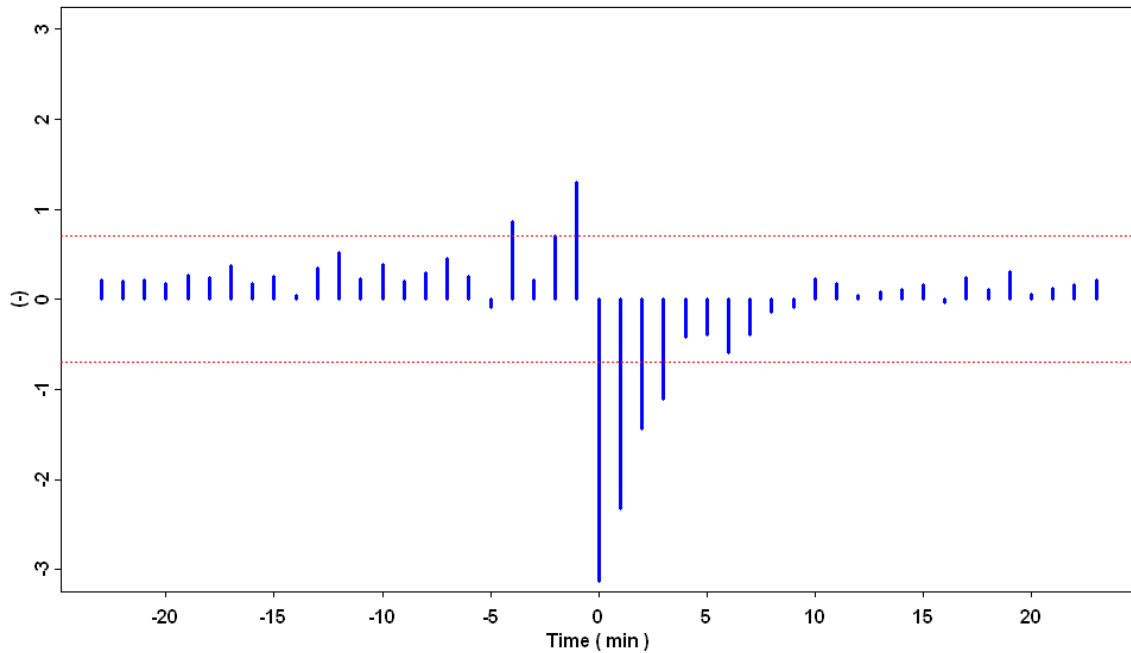


Figure 4.7: Estimated β_t for the data shown in Figure 4.5.

In the mixing box, the relation between MAT and OAT/RAT depends on the damper position. A simple mixing box model is:¹³

$$MAT = \left(\frac{DMP}{100}\right) * OAT + \left(1 - \frac{DMP}{100}\right) * RAT \quad (4.9)$$

Similar to the heating/cooling system scenario, the proposed approach is to compare the correlation between the estimated MAT (filtered DAT) with a number of MATs generated assuming that one or more faults exist. The one with the strongest correlation is chosen as the closest match and the corresponding assumption is concluded as the mixing box status.

As an example, using the filtered DAT from equations 4.7 and 4.8, Figure 4.8 shows the coherency and phase functions for three scenarios (no fault, reverse actuator fault, and stuck damper fault). Note that the no-fault case has the highest correlation, meaning that the mixing box works properly. The correlations are weaker comparing to those shown in Figures 4.4 and 4.5 because of the limited excitation existing in the damper position.

¹³This is a very simplified model of the mixing box. In reality, the mixed air temperature depends on other factors such as the shape of dampers, ductwork curves, air velocity, etc. However, most of these parameters are not easily measureable, so we use this simplified model.

As another example, Figure 4.9 shows simulated performance of a rooftop unit with the stuck damper fault. Using the same diagnostic framework, in Figure 4.10, you see how the stuck damper scenario shows a higher correlation comparing to other coherency functions.

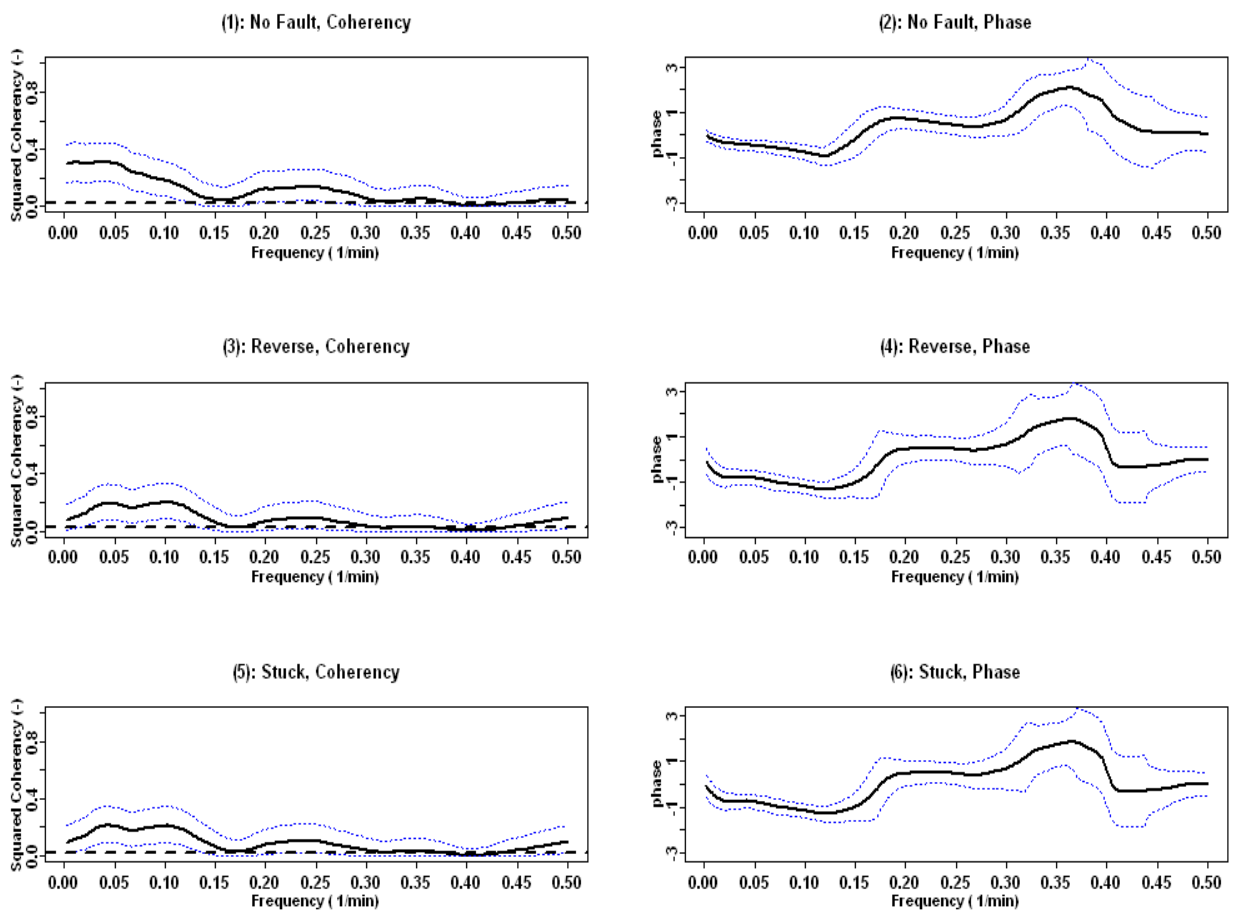


Figure 4.8: The coherency and phase functions for three different scenarios (no fault, reverse actuator, and stuck damper) for the RTU in Figure 4.5.

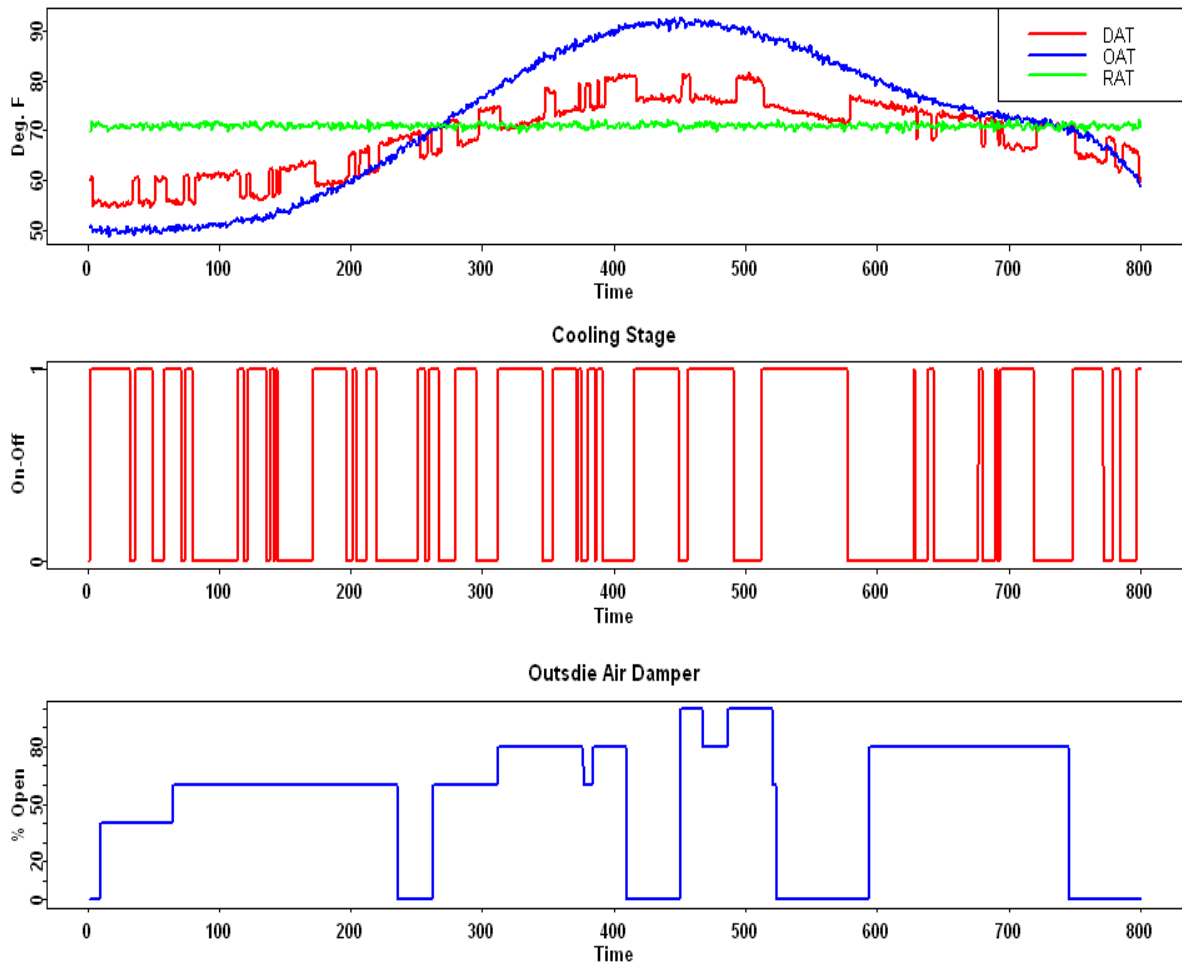


Figure 4.9: Simulated performance of a rooftop unit with stuck damper fault. The damper position has been manipulated deliberately to generate enough excitation.

