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ABSTRACT

Many studies have shown that energy savings of five to fifteen percent are achievable in commercial buildings by detecting and correcting building faults, and optimizing building control systems. However, in spite of good progress in developing tools for determining HVAC diagnostics, methods to detect faults in HVAC systems are still generally undeveloped. Most approaches use numerical filtering or parameter estimation methods to compare data from energy meters and building sensors to predictions from mathematical or statistical models. They are effective when models are relatively accurate and data contain few errors. In this paper, we address the case where models are imperfect and data are variable, uncertain, and can contain error. We apply a Bayesian updating approach that is systematic in managing and accounting for most forms of model and data errors. The proposed method uses both knowledge of first principle modeling and empirical results to analyze the system performance within the boundaries defined by practical constraints. We demonstrate the approach by detecting faults in commercial building air handling units. We find that the limitations that exist in air handling unit diagnostics due to practical constraints can generally be effectively addressed through the proposed approach.

1. Introduction

A commercial building's various energy systems creep from their original design goals as components fail or “fault”: dampers fail to open or close, fan belts break, and so on. Problems that do not result in occupant complaints are often not even recognized to have occurred, even if they result in a substantial increase in energy use. For example, failure of an HVAC fan may prevent cool air from one of the building’s air conditioning units from reaching occupied spaces, so this unit’s energy is simply wasted; but other units may be able to compensate by working harder – in an inefficient area of their operating design parameters – so occupants may fail to notice that something has gone wrong.

Studies of existing buildings find that energy savings of five to fifteen percent are typically achievable simply by fixing faults and optimizing building control systems [1]. However, current methods for detecting faults or “performance creep” 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 may never be performed, in most buildings. If the achievable five to fifteen percent energy savings are to be met in practice, building energy management systems must be capable of detecting when a failure has occurred, when performance is creeping, and 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.

In spite of good progress in the field of fault diagnostics for Heating, Ventilation, and Air conditioning (HVAC) systems in recent years [1] & [2], methods to manage faults in HVAC systems are still generally undeveloped; in particular, there is still a lack of systematic solutions for issues like modeling and measurement constraints. It is well known that the accuracy of system models can be improved up to certain levels; beyond that, it will be expensive, slow, and too customized, affecting the scalability attribute. On the other hand, sensor network architectures are not necessarily designed solely for diagnostic purposes; other factors like controls, financial constraints, and practical limitations are also involved. As a result, the functionality of two or more components may be monitored through only one sensor (or one set of sensors). However, if the sensor output is contaminated, for example due to one of the components malfunctioning, detecting or locating which of the components is faulting is not straightforward. In other words, the problem is no longer limited to the diagnosis of one component, but a network of components.

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 which is sufficiently described by existing measurements. An ideal diagnostic method should at first make the best use of available information (existing measurements, configuration data, etc), and then employ a systematic routine to cope with such constraints. The classical approach to account for modeling limitations is to relax the dependency of diagnostic mechanisms on precise modeling by focusing on system behavior patterns instead of error residuals. In other words, instead of analyzing system performance by comparing the outputs with model predictions (or other references) at one or few operating points, fault detection is achieved by evaluating the system behavior over a window of operation. Qualitative and semi-quantitative diagnosis methods are based on this concept [3], [4], [5], & [6].

This concept of analyzing system behavior patterns for diagnostic purposes has also been applied to study HVAC systems. For example, in [7] & [8], Haves et al developed a fuzzy-based diagnostic routine for detecting faults in VAV air handling units. The performance of each unit component is monitored at several operating points. Fuzzy logic is a popular choice here because flexibility is readily embedded in fuzzy sets and fuzzy rules. Fuzzy inference methods become infeasible, however, when the building problem is highly complex (due to system complexities, large numbers of disparate sensor data, many possible faults, etc). A prohibitive number of fuzzy rules are required to model the building system. Moreover, HVAC fault detection should be performed quickly, and may require more sophisticated inference methods to match the observed behavior with a set of predefined (or new) hypotheses.

