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Model-based fault detection and diagnosis of air handling units: A comparison of methodologies

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Abstract

This paper presents a comparison between two model based diagnostics methodologies that can be used to detect and diagnose various faults that occur in Air Handling Units. The process from model development to inference diagnostics is highlighted with emphasis on the requirements for implementing a successful model based diagnosis solution. Comparative results of both methodologies on an air handling unit are presented and thoroughly discussed using as a benchmark the rule-based approach known as air-handling unit performance assessment rule-set.

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Keywords: Fault Detection and Diagnosis, Air Handling Units

1. Introduction

Different fault detection and diagnosis (FDD) methodologies have been developed for heating ventilation and air conditioning (HVAC) systems and are mostly based on expert knowledge to help identifying the faulty condition and its source [1]. However, a new trend in FDD is that of using models of the HVAC systems providing a base line for optimal operation, and supporting the detection of deviation from this optimum [2]. Model-based methods offer the advantage of an increased flexibility and robustness to adapt to different and innovative HVAC systems and changes in the same system.

This paper compares two model-based diagnostic solutions, one that uses a qualitative model and one a quantitative model. Both diagnostic approaches are derived from a generic reduced-order Modelica model, and employ general diagnosis algorithms that isolate and identify faults that occur frequently and can cause significant loss of system performance in air-handling units, such as passing heating- and cooling-coil valves, and stuck dampers [3].

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Nomenclature

eff	effectiveness	[1]
Q	heat transfer	[W]
C	capacity flow	[W/K]
T	temperature	[ºC]
mflow	mass flow rate	[kg/s]

Subscripts, functions and operators

a	air
w	water
i	input
o	Output
min(·, ·)	smallest value between arguments
act	actual
nom	nominal

$\oplus,\otimes,\ominus$ addition, multiplication, and subtraction operators of interval arithmetic

2. Model based diagnostics of air handling units

Model-based diagnostics is based on an explicit representation of the functional behaviours of the components and about the plant structure, which determines how the components interact with each other (see Figure 1). Starting from a library of generic component models and the representation of the plant topology, a system model (possibly covering both the nominal and faulty behaviours) is obtained. This model is then exploited by a generic diagnosis algorithm, which is not plant-specific nor even domain-specific. This way, diagnostics tailored to a specific plant require only the specification of the plant structure; they are generated instead of being programmed.

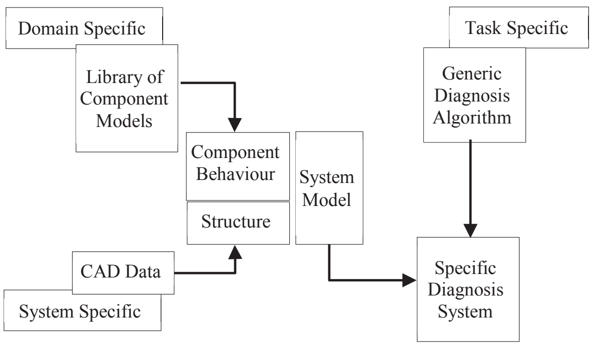

Figure 1 Generating Diagnostic Systems

Obviously, the existence of a generic model-based diagnosis algorithm is crucial to the approach and in this paper, the key ideas behind such algorithms are presented. For this research work two diagnostics approaches where developed and compared: quantitative (continuous) model based diagnosis (CMBD) and qualitative model based diagnosis (QMBD).

2.1. Model requirements

Before going into the diagnostics approaches and results it is convenient to discuss requirements and development of the models supporting the diagnostics approaches. In order to support the model-based diagnosis approach, the diagnosis models and, hence, also the numerical models to generate them from have to satisfy particular requirements:

- Strictly **component-oriented** modelling: the library has to be organized around the component types (with models that can be parameterized) that constitute the plant and that are units subject to diagnosis, e.g. heat exchangers, mass exchanger, mass movers, etc.;
- **Fault models** should be represented (perhaps with a parameter characterizing the fault, such as the opening of a passing valve);
- The plant model has to be configured strictly according to the **real physical interconnections** in the plant. It must not include computational artefacts that link certain variables that are not really interacting directly via a physical connection. This includes

using the concept of connectors in Modelica to reflect the channels of physical interactions between components (rather than connections via single variables as, for instance, in Matlab/Simulink).

- The models in the library have to be formulated in a context-independent manner and must not rely on implicit assumptions about the presence and correct functioning of other components, even though they may exist in most standard configurations. This is relevant for two reasons: it enables the re-use of the component models for different plants, and it is a precondition for the adequacy of the models in fault situations.