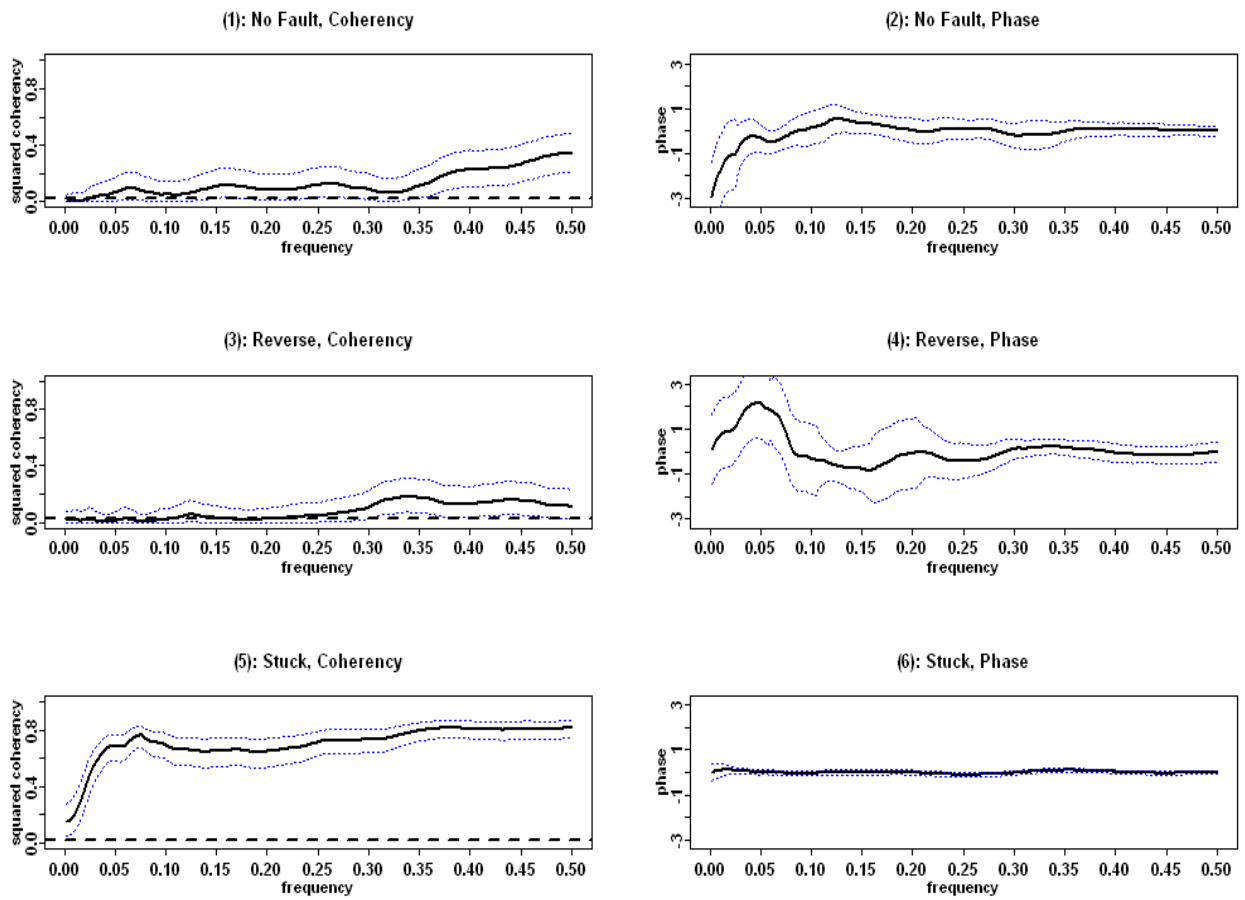
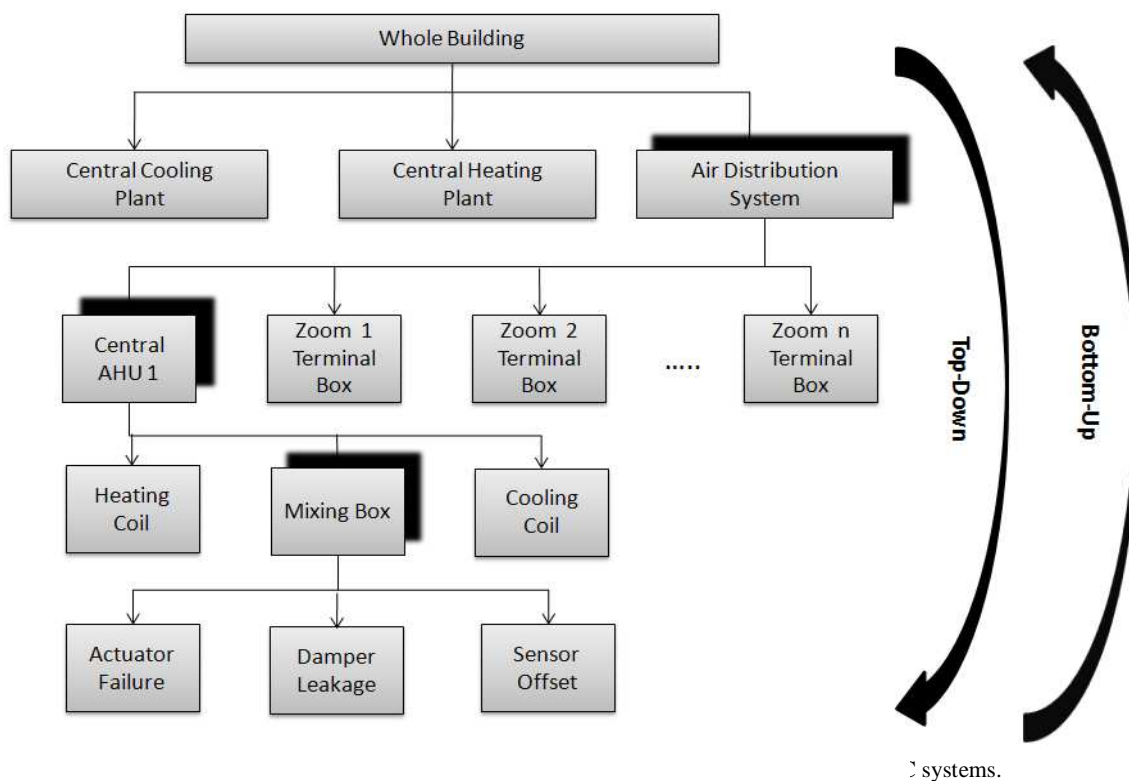


Figure 4.10: The coherency and phase functions for three different scenarios (no fault, reverse actuator, and stuck damper) for the RTU in Figure 4.9.

5. BOTTOM-UP VERSUS TOP-DOWN DIAGNOSTICS

As mentioned earlier, fault detection and diagnostics in building HVAC systems can be approached from two perspectives: bottom-up and top-down. In the bottom-up approach, lower-level performance measures of HVAC systems (Figure 5.1) are used to isolate the problem and propagate its effect on building performance. Conversely, in the top-down approach, higher-level performance measures are used to reason about possible lower-level causes of degradation to the higher-level measures.

Bottom-up diagnostic routines usually are initiated by the occupant complaints. When occupants complain about hot, cold, or an uncomfortable environment, a diagnostic routine is started from the complainant's area to trace the problem and locate the malfunctioning device. In contrast, top-down diagnostic processes—also known as whole building diagnostics—are normally motivated by the concern for a building-efficient operation. For example, when building energy usage increases unexpectedly, a top-down diagnostic process is performed to locate the inefficient division/section and trace the problematic device or cause.



From an automated diagnostics perspective, a variety of solutions exists for bottom-up diagnostics, whereas for top-down diagnostics, the story is different. Top-down diagnostic routines are still performed manually, with building experts going through performance graphs, looking for predefined signatures to analyze building performance.

When diagnostics is to be performed at the building level, the complexity of the problem extends to a new horizon. At the component level, there is limited number of faults to deal with; however, at the building level, there is a large set of faults and abnormalities that may occur. Added to this aspect is the complexity of *concurrent* faults. Another issue is detectability of faults: Some faults may not have that much effect on high-level measures to be detectable through a top-down diagnostic process. For example, in a four-story building, the damper leakage fault of a VAV system certainly will not have that much impact on the total energy used by the building to be differentiated from modeling and measurement errors.

The challenge is that there is no systematic solution to discriminate between detectable and non-detectable faults. Fault detectability varies as measurement errors improve or additional measurements are included in the diagnostic processes; further, there is no algorithmic solution to determine which faults should be included and which should be removed from the diagnostic process.

In this chapter, we extend the Bayesian network diagnostic approach presented in Chapter 2 for automated diagnostics from a top-down perspective.

5.1 Top-down Automated Diagnostics

A building's performance is a function of outside air condition, occupant behavior, and building characteristics. When a fault occurs, the building characteristics change, which leads to a change in the building performance (output). Similar to the framework presented in Chapter 2, we think of a building output as a random variable that is conditionally dependent on the input (outside air condition and occupant behavior) and fault condition (Figure 5.2). The input is assumed to be known, and the output is what is measured (e.g., building energy usage). The aim of diagnostics is to find a fault condition that results in a building performance similar to what is observed.

To solve the problem, we presented in Chapter 2 a Bayesian network model with three nodes: *Input node* that represents system inputs (or in whole-building diagnostics, it would be building input), *output node* that represents the building output, and the *fault node* that represents building faults and their combinations. The posterior distribution of the fault node is interpreted as the diagnostic belief or the fault condition that resembles the output. Using Bayesian network inference mechanisms, the posterior distribution can be estimated by:

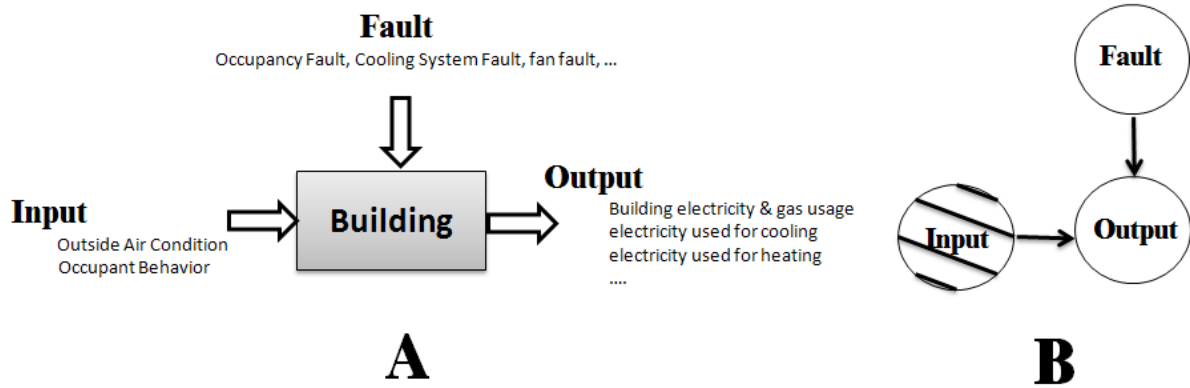


Figure 5.2: A) Diagnostic framework, B) Dual Bayesian Model.

$$P(f_i|I, O) = \frac{P(f_i)P(O|f_i, I)}{\sum_i P(f_i)P(O|f_i, I)} \quad (5.1)$$

where f is the fault set, $f = \{f_1, f_2, \dots, n\}$, I is the input(s), O is the output(s), and $P(f_i)$ is the fault prior distribution. As more data are observed, the posterior belief is updated recursively, leading to a better matching between the observed behavior and different hypotheses.

Equation 5.1 could be a good way of estimating posterior distribution if there were a small (or reasonable) set of faults. However, as in whole-building level diagnostics, we are dealing with a massive number of faults, direct calculation of the posterior distribution is impractical. Another method is to employ numerical algorithms to estimate the posterior distribution; however, first we need to structure the problem properly in order to be solvable numerically.

We categorize building faults based on their effect on high-level measures. Faults with more or less similar impact on building performance with different magnitudes are put in the same set. For example, in a four-story building, the effect of two floors with occupancy fault on the building energy consumption pattern is similar to that of four floors with occupancy faults. The magnitude (or severity) of the effects is different, but the fingerprints are the same. Therefore, all different combinations of occupancy fault—first floor, second floor, different combination of floors, and so on—are grouped in one set. A similar analogy can be made for fan malfunction (broken fan), cooling system fault (non-functional cooling systems), and so on. An example of different fault categories can be:

- **Category 1:** no occupancy fault, Floor 1 occupancy fault, Floor 2 occupancy fault, ... , Floors 1 & 2 occupancy fault, ... , Floors 1 & 2 & 3 occupancy fault, ...
- **Category 2:** no fan fault, VAV 1 fan fault, VAV 2 fan fault, ... VAV 1 & 2 fan fault, ...