In this paper, a Bayesian network based diagnostic approach is presented as a more effective solution to deal with modeling and measurement constraint issues. The proposed method is capable both of using knowledge of first principle modeling and empirical results to capture the system behaviour patterns, and of analyzing the observed performance within the boundaries defined by modeling error, sensor offset, etc. The measurement constraint issue is also addressed systematically by defining the missing measurements as hidden variables in the designed Bayesian model.

Note that although the focus of this paper is on HVAC diagnostics, the proposed diagnostic approach can also be applied to other applications suffering from similar constraints. It is also worth mentioning that the application of Bayesian networks in the diagnostics area has been studied before e.g. [9], [10], & [11]. For example, in [11] Chien et al applied Bayesian networks for fault diagnostics in a power delivery system. In [10], a Bayesian network is implemented for controlling an unsupervised fault tolerant system to generate oxygen from the CO2 on Mars. However, what is different here is the manner in which Bayesian networks are employed for diagnostic purposes. Those studies are more based on cause-effect-relationship approaches, while in this paper the focus is on behavioral pattern analysis.

In Section 2, we provide a brief introduction to air handling units and how they are used in HVACs to condition, ventilate, and circulate the building air. As the proposed diagnostic approach will be demonstrated by applying it to air handling units, this introduction provides a background to the air handling unit functionality, its components, and the practical limitations. Section 3 explains the proposed diagnostic mechanism and its characteristics. In Section 4, we extend the approach from diagnosing faults in one building component to detecting faults in a network of components, and also show how it can routinely manage limitations coming from measurement constraints.

2. Air Handling Unit

An air handler, or air handling unit (often abbreviated to AHU), is a device used to condition and circulate the air as a part of the HVAC system. It is usually a large metal box containing one or two fans, a mixing box, and heating / cooling coils[1]. Figure 1 shows a schematic diagram of a typical air handling unit. The "mixing box" mixes air returning from the building (return air) with fresh outside air – the minimum ratio of outside air to recirculated air is specified by building codes. The coils cool or heat the mixed air to maintain the required temperature and humidity.

An air handling unit malfunctions when any number of its internal components faults. For instance, the mixing box outside or return dampers may leak, reverse or stick, valves may reverse or the heating/ cooling coil may foul. An air handling unit, in general, contains three temperature sensors to measure (1) supply air temperature (SAT), (2) return air temperature (RAT), and (3) outside air temperature (OAT). It also contains an airflow sensor to measure the supply air rate, and may contain a temperature sensor between the mixing box and heating/cooling coils to measure the mixed air temperature (MAT). When any of these sensors faults, the control system must continue to monitor and operate the AHU with the remaining sensor readings. For example, the temperature sensor between the

[1] It may contain both or either.

mixing box and the coils returns uncertain data, routinely, due to incomplete upstream mixing. This means the downstream supply-air-temperature sensor must be used to infer both the mixing box and heating/cooling coils temperatures (see Figure 2). This is a classical example of the situation explained earlier, in which the functionality of three components (mixing box, heating, and cooling coils) are monitored through one sensor. The goal of this paper is to develop a systematic solution to improve the observability of the system when faced with limited data.

3. Bayesian Network Based Diagnostic Mechanism

The proposed diagnostic mechanism is a Bayesian network containing three nodes (Figure 3):

Fault node: representing different faults of the system and their combinations. If it is a mixing box, this would be some combinations of the mixing box faults listed in Section 2.

Input node: representing system inputs and other known parameters. In mixing box case, this would be the outside air temperature (OAT), return air temperature (RAT), and damper position command (DMP).

Output Node: representing system outputs or what is measured from the system. In the case of the mixing box, this would be the mixed air temperature (MAT).

The input node is assumed to be measured. The output node depends on the input node and the fault node. The impact of the fault node can be realized in different ways: There could be a different mapping function for each fault, or the output may be a linear combination of a set of basis functions generated at the input node with coefficients defined by the fault node. The mapping function is indeed a simplified physical model of the system. The level of simplification depends on available knowledge from first-principle modeling, complexity, etc. The uncertainty of the output node due to model simplifications and other factors (e.g. sensor noise. etc) is interpreted as the variance of the output node variable(s), which can be quantified analytically or statistically. If there is an undefined part in the mapping function, it will be addressed in the training phase. This may include (but not limited to): the variance of the output node variable(s), the coefficients of linearly combined basis functions, etc. If the distribution of the output node random variable is Gaussian, it is straightforward to estimate the output node variance and coefficients of linearly combined basis functions.