Model development was driven by the specific application needs which encompass, apart from what has been previously stated, best use of manufacturer's data for setting up models and ease of use. These last two criteria are closely related, since the manufacturer's data is the first source of information a model developer will have at hand. This information is often provided as a set of values for interacting variables for one operation scenario of the component. The models developed are such that manufacturer's data is used as parameters input when setting up the models. By using the manufacturer's data as parameters we ensure a first calibration of the model under manufacturer's nominal conditions. Table 1 shows the parameters, from the manufacturer's data, to be provided to each component model.

Table 1. Manufacturer's datasheet operation point values needed as parameters for model setup

Component	Parameter	Component	Parameter
Mixing Box	No data required	Cooling Coil	air input and output temperature and relative humidity
			air mass flow rate
			water input and output temperature
			water mass flow rate
Heating Coil	air input and output temperature and relative humidity	Humidifier	Maximum steam mass flow rate
			Steam temperature
	air mass flow rate		
	water input and output temperature		
	water mass flow rate		

2.2. Model development

A typical air handling unit (AHU) as the one under study (see Figure 3), comprises the following components: dampers/mixing box, cooling and dehumidification coil, heating coil, humidifier, ducts, filters, and fans. In this paper, the focus is in the so-called active elements that are used for changing air temperature and humidity to match those required by the space being served. To this end, it is assumed that ducts and filters have negligible effects on air temperature and humidity and fans just causes an air temperature increase and has no effect on the air moisture content (humidity ratio). Additionally, steady state conditions and no frictional losses are assumed for model development. The developed models are based in first principles representation of the heat and mass interactions between the components. The mixing box is based on model presented by [4], heating and cooling coil models are based on ASHRAE fundamentals [5] and [6]. The humidifier model is based on [7]. Details about the models are out of the scope of this paper but shall the reader desire to deepen in the modelling approach please refer to [8]. Finally, the models where calibrated to match real operation data as per [8].

Models were developed using the Modelica modelling language [9]. A deep discussion on the development of the models is outside the scope of this paper and can be found, together with the calibration methodology, in [8]. However, an example using the heating coil model and its calibration is presented for illustrative purposes.

The heating coil model calculates the outlet steady-state conditions for both, water and air, using equations derived from the conservation of energy principles and the definition of effectiveness in the classical eff-NTU method given by equations (1), (2) and (3) [5]:

$$Q = C_a * (T_{a_o} - T_{a_i}) \tag{1}$$

$$Q = C_w * \left(T_{w_i} - T_{w_o}\right) \tag{2}$$

$$Q = eff * min(C_a, C_w) * (T_{w_i} - T_{a_i}) \tag{3}$$

The effectiveness eff, depends on the coil configuration (parallel flow, counter flow, or cross flow with both streams unmixed) [10].

For the heating-coil component, there are inputs and outputs for flow of air through the ducting, and flow of hot water through the heating coil. Hence, mass- and energy-balance equations must be defined for the airflow and water-flow. The imposition of energy- and mass- balance provides the remainder of the Modelica model equations. The other models (cooling-coil, mixing box and humidifier) follow a similar modelling approach.

3. Diagnostics approaches

3.1. Quantitative Model based diagnosis

The basic idea of quantitative model based diagnostics (CMBD) is to perform multiple simulations for various hypothesized states of the system, called health states. Then, the output of these multiple simulations is processed and combined into a single diagnostic output. In this work, we explicitly encode failure modes of components in our Modelica model, i.e., the fact that components can operate both in nominal and in faulty states. For example, a damper may open and shut normally, or it may be stuck in a particular position. For each normal or failure state of a component, we must explicitly encode the behaviour associated. This contrasts with a typical Modelica model, which assumes that the system operates nominally, i.e., each component has only a single nominal state.

The CMBD approach uses the (fault-encoded) Modelica model to simulate the system so that we can compare the actual sensor data (D_S) with simulated data from the model (D_M). By computing a difference measure between D_S and D_M, called a residual $R(D_S, D_M)$, we can identify if the model correctly captures the real performance of the AHU. A residual above a threshold value indicates that the (nominal) model is incorrect, i.e., there must be some fault. By encoding a fault hypothesis in the Modelica model, a diagnosis corresponds to the diagnostics hypotheses from a fault-model output D_M' that produces a residual $R(D_S, D_M')$, that is below a threshold.

CMBD takes a statistical approach to diagnostics inference: it use statistical hypothesis ranking instead of hypothesis acceptance/rejection, thereby using standard statistical inference to first identify the anomalies that are significantly different than nominal (without resorting to fixed thresholds), and then using Bayesian methods to identify the most-likely fault given the fault assumptions identified from the significant anomalies. These statistical methods, widely used in aerospace and process-control, enable adaptive diagnostics that can optimise the type of diagnostics generated, e.g., system can be tuned to minimise false-positive diagnoses, or trade off false-positive and false-negative diagnoses.