- **Category 3:** no cooling system fault, ...

Now, the estimation of the posterior distribution can be thought as estimating the posterior distribution in each fault category. If none of the faults existing in a fault category occurred, the no-fault member should have the highest value. If the building malfunction is due to *concurrent* faults, each in a different fault category, the posterior distribution of each fault category will show higher values for these faults.

To estimate the posterior distribution, we employ a Markov Chain Monte Carlo (MCMC)¹⁴ algorithm to solve the problem numerically. The MCMC algorithm searches through a multi-dimensional space in which each dimension is designated to a fault category whose members are possible outcomes.

Note that all members of a fault set are not necessarily detectable. Non-detectable faults will end up having relatively equal posterior distribution, meaning that they are not distinguishable through existing measurements and errors (an example is provided later).

Another issue is *fault priors*. Appropriate distribution for fault priors is important to avoid bias estimations. Here, the priors are defined based on the likelihood of fault occurrences. Concurrent faults are less likely to happen than are single faults; therefore, they are assigned smaller priors. All single faults are assigned a uniform prior distribution. As the number of faults happening simultaneously increases, the associated prior value decreases.

5.2 Illustrative Example: Diagnostics of an Office Building

In this section, we illustrate a top-down approach to fault detection and diagnosis using a prototypical 511 m^2 office building. The building is one of the benchmark buildings developed with EnergyPlus [24]. It consists of five effective “energy” zones (Figure 5.3). Each zone is served by its own heating and cooling system consisting of a gas-driven forced-air furnace, a single duct terminal unit, a fan, and a unitary DX (Direct Expansion) cooling system. The building also contains a gas water heater. In the example that follows, we apply Chicago summertime weather conditions.

¹⁴ Markov Chain Monte Carlo (MCMC) methods—which include random walk Monte Carlo methods—are a class of algorithms for sampling from probability distributions based on constructing a Markov chain that has the desired distribution as its equilibrium distribution. The state of the chain after a large number of steps is used as a sample from the desired distribution. The quality of the sample improves as a function of the number of steps. For more information, please refer to [70].

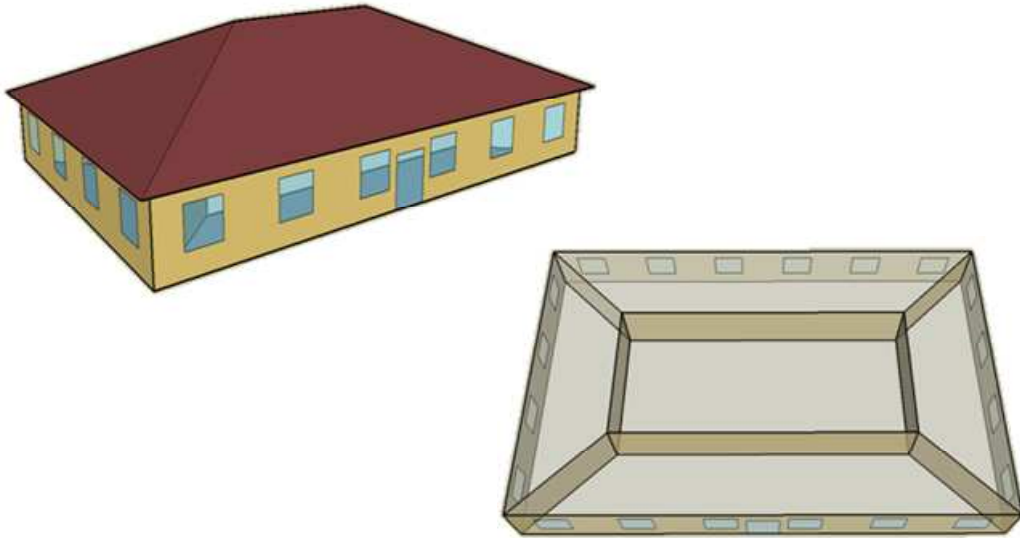


Figure 5.3: Schematic and floor plan of the prototypical office building [77].

We will apply the algorithm to detect and diagnose examples of four common faults: malfunctioning of cooling systems, malfunctioning of fans, occupancy misscheduling (misscheduling of heating/cooling systems, etc), and misscheduling of outdoor/perimeter lights. We consider all possible combinations of these faults—more than 6,000 different scenarios. A larger number and types of faults could have been considered, but we kept the number small here to be able to discuss the results in detail.

Three measurements are used to analyze building performance: total electricity used by the building, total electricity used by cooling systems, and total electricity used by fans. We introduced error in the measurements by adding a 20%-30% error to the model prediction.

In the first example, we consider an occupancy fault scenario in which the operation of one or more zones in the building does not properly switch from daytime schedule to an evening schedule. Figure 5.4 shows the building performance with the induced occupancy fault. For better comparison, we have also included the building performance in fault-free condition (blue graphs).

Using the proposed algorithm, the updated posterior distribution is shown in Figure 5.5. The x-axis shows the severity of the fault, as described by the number of units out of the total that are faulting. For example, “4/5” means that four out of five zones have occupancy fault.

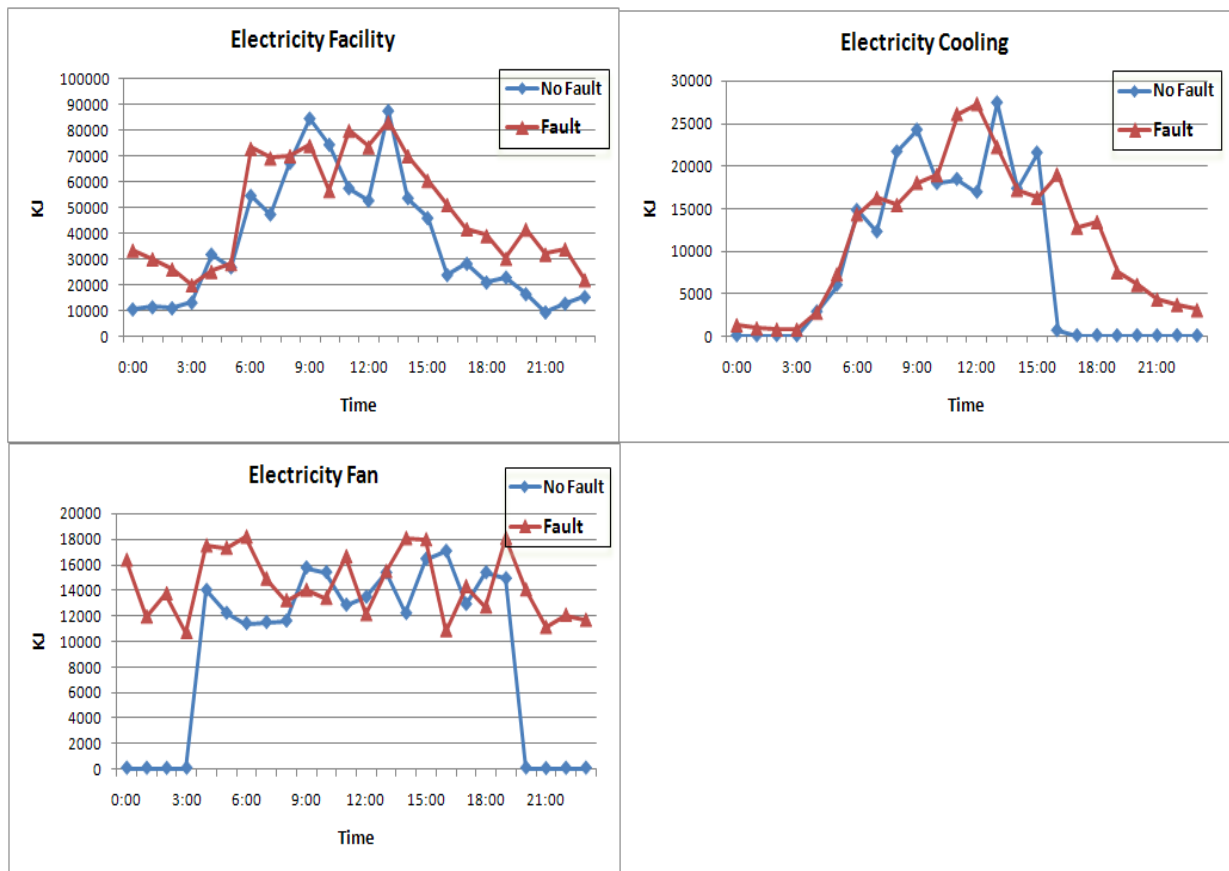


Figure 5.4: Baseline model prediction for energy use for (a) electricity used by the entire building, (b) electricity used by cooling systems, and (c) electricity used by fans. The blue lines show normal (non-faulty) operation, and the red ones show operation with induced occupancy fault.

The diagnostic results indicate that at least four out of five zones in the building are misscheduled. However, the result is inconclusive about the operation of cooling systems: It is unclear whether all cooling systems are operating normally with no fault or if only one of unitary DX cooling systems is faulty.

The inconclusiveness of diagnostic results for the cooling systems is due to non-detectability of small cooling system faults. In other words, the effect of one cooling system fault on measured parameters is so small that it cannot be differentiated from modeling and measurement errors. To improve the diagnostic result, we either need to reduce the modeling/measurement errors or include other measurements—additional sensors—in the diagnostic process.

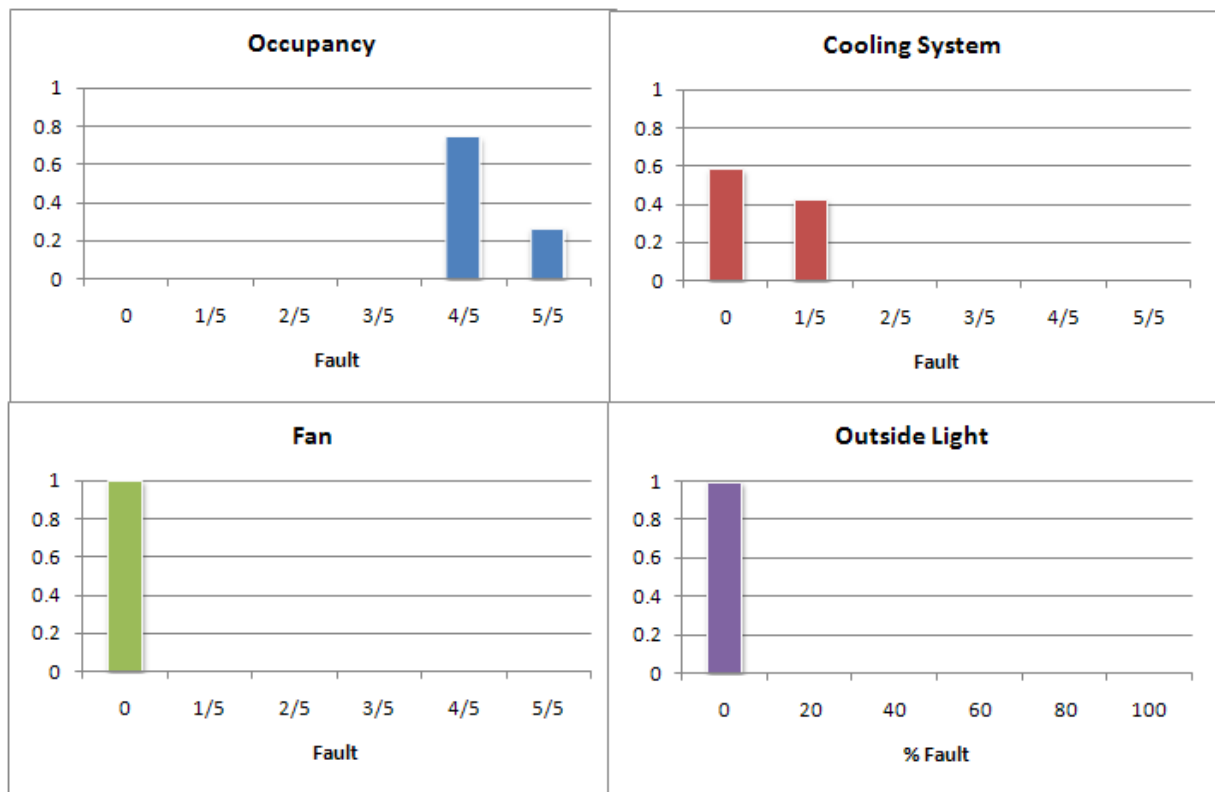


Figure 5.5: Diagnostic result, updated posterior distribution of the fault node in Figure 5.2. Each graph shows the histogram of the posterior distribution of the associated fault category. The x-axis shows the severity of fault, as described by the number of units out of total that is faulting. For example, “4/5” means that four out of five zones have an occupancy fault.