The posterior probability of the fault node is interpreted as the belief level about the existence of each fault in the system. Using Bayesian network inference mechanism, this can be calculated as:

$$P(f_i|I,O) = \frac{P(f_i)P(O|f_i,I)}{\sum_i P(f_i)P(O|f_i,I)} \qquad \textbf{(1)}$$

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. It can be estimated statistically, or as a quick solution, it may be assumed to be uniformly distributed. As more data are observed, the posterior belief is updated recursively leading to a better matching between the observed behavior and different hypotheses.

Now, let's apply this model to the problem of mixing box diagnostics. 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).

$$OAF = \frac{T_{mat} - T_{ret}}{T_{out} - T_{ret}} \qquad \textbf{(2)}$$

OAF is an indication of the influence of the outside air temperature on the mixed air temperature. It is ideally one when the outside air damper is fully open, and zero when the damper is closed. Figure 4 shows the variations of OAF versus damper positions in a non-faulty operation. Inside the envelope is the acceptable performance. The wide range of the acceptable performance is due to the uncertainty of parameters not easily measurable in practice (fluid resistance, air velocity, thermal resistance, etc). Figure 5 shows OAF variations in different fault modes. The designed diagnostic mechanism is shown in Figure 6. 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 ($\theta_1$and θ_2) – defined by the fault node – to estimate the OAF. Once OAF is estimated, the mixed air temperature (MAT) can be obtained from Equation 2.

The diagnostic results are shown in Figures 7 and 8. The data is from the facility of the Iowa Energy Center, an experimental facility for research, education, and demonstration [12]. During the experiment, the coils were shut off to use the supply air temperature instead of the mixed air temperature.

4. Diagnosis of Mixture of Components

As mentioned earlier, the architecture of a sensor network may impose extra challenges to the diagnosis process. The diagnostic mechanism may be restricted to monitor the performance of two or more components through one sensor (or one set of sensors). An example of this was shown in Section 2, in AHU diagnostics, where practical limitations require monitoring of the performance of three components, mixing box and heating/cooling coils, through the supply air temperature sensor. In such a scenario, it may not be straightforward to discriminate the effect of each component on sensor readings. A potential solution is to analyze the functionality of each component while the effects of other components are neutralized (shutting down or taking to certain states). This requires departure from normal operation which may not be a feasible option especially in online diagnostics.

The proposed approach is to extend the designed Bayesian model to a mixture model of components. An example of such a model is shown in Figure 9. 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, specifications, etc. 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 depending on measurement constraints.

Now, when a component of the mixture model malfunctions, the relation between the input and output nodes is contaminated. In a bigger perspective, this contamination leads to a change in the system behavior pattern, as each component affects it adjacent ones and so on. To detect and isolate such the abnormality, the system behavior pattern is compared with different hypotheses, in which each hypothesis is based on the assumption that one or more components are in fault modes. If an input or output node is partially observed, due to measurement constraints, the unobserved random variable will be considered as a hidden variable and will be summed out over all its possible values. For instance, in Figure 9, if it is assumed that the output of the first component, which is also the input of the second component, is hidden, the posterior probability of the fault nodes can be calculated by:

$$P\left(f_{c1,i}, f_{c2,i} \middle| I_{c1}, O_{c2}\right) = \frac{\sum_{O_{c1}} P(f_{c1,i})P(f_{c2,i})P(O_{c1,k}|f_{c1,i},I_{c1})P(O_{c2}|f_{c2,j},O_{c1,k})}{\sum_{f_{c1}}\sum_{f_{c2}}\sum_{O_{c1}} P(f_{c1,i})P(f_{c2,i})P(O_{c1,k}|f_{c1,i},I_{c1})P(O_{c2}|f_{c2,j},O_{c1,k})} \quad \textbf{(3)}$$

Where $f_{c_1} = \{f_{c_1,1}, f_{c_1,2} .... f_{c_1,n}\}$is the fault list of the first component, $f_{c_2} = \{f_{c_2,1}, f_{c_2,2} .... f_{c_2,n}\}$ 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 $O_{c_1} = I_{c_2} = \{O_{c_1,1}, O_{c_1,2} .... O_{c_1,n}\}$ is the output of the first component.