The CMBD approach library consists of the following building blocks:

- Generator of Diagnostic Assumptions: A diagnostic assumption is a set of hypothetical assignments for the health or fault state of each component in the system. The “all nominal” diagnostic assumption assigns healthy status to each component. Given an anomaly identified by the monitoring process, CMBD will identify diagnostics assumptions that might account for the observed anomaly;
- Simulation Engine: Given a diagnostic assumption, CMBD will run models to compute values DM for one or more observable variables. The values of these observable variables are also referred to as a prediction;
- Residual Analysis Engine: A prediction is compared to the sensor data by a residual analysis engine, to identify R(DS, DM);
- Candidate Selection Algorithm: This phase aims to identify candidates generated by the residual analysis engine with lowest residual values, which are then used for computing the final system health. The candidate selection algorithm discards each candidate whose residual is larger than the residual of the “all nominal” candidate;
- System State Estimation Algorithm: CMBD uses the set of candidates that is computed by the candidate selection algorithm to compute an estimate for the health of each component. This is done by the system state estimation algorithm. Finally, CMBD computes the components with highest probability of failure. These are reported as the isolated fault.

3.2. Qualitative model based diagnosis

The diagnostics models used in qualitative model based approach (QMBD) are stated in relative, rather than absolute terms: they capture the deviation of variable values from the respective under nominal behaviour.

Following [11]: the qualitative deviation of a variable x is defined as:

$$\Delta x := sign(x_{act} - x_{nom}) \tag{4}$$

In equation (4), the function ‘sign’ returns the sign (+,-) of the argument, captures whether an actual (observed, assumed, or inferred) value is greater, less or equal to the nominal value. The latter is the value to be expected under nominal behaviour, technically: the value implied by the model in which all components are in performing as expected (OK mode).

Qualitative deviation models can be obtained from standard models stated in terms of (differential) equations by canonical transformations, such as equations (5) and (6).

$$a + b = c \Rightarrow \Delta a \oplus \Delta b = \Delta c \quad (5)$$

$$a * b = c \Rightarrow (a_{act} \otimes \Delta b) \oplus (b_{act} \otimes \Delta a) \ominus (\Delta a \otimes \Delta b) = \Delta c \quad (6)$$

In equations (5) and (6), $\oplus$, $\otimes$, $\ominus$, are addition, multiplication, and subtraction operators of interval arithmetic. For strictly monotonic functions, i.e. df/dt > 0 or df/dt < 0, equation (7) is obtained.

$$\Delta f(x) = \Delta x \text{ and } \Delta f(x) = -\Delta x \quad (7)$$

Respectively, if functions are piecewise monotonic, this holds for sections in which the derivative does not change its sign.

It is important to note that these equations do not contain and require values for the reference values (x_{nom}) and, hence, can be applied to different plants and under distinct operating modes. The qualitative deviation models, obtained from the Modelica models, reflect current modelling assumptions, (steady state, and no deviation in airflow) and become very compact due to their qualitative nature and because constants can be dropped and just replaced by their signs. Internally, this model is automatically transformed into an efficient data structure representing a set of finite relations.

The complete workflow and system modules required to build a qualitative model base diagnostic solution for a class of plants and to deploy it for a single plant and run it on-line, which is illustrated in Figure 2. There are three tiers of activities:

- The creation of a component library for a domain-specific solution (top row), which consists of producing a library of component models that qualitatively capture the behavior of the components in the domain in nominal and failure modes;
- The adaptation of the solution to a particular plant (middle row), which means generating a diagnosis model of this plant using the structural information about the system and the component library;
- On-line diagnosis based the diagnostic plant model (bottom row), a stream of building management system data, and a numerical model of the nominal behaviour.