We now consider another example in which two faults are occurring simultaneously: a cooling system fault and misscheduling of outside lights. Figure 5.6 shows the building performance in which the cooling systems in three zones are faulty, and the outside lights are operational in daytime. At first glance, we see a reduction in the cooling system electricity usage, which raises the idea of a cooling system malfunctioning. However, as we do not observe a similar effect on the total electricity usage, we suspect that there might be other explanations.

The inconsistency is due to the effect of the outside light fault. The increase of electricity usage from the operation of outside lights in daytime has covered the effect of the cooling system fault. In other words, if the only parameter used to analyze the building performance were total electricity usage, these two types of faults would not be distinguishable.

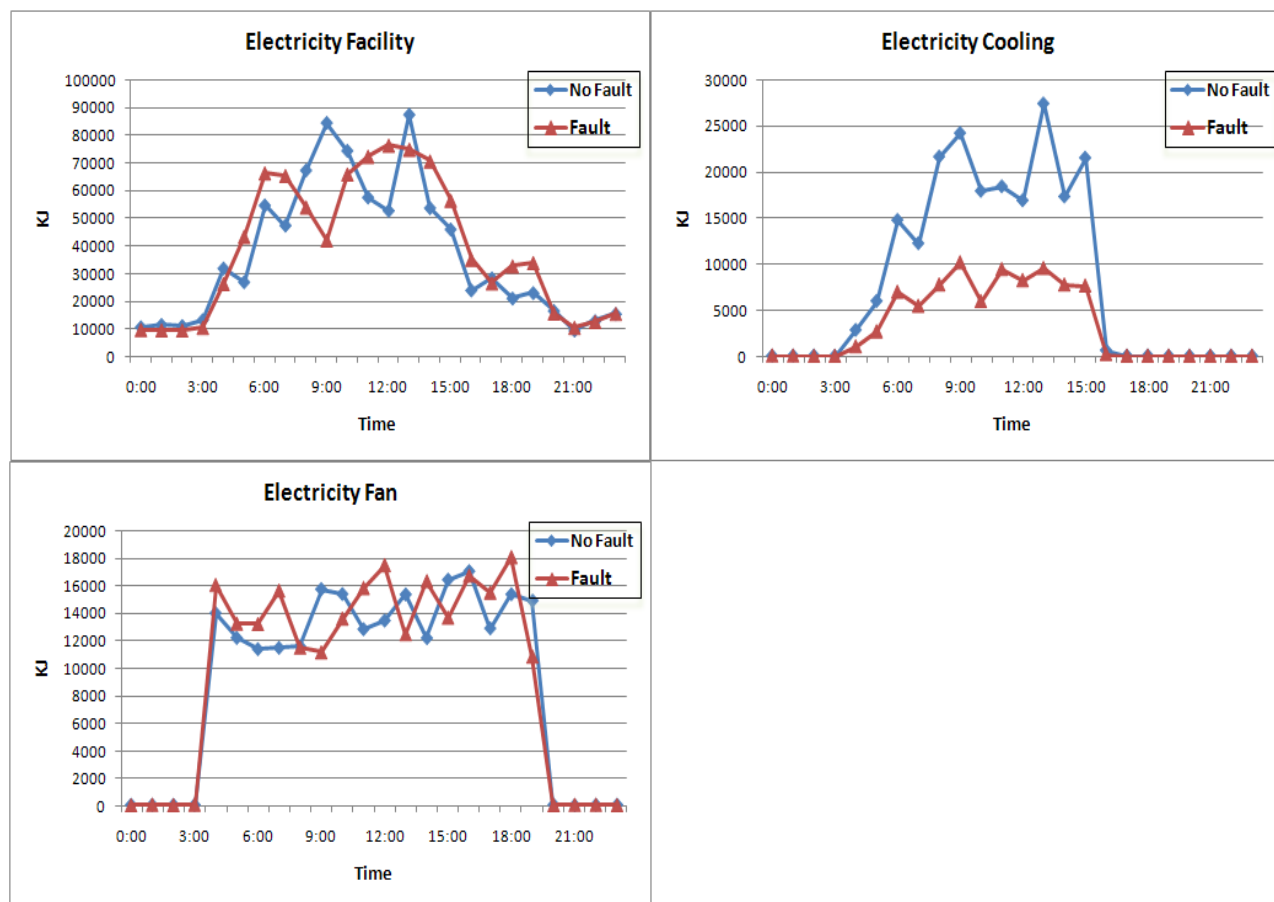


Figure 5.6: Baseline model prediction for energy use for (a) electricity used by the entire building, (b) electricity used by cooling systems, and (c) electricity used by fans. The blue lines show normal (non-faulty) operation, and the red ones show operation with cooling system fault and misscheduling of outside lights.

The diagnostic result, the update posterior distribution, is shown in Figure 5.7. It indicates a cooling system fault in three or four zones and misscheduling of the outside lights. However, the result does not specify which zones have malfunctioning cooling systems. This goes back to the question of what level of diagnostic precision is achievable through available measurements and/or existing measurement/modeling errors. By monitoring only the electricity used by the building, cooling systems, and fans, we cannot expect a more detailed diagnostic result—especially if fans, cooling/heating systems, and so on, are more or less the same size. If a higher diagnostic resolution is desired, one solution is to use lower-level measures.

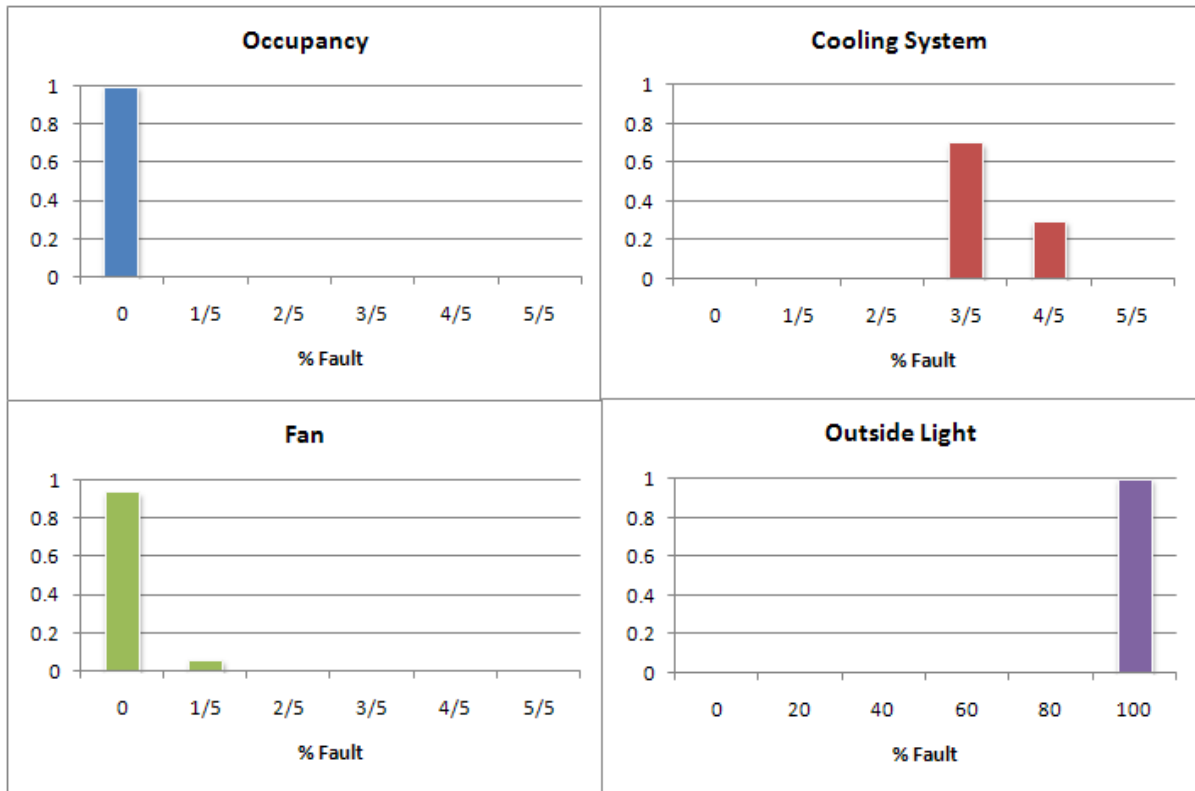


Figure 5.7: Diagnostic result, updated posterior distribution of the fault node in Figure 5.2. Each graph shows the histogram of the posterior distribution of the associated fault category. The x-axis shows the severity of fault, as described by the number of units out of total that is faulting. For example, “4/5” means that four out of five zones have an occupancy fault.

As the final example, we consider a fan fault scenario. It is likely that a fan fault condition would be caught quickly by the operators or occupants, especially in a hot or cold climate; however, we are interested to see how the diagnostic algorithm analyzes such a situation. Fans were deliberately turned off, and data were fed to the algorithm to analyze the building performance. Figure 5.8 shows the diagnostic result. As you can see, the result correctly indicates the fans are faulty, although it is inconclusive about the cooling systems operation and occupancy scheduling. In other words, it does not give us that much insight about cooling system and occupancy faults.

To explain the result, note that when fans are non-functional (broken), no air circulates through the units; consequently, no energy is transferred to the zones. When no energy is transferred, there will be no consumption of cooling/heating energy. Such a scenario confuses the diagnostic algorithm as it cannot verify whether the decline of cooling electricity usage is due to a cooling malfunction, fan malfunction, or both. All will have a similar effect on the pattern of cooling electricity usage. In other words, the information existing in current measurements are insufficient to distinguish these faults, which is why we see such inconclusive results. If other

lower-level measures, such as room temperature, were used, the diagnostic result would be different.

In the above examples, we focused more on the faults that relate to functionality or scheduling of HVAC devices. However, sometimes a fault is due to the change of one or more parameter values. For example, fan efficiency may degrade due to a problem with the blades, belts, and so on. For this type of fault, the target parameter can be thought of a random variable whose posterior distribution is to be estimated based on observed data. In the proposed Bayesian model, this will be formulated as another dimension to the fault node.