Going back to the air handing unit case, Figure 10 shows the mixture model of an air handling unit with a mixing box and a heating coil. As it 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[2], entering hot water temperature (TWin), and the valve command (VLV), and the output is the supply air temperature (SAT). The heating coil model is shown in Figure 11 which is based on NTU method [13]. Diagnostic results are shown in Figures 15 and 16.

It is important to note that this systematic way of dealing with measurement constraints does not come for free. There will be some level of degradation in the diagnosis performance which needs to be understood in advance. Comparing Figures 12 and 13, you notice that in the mixture model case, the diagnostic mechanism takes more time to reach a solid conclusion about the system health status. This is the cost of the missing sensor. In this application, it has shown up as slower diagnostic analysis; in other applications, it may show up in the level of confidence about the system health status.

5. Conclusion

Modeling errors and measurement constraints are the main challenges in fault diagnostics for HVAC systems. Due to their inability to address these issues effectively, most developed approaches in this area suffer from a lack of interoperability, the capability for quick implementation with minimum prior adjustment and investment. The approach presented in this paper has the advantage of dealing with these limitations systematically. We showed how in the case of an air handling unit, this method can effectively deal with modeling limitations and cope with measurement constraints involved in the diagnostic problem.

Although the focus of this paper was on HVAC diagnostics, we believe the proposed approach has the potential to be applied in other applications with similar restrictions. The next step is to focus on scenarios with higher levels of complexity. A commercial building, for example, contains several air handling units and other complex components, which substantially increases the system complexity as a

[2] CFM is short for cubic feet per minute, measurement of air volume flow rate

network of components. Research needs to be done to determine what challenges exist because of the added complexity (for example, dimensionality) and what further development might be needed to make the proposed approach applicable to such systems.

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6. References

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Graphs, Tables, and Photographs