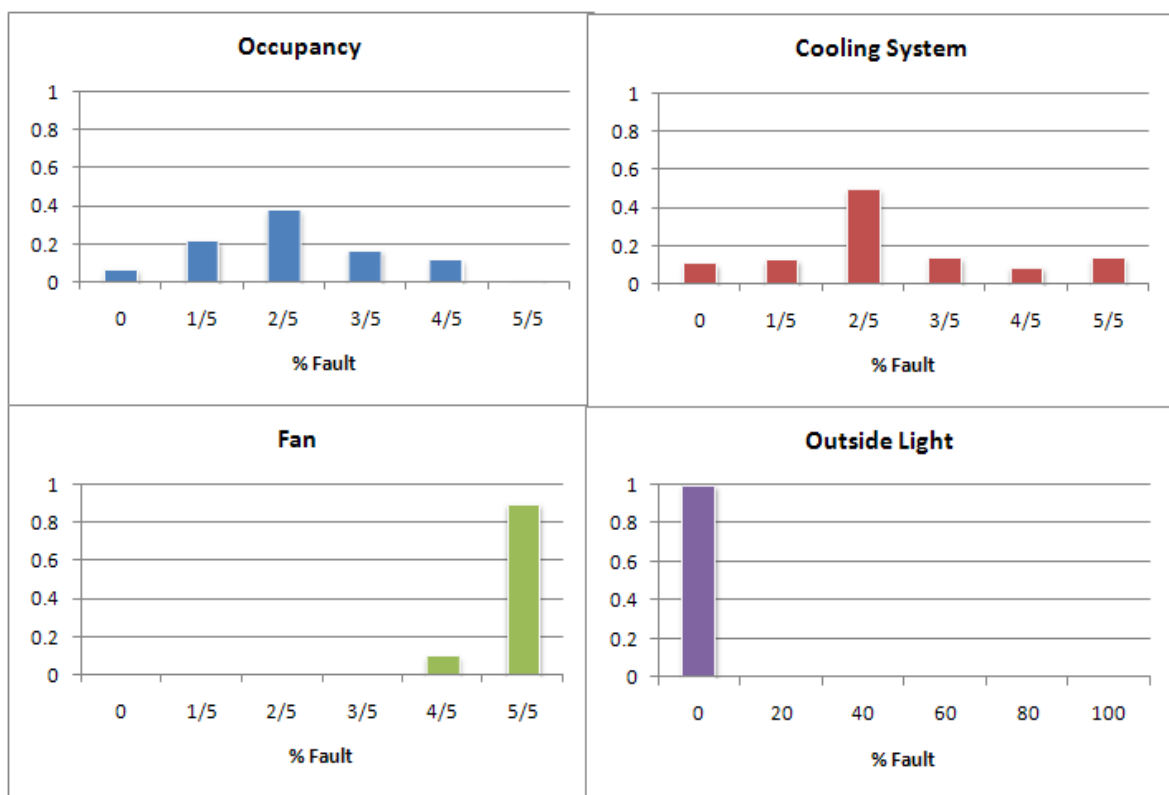


Figure 5.8: Diagnostic result, updated posterior distribution of the fault node in Figure 2. Each graph shows the histogram of the posterior distribution of the associated fault category. The x-axis shows the severity of fault, as described by the number of units out of total that is faulting. For example, “4/5” means that four out of five zones have an occupancy fault.

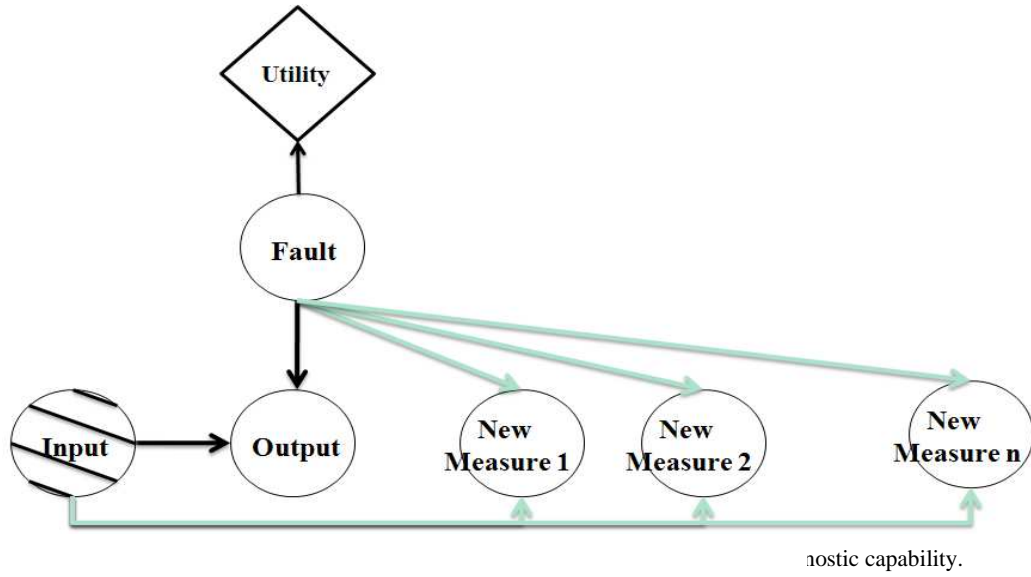
6. MEASUREMENT CONSTRAINT AND DIAGNOSTIC CAPABILITY

As discussed earlier, measurement constraints can greatly extend the complexity of diagnostic problems in building HVAC systems (or even other applications). An important question to ask is how the relation between measurement constraints and diagnostic capability can be systematically quantified. A reliable solution to this problem may reveal a new horizon in the diagnostics of building HVAC systems and could be used as a framework to analyze the effect of new measurements on diagnostic strength, thereby leading to better design or optimization of sensor network architecture from a diagnostic perspective.

To analyze the relation between measurement constraint and diagnostic capability, the first step involves quantification of diagnostic improvement. In other words, the question is how two diagnostic assessments can be compared quantitatively to determine which one is superior. In Chapter 3, we presented the idea of using the information entropy associated with a diagnostic assessment as a mean to evaluate diagnostic results. Information entropy is a measure of the uncertainty associated with a random variable; the bigger the uncertainty, the bigger the information entropy. A diagnostic assessment is said to be improved when the associated information entropy is reduced. In this chapter, we use the information entropy as a mean in order to analyze the improvement or degradation of diagnostic results. We present a framework that connects the effects of new and/or additional measurements to the information entropy and show how this framework can effectively identify measurements that have better effects on diagnostic analysis.

6.1 A Framework for the Quantification of the Impact of Additional Measurement on Diagnostic Capability

A schematic diagram of the proposed framework is shown in Figure 6.1. It is another extension of the Bayesian network-based diagnostic framework introduced in Chapter 2. As before, the input node represents the system inputs and the output node represents the current outputs (current measurements). The new measure 1 (NM_1), new measure 2 (NM_2), ... and new measure n (NM_n) nodes represent potential new measurements that can be included in the diagnostic process. The utility node contains the utility function that quantifies the preference of diagnostic results. As mentioned earlier, it is the information entropy of the fault node.



The aim is to identify which new measure (from the set of $NM_1, NM_2 \dots NM_n$) would better improve the diagnostic assessment. In other words, we want to locate the new measurement that maximally reduces the information entropy. The challenge is that, for each potential new measure (new sensor), we do not know the sensor reading in advance in order to estimate its effect on the information entropy. Therefore, instead of focusing on the actual value of the information entropy, we calculate its expected value.

For any new measure (NM_i), there is a set of possible readings/outputs ($NM_{i,k}$ $k = 1, 2, \dots, m$). Each output leads to a different diagnostic assessment and, consequently, a different utility function outcome:

$$U(f|I, O, NM_{i,k}) = - \sum_{j=1}^n (P(f_j) \log_e P(f_j) | I, O, NM_{i,k}) \quad (6.1)$$

The expected value of the utility function is calculated by averaging over all possible values:

$$E\{U(f|I, O, NM_i)\} = \sum_{k=1}^m U(f|I, O, NM_{i,k}) P(NM_{i,k}|I, O) \quad (6.2)$$

Using the Bayesian network interface algorithm, $P(NM_{i,k}|I, O)$ can be calculated by:

$$P(NM_{i,k}|I, O, I_n) = \frac{\sum_{j=1}^n P(f_j) P(O|f_j, I) P(NM_{i,k}|f_j, I)}{\sum_{k=1}^m \sum_{j=1}^n P(f_j) P(O|f_j, I) P(NM_{i,k}|f_j, I)} \quad (6.3)$$

Now, the selected new measure minimizes the expected value of the utility function:

$$\text{New Measure} = \arg \min_{NM_i} \{E\{U(f|I, O, NM_i)\}\} \quad (6.4)$$

6.2 Illustrative Example: Analyzing the Impact of New Measurement on an Office Building's Diagnostics

In this section, we apply the proposed framework in order to analyze the impact of new measurement on the top-down diagnostics of a 511 m^2 office building. The building is a benchmark model developed by Energy Plus [77] consisting of three effective “energy” zones (Figure 6.2). Each zone is served by a separate heating and cooling system, each of which consists of a gas-driven forced-air furnace, a single duct terminal unit, a fan, and a unitary DX (Direct Expansion) cooling system. In the examples that follow, we apply Chicago summertime weather conditions.

Similar to the example in Chapter 5, we focus on four common types of faults: cooling system faults (when one or more cooling systems are non-functional), fan faults (when fans are non-functional), occupancy faults (when zone occupancies are mis-scheduled), and mis-scheduling of exterior/perimeter lights. All possible combinations of these faults are considered. A larger number and range of faults could have been considered, but we kept the number small here to improve understanding of the overall approach.

First, we analyze the building performance by monitoring only the total electricity usage. In the second step, we use the proposed framework to determine what additional measurement (from the set of the electricity used by cooling systems, the electricity used by fans, and the electricity used by exterior lights) would better improve the diagnostic result.

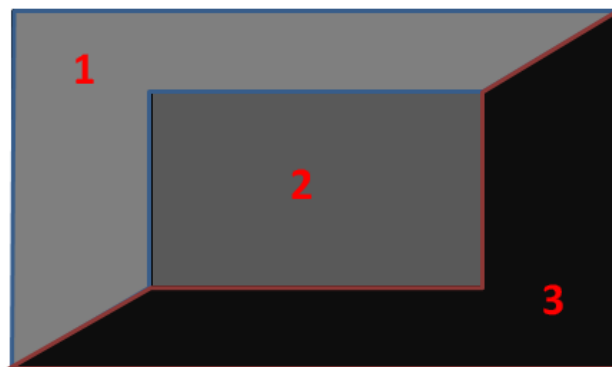


Figure 6.2: Schematic diagram of the office building prototype.

Figure 6.3 shows the 24-hr operation (with a 1-hr sample rate) of the building's performance with an induced occupancy fault (two zones have occupancy faults). To provide a better comparison, the non-faulty operation of the building (blue lines) is also included. We introduced error into the measurements by adding a 40%-50% error to the model's prediction.

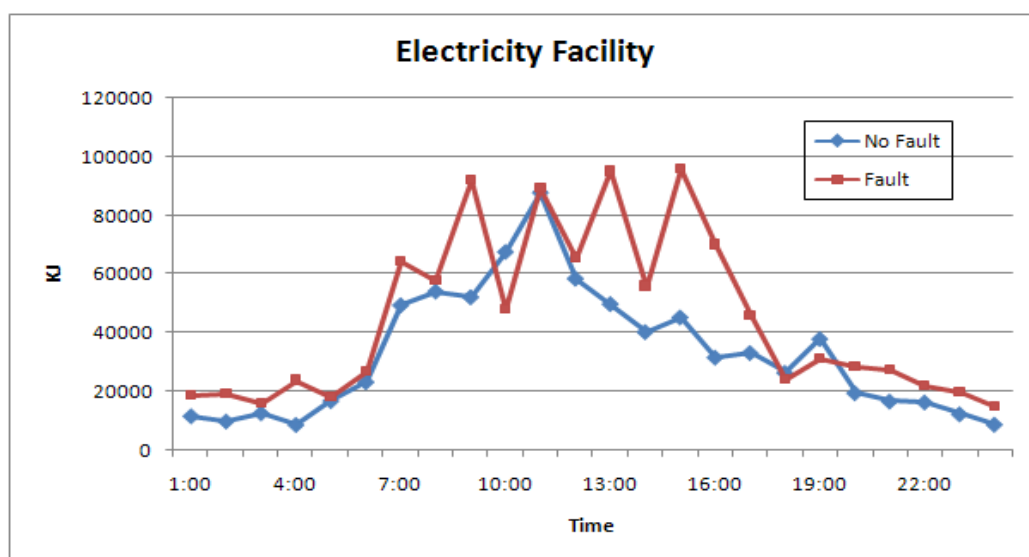
The diagnostic assessment, update posterior distribution of the fault node, using the algorithms explained in Chapters 2 and 5 is shown in Figure 6.4. As the figure clearly shows, the diagnostic result is not very informative concerning the building's health status; it does not lead us to any conclusion about the operation of fans, cooling systems, etc. To improve the diagnostic assessment, we need to identify which additional measurement can better help the diagnostic process.

Expanding equations 6.1 and 6.2 from one sample ($t = t_1$) to 24 samples ($t = t_1, t_2, \dots, t_{24}$), we have:

$$\begin{aligned} U(f|I_{t_1} \dots I_{t_{24}}, O_{t_1} \dots O_{t_{24}}, NS_{i,t_1} \dots NS_{i,t_{24}}) \\ = - \sum_{j=1}^n (P(f_j) \log_e P(f_j) | O_{t_1} \dots O_{t_{24}}, NS_{i,t_1} \dots NS_{i,t_{24}}) \end{aligned} \quad (6.5)$$

$$\begin{aligned} E\{U(f|I_{t_1} \dots I_{t_{24}}, O_{t_1} \dots O_{t_{24}}, NS_{i,t_1} \dots NS_{i,t_{24}})\} \\ = \sum_{NS_{i,t_1} \dots NS_{i,t_{24}}} U(f|I_{t_1} \dots I_{t_{24}}, O_{t_1} \dots O_{t_n}, NS_{i,t_1} \dots NS_{i,t_{24}}) P(NS_{2,t_1} \dots NS_{i,t_{24}} | I_{t_1} \dots I_{t_n}, O_{t_1} \dots O_{t_{24}}) \end{aligned} \quad (6.6)$$

In practice, we may not need to include all the samples. There is not necessarily much variation in the characteristics of the building's performance at each measuring interval. For example, from 2:00 A.M. to 3:00 A.M., there is not much change in building performance. On the other hand, when more sampling measures are included in the analysis process, the computational load extends exponentially. The question of how many samples and/or which samples are optimum from the perspective of both the reliability of the result and the computational load is a research study in itself. In this example, we chose sampling measures at 2:00 A.M., 11:00 A.M., 1:00 P.M., and 9:00 P.M. from the data in Figure 6.3.



icago. The blue line
induced occupancy

Figure 6.5 shows the expected information entropy for each additional measurement. As the figure clearly shows, measuring the electricity usage of the cooling systems is expected to reduce the information entropy of the diagnostic result more than others.¹⁵ In Figures 6.6, 6.7, and 6.8, we show the diagnostic result with each additional measurement. Figure 6.6 shows the result when cooling system electricity was included, Figure 6.7 shows the result when fan electricity was included, and Figure 6.8 shows the result when exterior light electricity was included. In Figure 6.6, which is related to the case of cooling system electricity, it can be seen that there is less uncertainty about the operation, as was predicted in Figure 6.5.

As another example, we consider a no-fault case scenario. The building performance is shown in Figure 6.3 (blue lines), the diagnostic result based on one measurement (total electricity usage) is shown in Figure 6.9, and the expected information entropy for each additional measure is shown in Figure 6.10. Again, the cooling electricity scenario has the lowest information entropy. The diagnostic results of each additional measurement are shown in Figures 6.11, 6.12, and 6.13. It can also be seen that, as expected, in the case of cooling system electricity (Figure 6.11), there is less uncertainty about building performance.

The superiority of cooling electricity to other measurements could be due to the fact that measurement of cooling electricity usage might provide insight about the functionality of both cooling systems and fans. As the example in Chapter 5 shows, fans' faults can affect cooling

¹⁵ It may seem like there is not much difference between the information entropies in Figure 6.5. This is due to the fact that only four measuring samples were used to estimate the expected information entropy. Should more samples be included, a larger difference would result.

system performance. When fans are non-functional, there is no air circulating through the units, and consequently no energy is transferred to the zones, which means no consumption of cooling/heating energy. This could be the reason why the measurement of cooling electricity is superior. However, more experiment and analysis is required to confirm such a conclusion. We did not have enough experiment to confirm this claim. Our main focus has been to provide an illustrative example showing that the proposed framework can successfully identify effective measures.

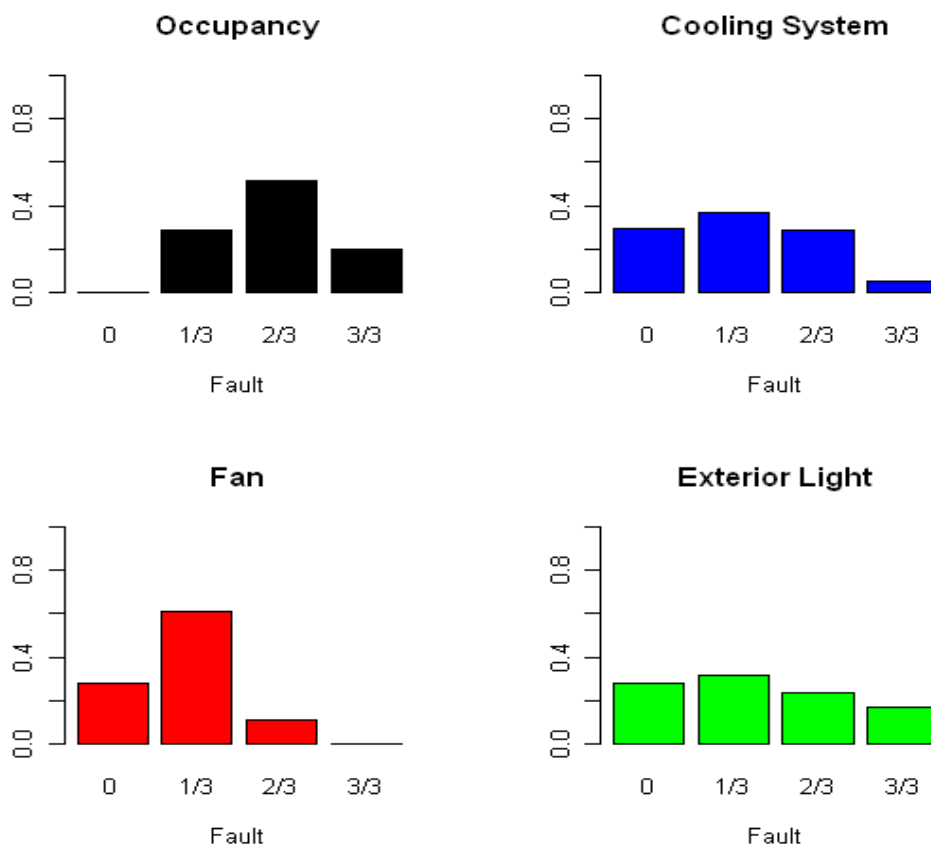
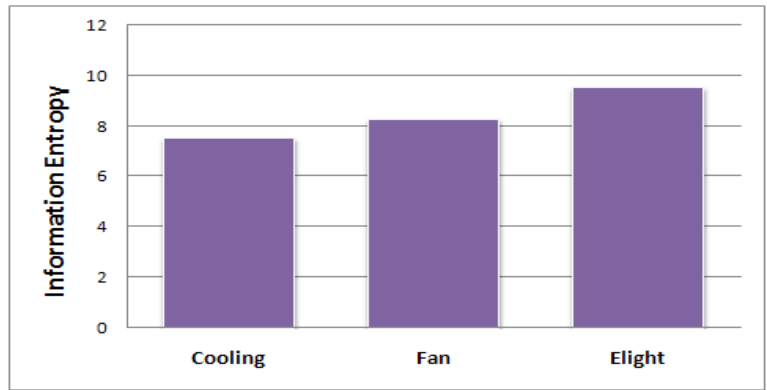
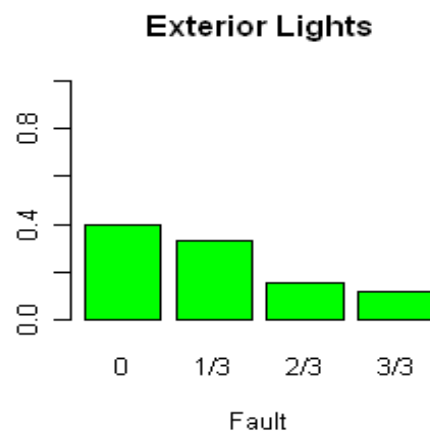
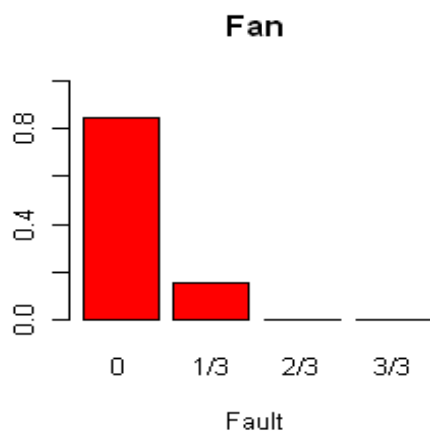
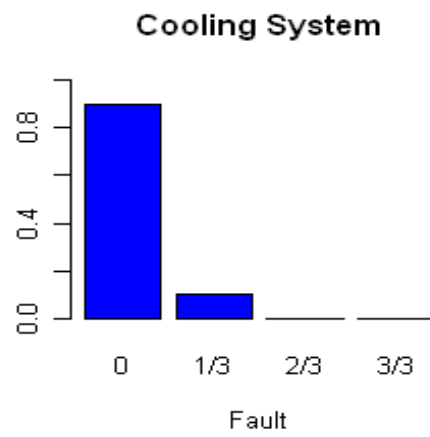
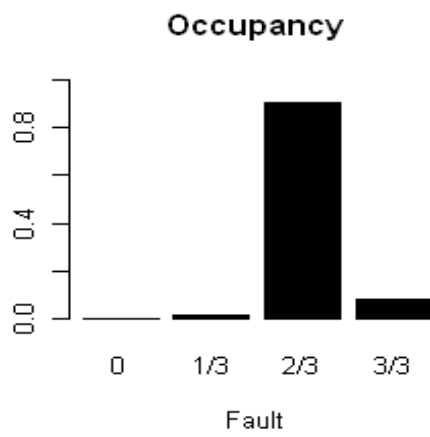


Figure 6.4: Diagnostic results based on analysis of the total electricity used by the building.



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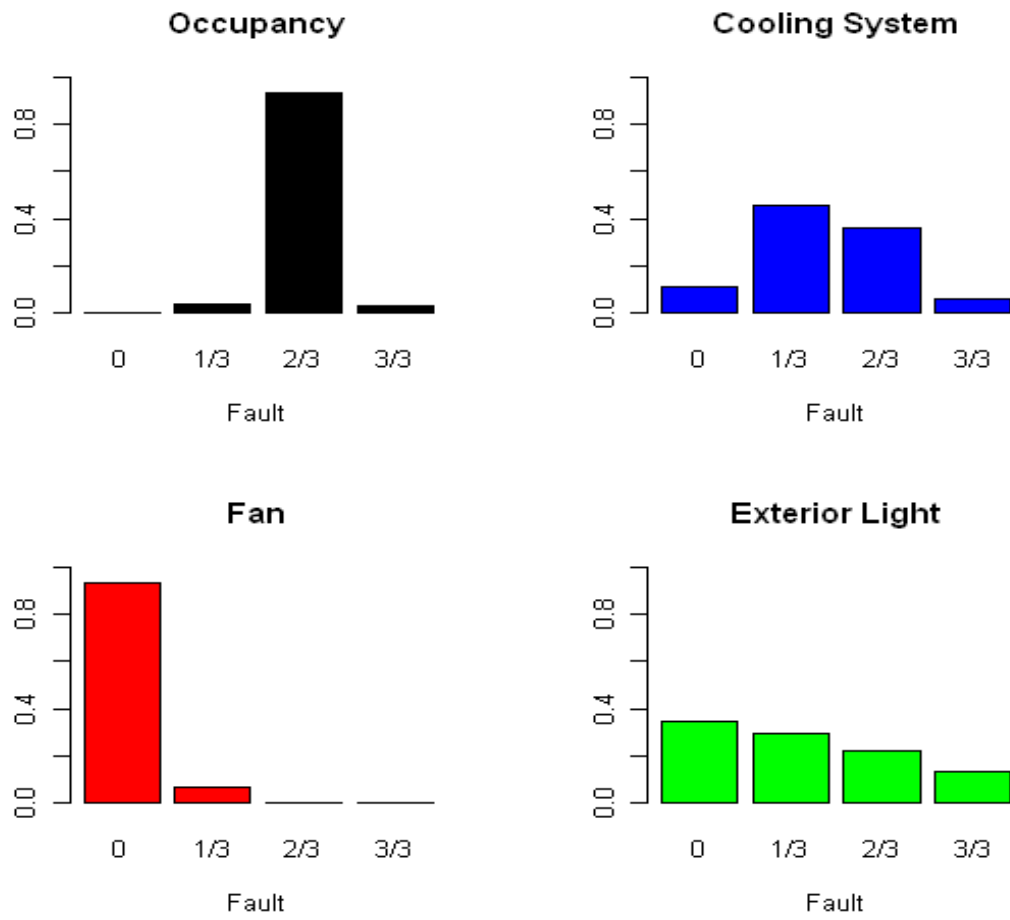


Figure 6.7: Diagnostic results based on analysis of total electricity usage and the electricity used by fans.