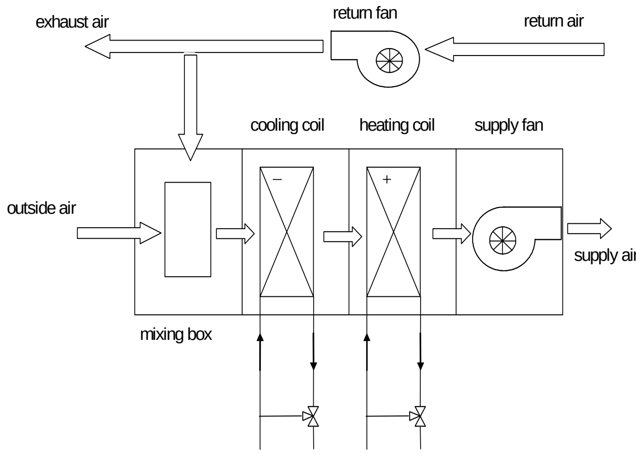


Figure 1, Schematic diagram of air handling unit

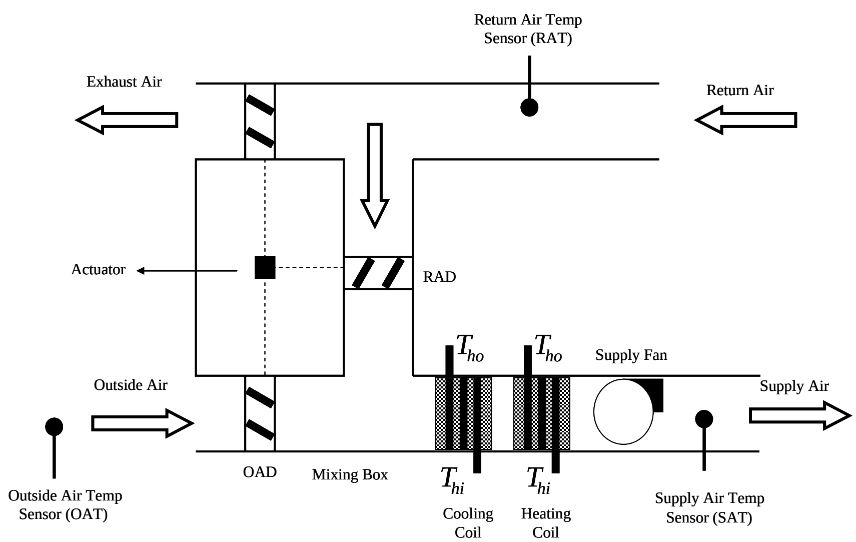


Figure 2, Air handling unit functionality

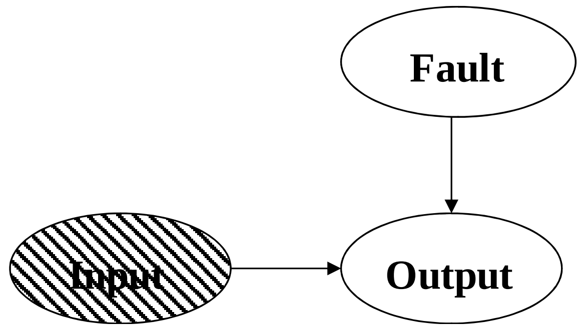


Figure 3, Bayesian network based diagnostic mechanism

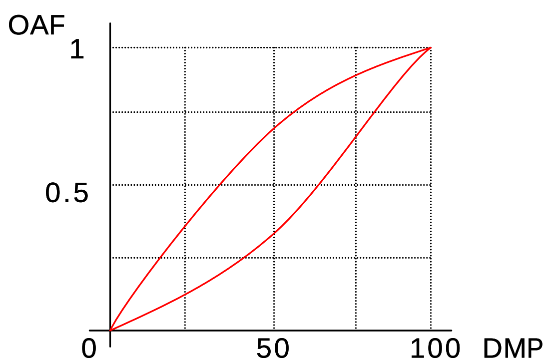


Figure 4, Variations of outside air fraction (OAF) versus outside air damper position (DMP) in normal operation. Inside the envelope is the acceptable performance

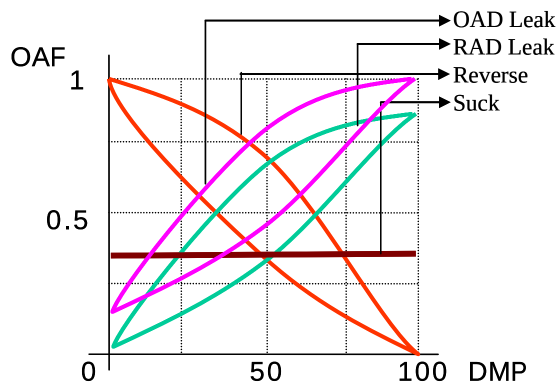
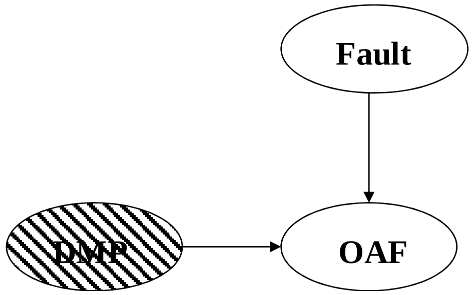