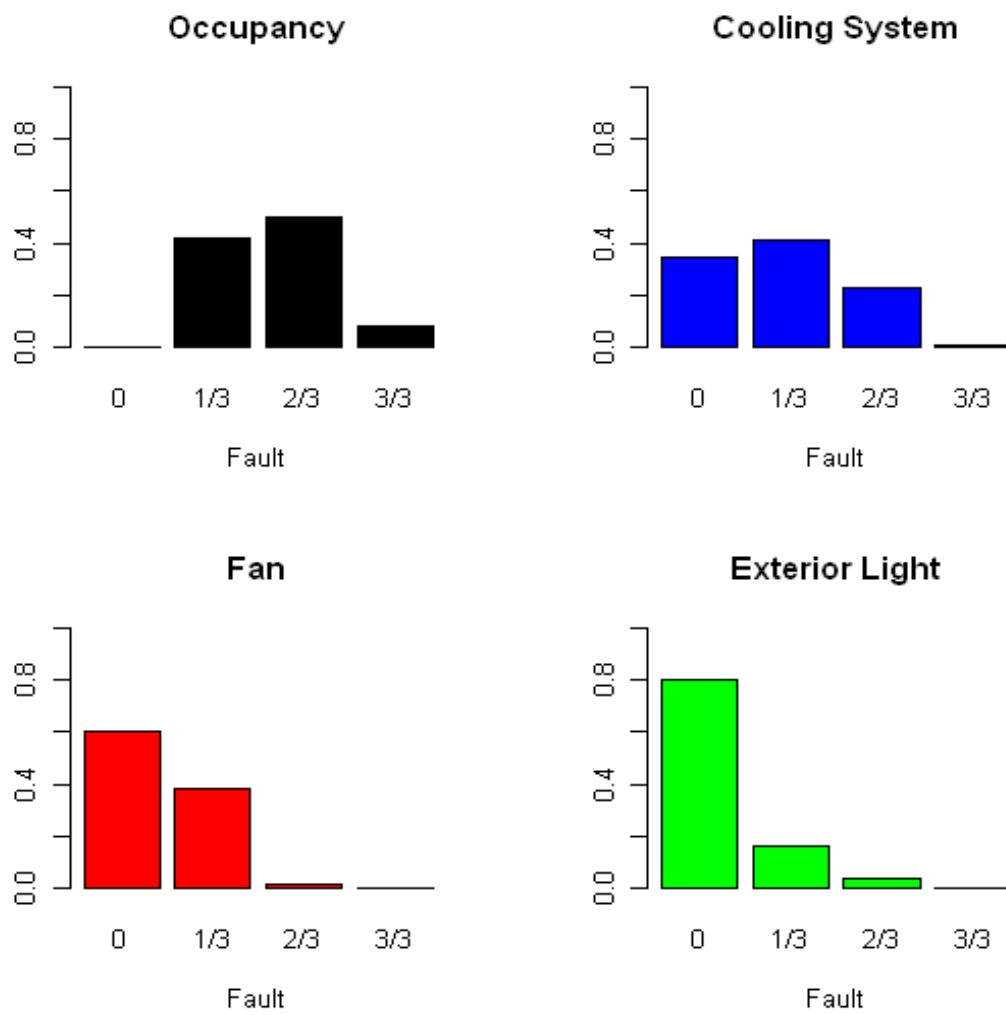


Figure 6.8: Diagnostic results based on analysis of total electricity usage and the electricity used by exterior lights.

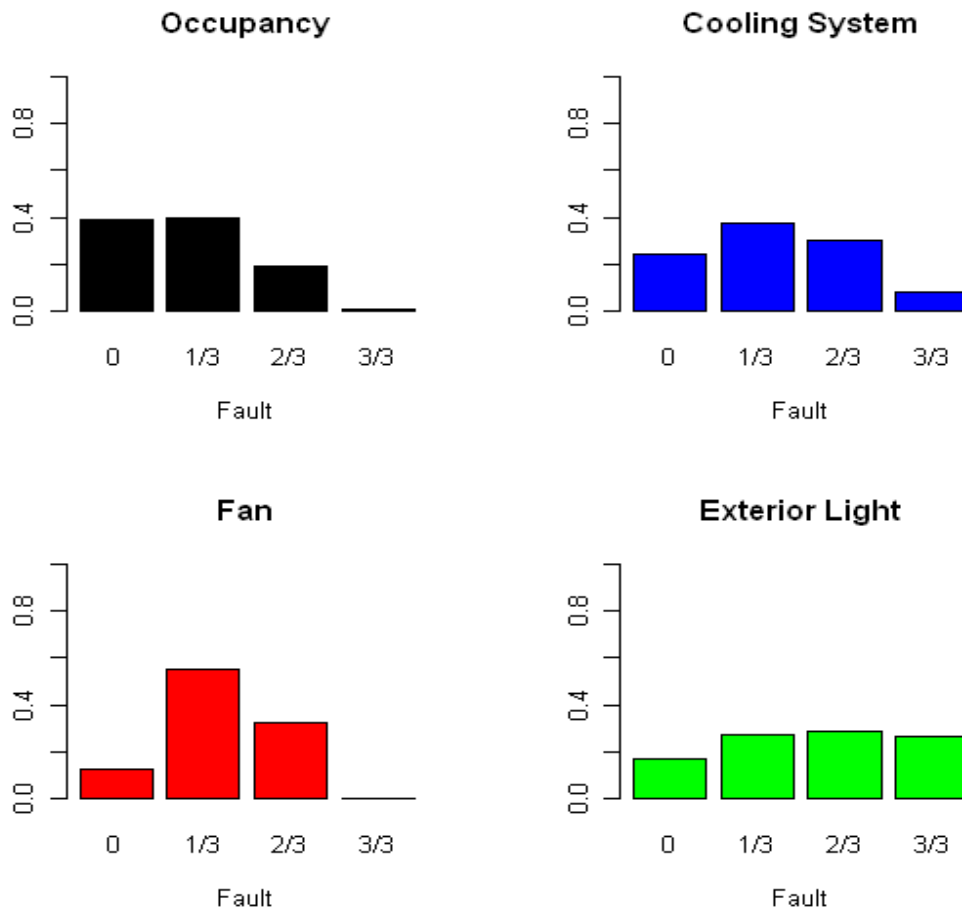


Figure 6.9: Diagnostic results based on analysis of the total electricity used by the building.

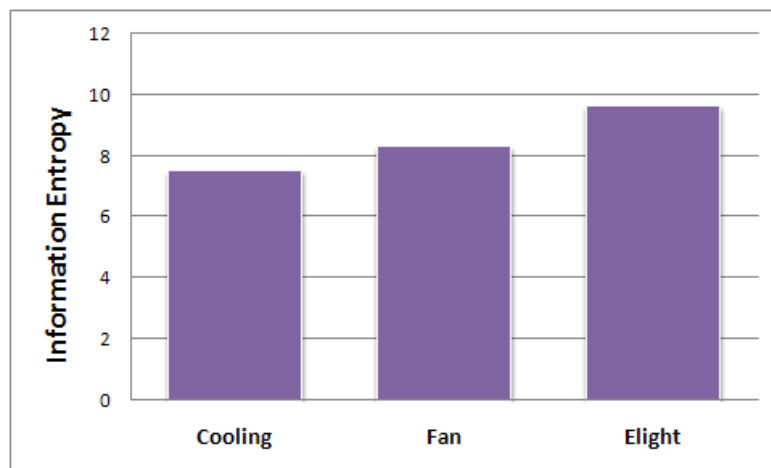


Figure 6.10: Expected information entropy for each new measurement: the electricity used by cooling systems, the electricity used by fans, and the electricity used by exterior lights.

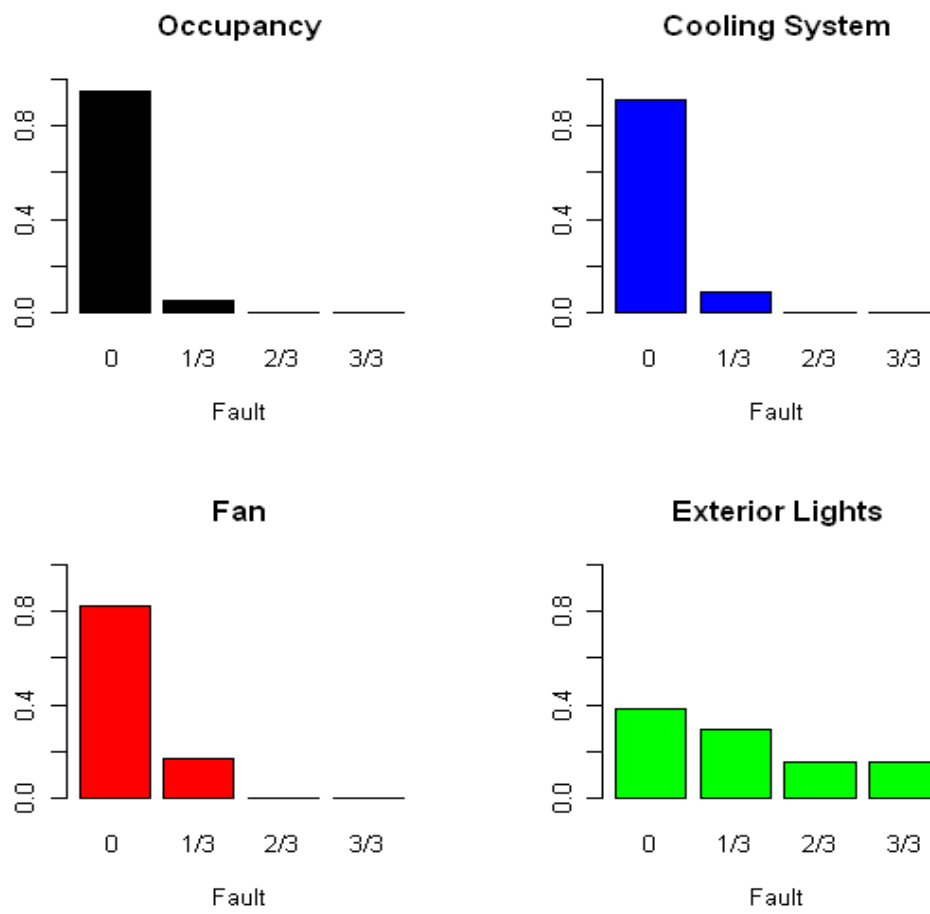


Figure 6.11: Diagnostic results based on analysis of total electricity usage and the electricity used by cooling systems.

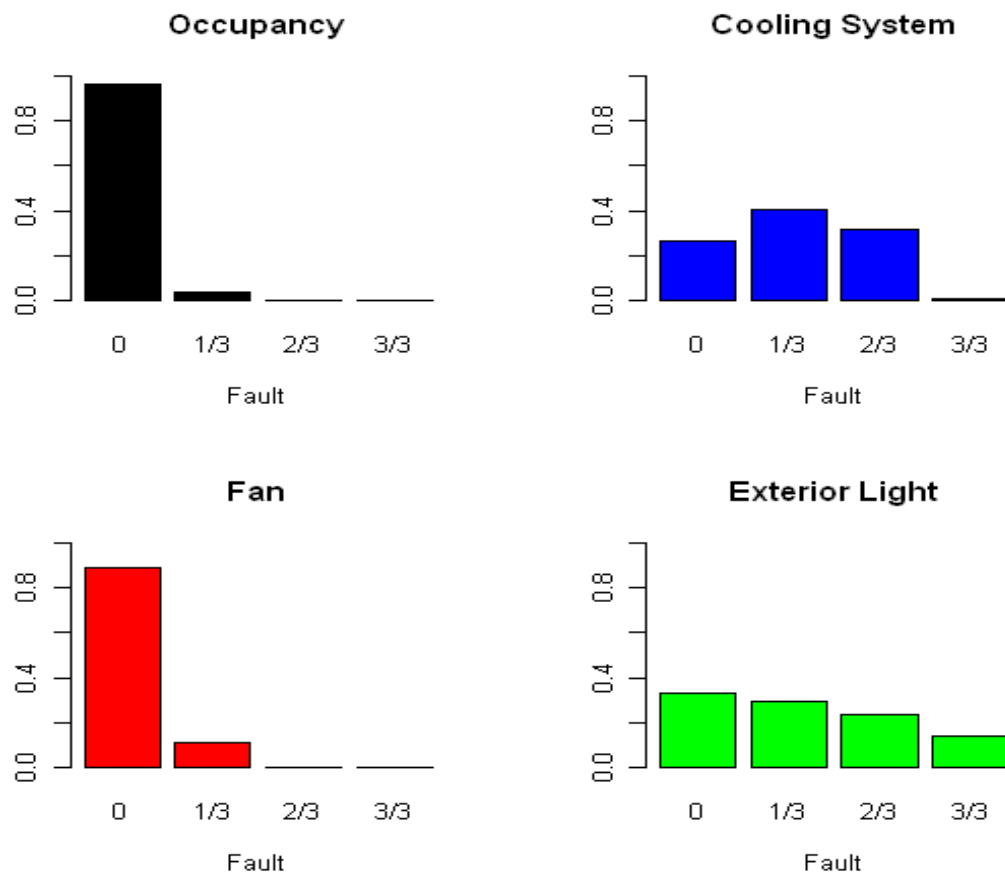


Figure 6.12: Diagnostic results based on analysis of total electricity usage and the electricity used by fans.

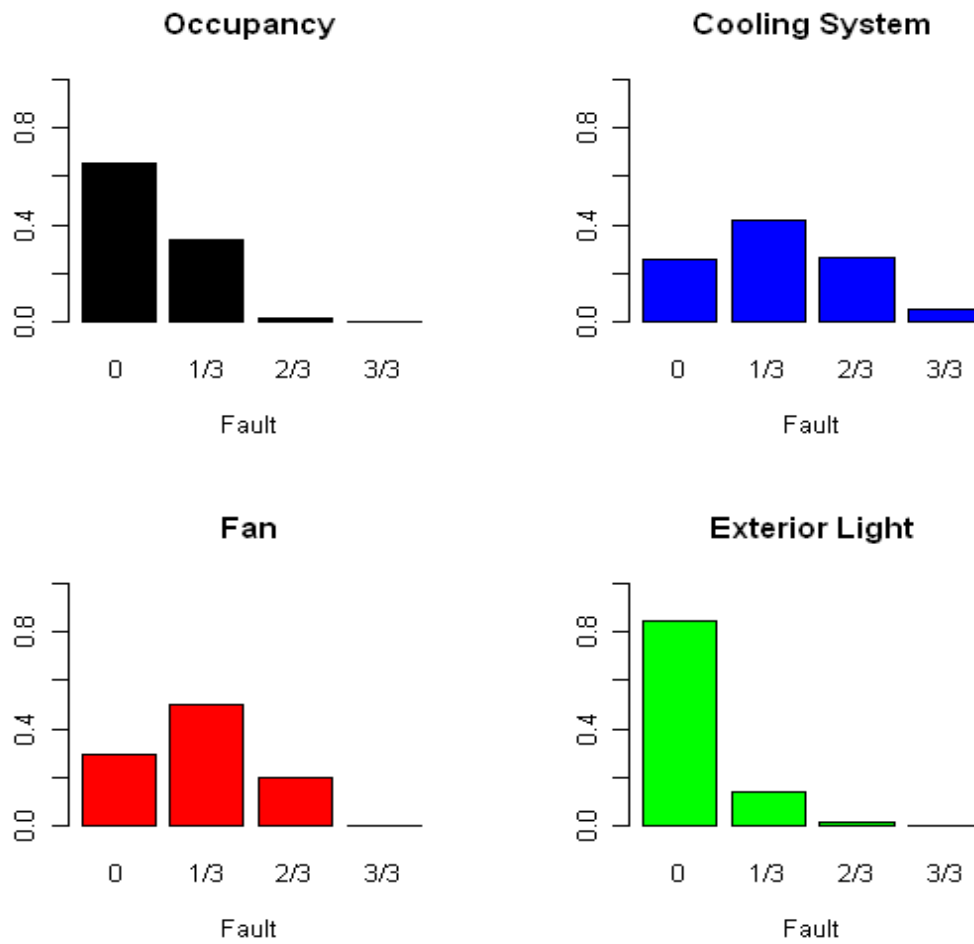


Figure 6.13: Diagnostics results based on analysis of total electricity usage and the electricity used by exterior lights.

7. CONCLUSION

In this thesis, we focused on a number of crucial issues regarding the development of reliable, scalable, and affordable solutions for building HVAC systems. We discussed in detail how modeling limitations are one of the main challenges facing the diagnostic problems. The principle of building HVAC systems is sufficiently well known for a suitable model structure; however, the accuracy of these models can only be improved up to certain levels, and beyond that, it would be expensive and time-consuming and would affect the scalability attribute.

We proposed two diagnostic algorithms with the ability to address modeling limitations systematically: a model-based approach (Chapter 2) and a non-model-based approach (Chapter 4). In Chapter 2, we presented a Bayesian network-based diagnostic mechanism, in which a system output is interpreted as a random variable that is conditionally dependent on the input and fault condition. With such an interpretation, we were able to quantify the uncertainty in the output, caused by modeling and measurement errors, in the variance of the random variable. A diagnostics assessment was then formulated as the estimation of the posterior distribution of the fault node. We demonstrated how the proposed diagnostic approach can effectively analyze the performance of an air handling unit.

The diagnostic approach presented in Chapter 2 has the advantage of being systematically extendable for more complex scenarios. In Chapter 5, we showed how the approach can be extended for top-down diagnostics of building HVAC systems in which a massive number of potential faults and abnormalities exist. We showed how, by employing numerical algorithms such as Markov Chain Monte Carlo (MCMC), the diagnostic mechanism can effectively analyze building performance from a top-down perspective and deal with challenging issues like fault-detect-ability.

Further development and research still require managing the computational load of the proposed top-diagnostics approach discussed in Chapter 5. Estimating the posterior distribution of the fault node numerically, due to a large set of faults, increases the computational load considerably. In addition, the process speed heavily depends on the performance of the employed building simulation tool. At each iteration, the numerical algorithm runs the simulation tool with a different configuration. If the simulation process is slow, it will affect the overall diagnostic process.

With the continuous improvement exists in computer processing and new investments being made on building simulation tools, this may not be a concern in a few years. However,

employing approximation modeling techniques such as surrogate modeling, response surface models, and others might be helpful in reducing the computational load (future work).

In Chapter 4, we presented another diagnostic solution, a model-free approach, for rooftop units. The key attribute of the approach was its independence of any detailed model, which makes it appealing from a scalability perspective. The approach was based on analyzing the correlation among parameters and comparing them with various hypotheses to evaluate the system performance. We demonstrated the effectiveness of the approach using data from rooftop units located at several retail stores.

Another important attribute of the diagnostic approach presented in Chapter 4 is its flexibility with steady state conditions. As discussed, one main challenge of using simplified models for building HVAC diagnostics is that most of these models are limited to simulating only the static behavior of the system, meaning that the measurement should be obtained when the system is in the steady state condition. This is not an easy constraint to deal with, as steady state conditions do not occur frequently because of cycling during routine operations, high frequency disturbances, or control loop oscillation. An appealing characteristic of the proposed approach is that it does not have the restriction of steady state conditions.

Although the focus in Chapter 4 was on rooftop unit diagnostics, the proposed approach has the potential to be extended to air handling unit diagnostics as well. This would be another topic for further research and development.

Limitations derived from sensor network architectures were another focus in this thesis. As discussed previously, in building HVAC systems, sensor network architectures are not necessarily designed solely based on diagnostic purposes; other factors such as controls, financial constraints, and practical limitations are also involved. As a result, it is common to have one or more components being monitored through only one sensor (or one set of sensors). In such a scenario, when the sensor output is contaminated, it could be due to the malfunctioning of any of the involved components, and it may not be a simple process to locate the affected one.

In Chapter 2, we demonstrated how the measurement constraint issue can be addressed systematically by extending the Bayesian network-based diagnostic model to a mixture model of components, in which the missing measures are formulated as hidden variables in the Bayesian interface routine. In another approach, the model-free diagnostic algorithm (presented in Chapter 4) deals with the measurement constraint issue in a different manner. The issue is addressed by filtering the effect of one component from the measuring parameter(s) and then analyzing the correlation between the filtered parameter(s) and the second component to detect and isolate faults.

It is important to note that these systematic solutions for the measurement constraint issue do not come without a price. There will be some level of degradation in the diagnosis performance, which must be understood in advance. For example, in Chapter 2, the diagnostic solution of the mixture model of components requires more time to reach a solid conclusion about the system fault condition. This is the cost of the missing sensor. In other scenarios, the drawback may be observed in the confidence level of the diagnostic results.

On the measurement constraint topic, another focus was quantifying the relation between measurement constraints and diagnostics capability. We aimed to develop an algorithm quantifying the impact of the measurement constraint on diagnostics capability. A systematic solution to this problem can be used as a framework to analyze the effect of new measurements on diagnostics strength, which subsequently would lead to better designs and the optimization of sensor network architectures from a diagnostics perspective.

In Chapter 6, we showed that the impact of measurement constraints can be traced in the information entropy of diagnostic assessments. The designed algorithm connects the effect of new measurements to the expected value of the information entropy. Initial results show how the framework can successfully identify effective and crucial measurements in building diagnostics.

Another topic that we focused on was proactive diagnostics or proactive testing. In the past, the topic of proactive fault diagnostics has not been given enough attention, while the capability of conducting and supervising automated proactive testing is essential to replace manual troubleshooting with automated processes. Most research studies regarding HVAC fault detection and diagnostics have focused on the other side of the problem: analyzing system outputs for diagnostic purposes.

In Chapter 4, we defined the proactive testing problem as an optimization problem and showed how it can be formulated as a decision-making problem, coupled with the Bayesian network-based diagnostic mechanism developed in Chapter 2. We illustrated how the framework can adaptively conduct proactive testing processes and how it can adjust itself to the diagnostics capability, taking into account the strengths and weaknesses of the diagnostic mechanism, practical limitations, etc.

The proposed proactive testing framework is novel and unique; however, it is subjected to further development and improvement. Further development might be required in the context of more complex scenarios, when different components or devices interact with each other. Another area that would benefit from additional research is other substitutes or more advanced substitutes for the utility function, other than the information entropy of the fault node.

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