Figure 5, Variations of outside air fraction (OAF) versus outside air damper position (DMP) in different fault modes



$$B_1 = 1, B_2 = (DMP/100)$$

$$\mu_{OAF} = \theta_1 B_1 + \theta_2 B_2$$

$$\sigma_{OAF} = (DMP/100) - (DMP/100)^2$$

Figure 6, 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

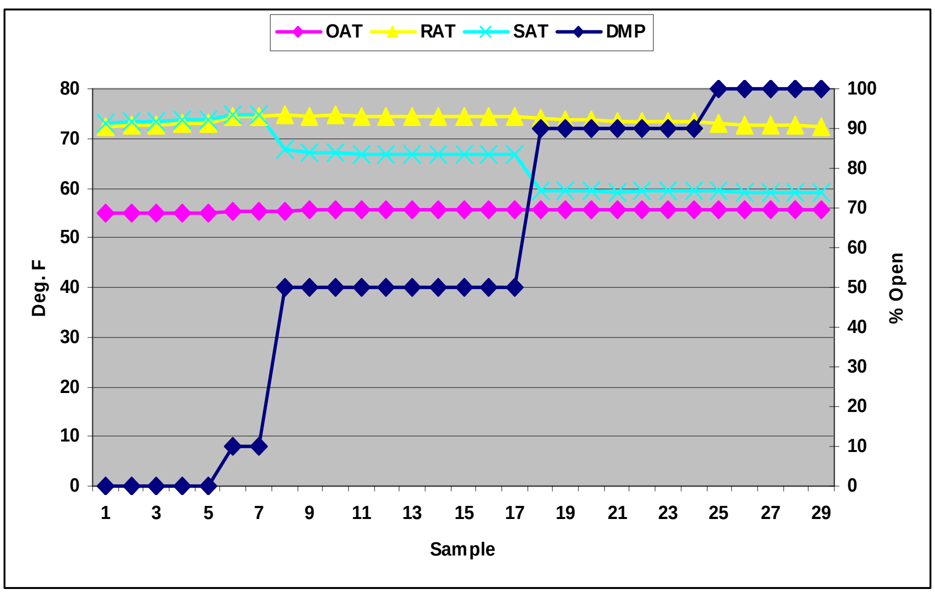


Figure 7, OAT: outside airtemperature, RAT: return air temperature, SAT: supply air temperature, DMP: damper. The data is from a test run on one of the air handing units at Iowa energy center. The diagnostic result is shown in Figure 8

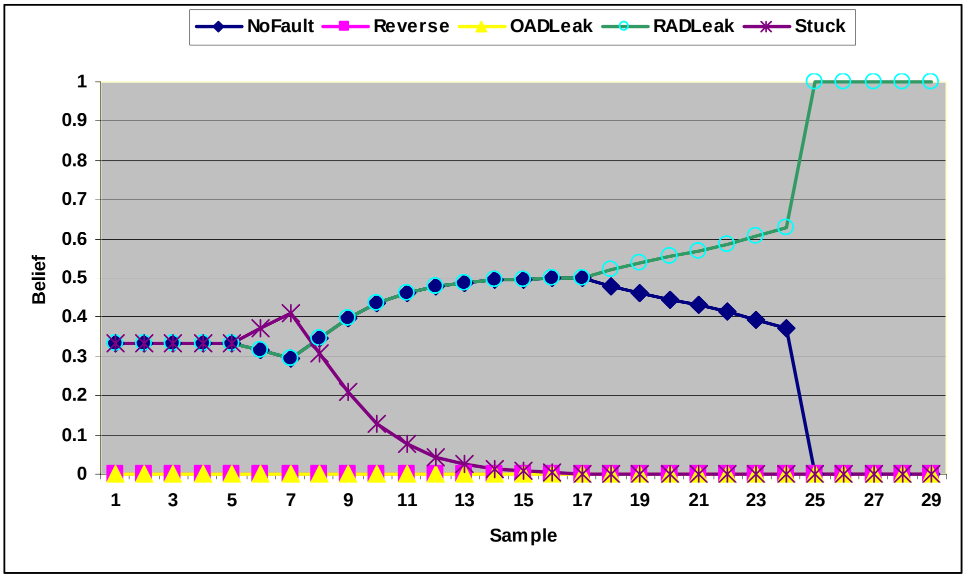


Figure 8, Diagnostic results, Note how belief about the system health status improves as more data are observed. It seems that there is a Return Air Damper Leakage (RADL) fault in the system, However, as RADL fault cannot be isolated until the damper goes to hundred percent open (due to the nature of the fault), you see the diagnostic mechanism waits until it sees the system response at that state, and then finalizes its evaluation.

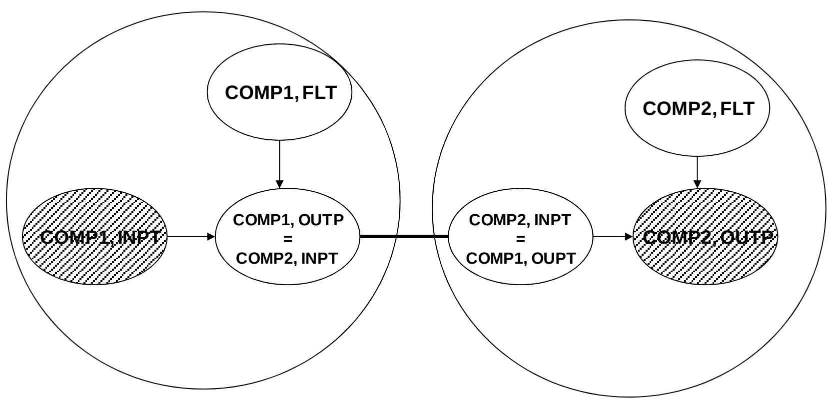


Figure 9, a mixture model example with two components, the output of the first component constructs the input of the second one

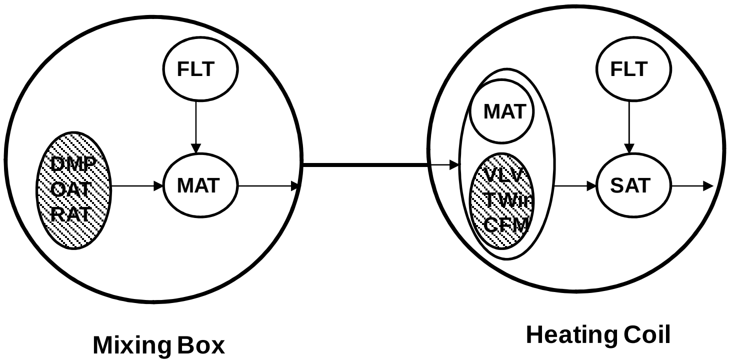


Figure 10, the mixture model of an air handling unit with
a mixing box and a heating coil

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

$$\varepsilon = \frac{1 - \exp(-NTU*(1 - \frac{C_{\min}}{C_{\max}}))}{1 - (\frac{C_{\min}}{C_{\max}})\exp(-NTU*(1 - \frac{C_{\min}}{C_{\max}}))}$$

$$C_{\min} = \min(C_h, C_c)$$

$$C_{\max} = \max(C_h, C_c)$$

$$NTU = \frac{UA}{C_{\min}} \qquad U = \frac{1}{r_t}$$

$$r_t = r_a * v_a^{-0.8} + r_m + r_w * v_w^{-0.8}$$

$v_w, v_a =$ water and air velocity

$C_h =$ hot fluid capacity rate

$C_c =$ cold fluid capacity rate

$r_m, r_w, r_a =$ metal, water, and air thermal resistance

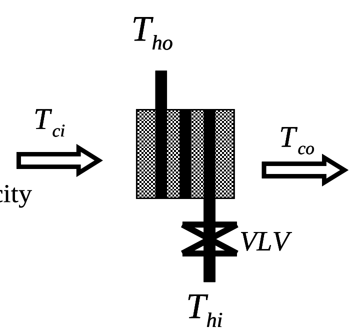


Figure 11, Heating coil model

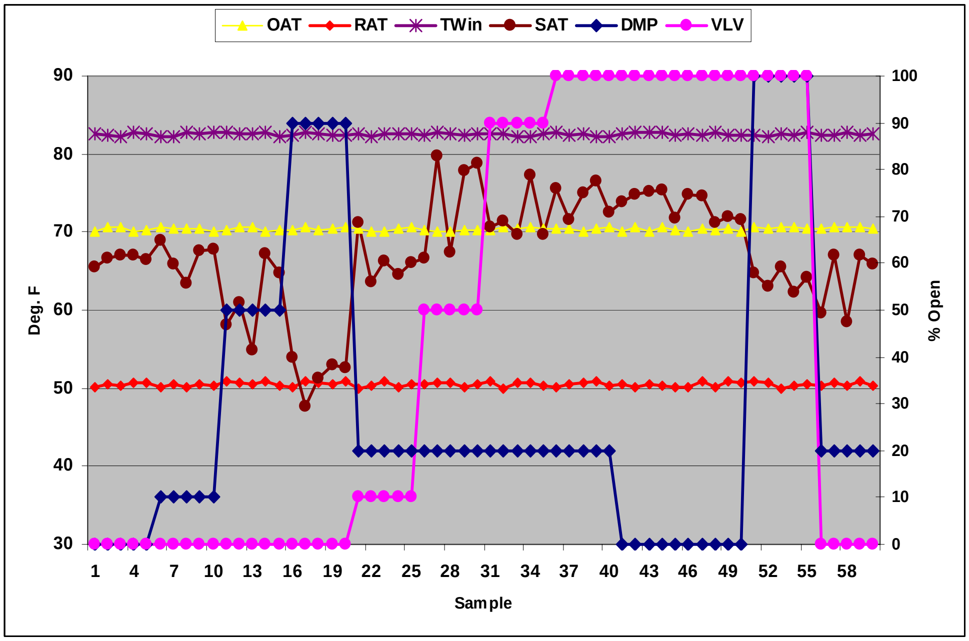


Figure 12, OAT: outside air temperature, RAT: return air temperature, Twin: hot water temperature entering the coil, SAT: supply air temperature, DMP: damper position, VLV: valve position. The diagnostic result is shown in Figure 16.

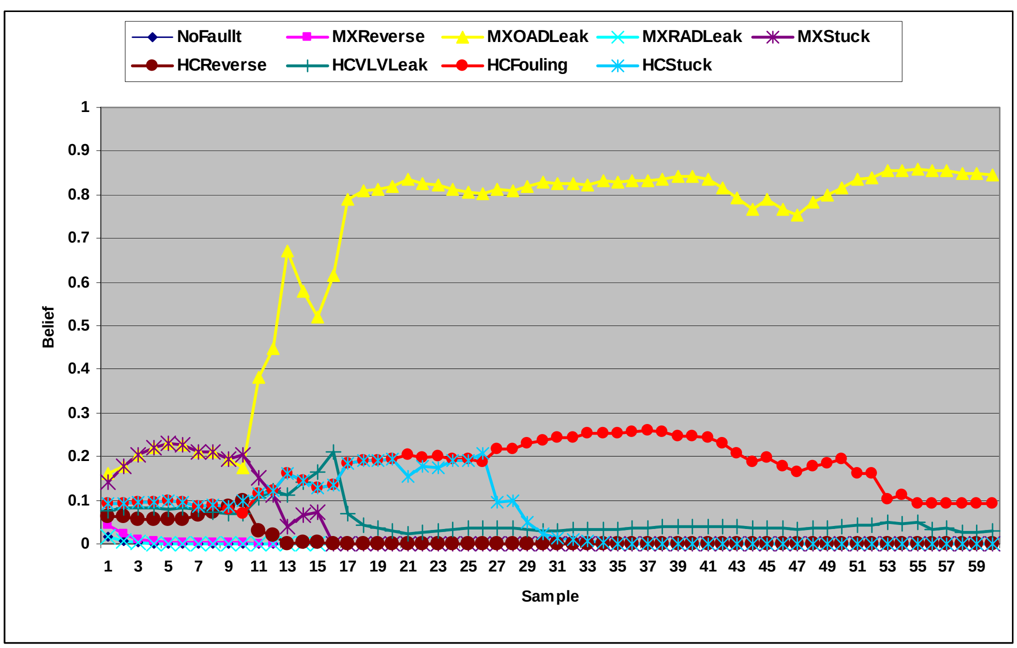


Figure 13, Diagnostic Results, MX and HC are short for mixing box and heating coil respectively. Note, how the belief about the system health status improves gradually as more data are observed, especially for the case of heating coil fouling. It seems that there is an outside air damper fault in the system.