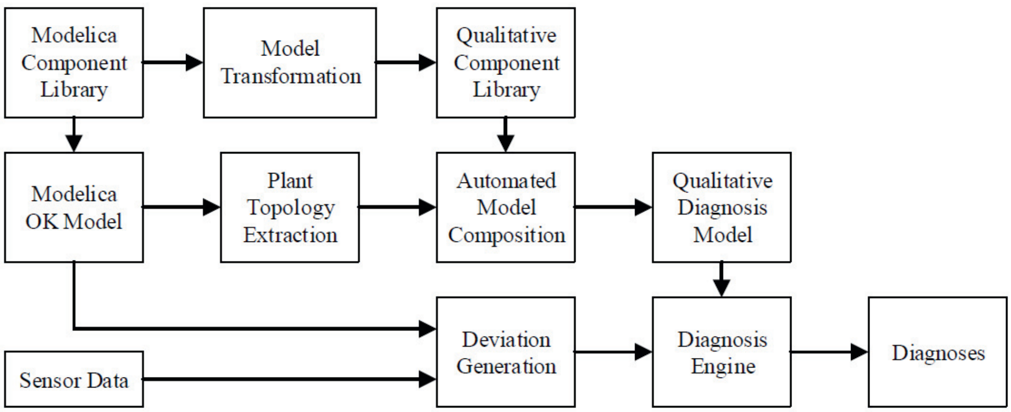

Figure 2. From model to diagnosis, the QMBD chain

4. Case study

The case study comprises an AHU, for which a schematic is shown in Figure 3. An AHU is in charge of preconditioning the air that is going to be supplied into any building to match predefined environmental and safety conditions (e.g. temperature, freshness, humidity), it does so with a number of different elements to mix air streams, humidify, cool and heat the air. The AHU under study has the following active elements and functions:

- Mixing Box (MB): the MB is used for heat recovery, it mixes the air returning from the conditioned space with fresh air from outside. In this way heat that otherwise would be wasted in the exhaust air is sent back to the facility;
- Cooling and dehumidification coil (CC): the CC is in charge of cooling and dehumidifying the incoming air to suit indoor environmental conditions. It does its function by having cold water passing through pipes which are placed on the flow path of the air;

- Heating coil (HC): the HC is in charge of heating the incoming air to suit indoor environmental conditions. Its works similar to the CC but instead of cold water hot water is flowing through the pipes;
- Humidifier (H): the H adds water to the air in form of steam or spray and it is used to increase the level of humidity of the incoming air if the conditioned space so requires.

An active element, in the context of this work, refers to the components that are used to control environmental conditions (temperature and humidity) in the serviced area. The AHU serves a facility consisting of an audio laboratory of around 50 m^2, where conditions of temperature and humidity should be regulated to meet a minimum air quality due to the presence of highly sensitive musical instruments (e.g. grand pianos). The building is located in Cork city in the Republic of Ireland.

4.1. Sensor Instrumentation

The air-handling unit under study is a reasonably well instrumented AHU, making it suitable for research purposes. The available sensors can be seen in Figure 3, where 'T' stands for temperature sensor, 'RH' for relative humidity sensor, 'AV' stands for air volumetric flow rate sensor and '%' is represents the opening of valves and dampers. The signals and sensor data is recorded with a frequency of one minute. Technical manufacturer (as installed) data for each of the components of the unit is available.

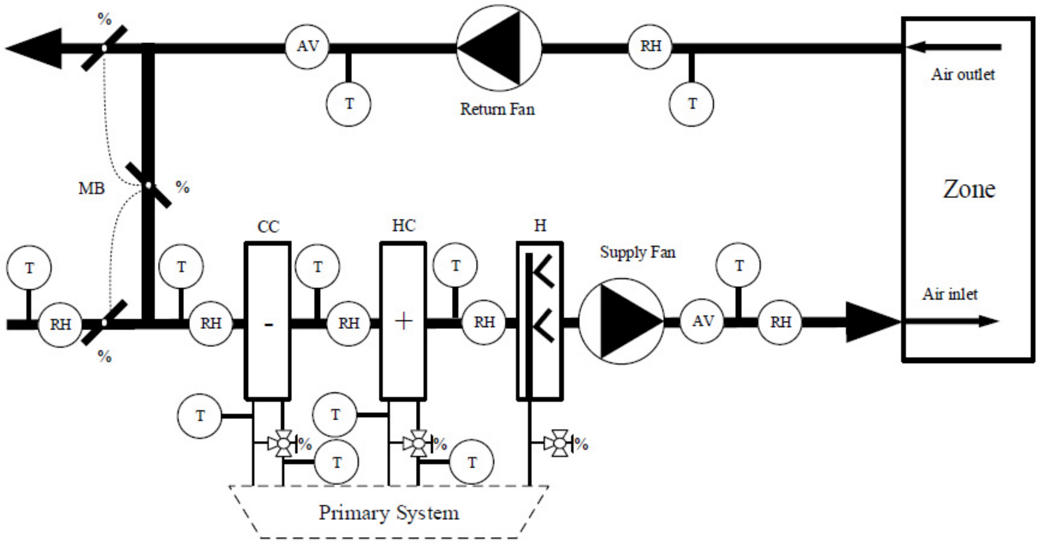

Figure 3. Air Handling Unit Schematic

4.2. Experiments

We conducted a number of experiments in a systematic manner, with a faults introduced to the system by modifying a single component and observing the reaction. This procedure ensured that the best possible data was captured. The initial experiments did not include humidity as an environmental parameter; we plan to study this in later work.

In the experiments, to simulate a passing valve in one of the coils, the valve is initially set at the minimum position (0%) and the reaction of the system is then observed for ten minutes. The valve position is then opened by 10% of the maximum opening and again the system is left to settle for a period of ten minutes. This step is performed incrementally with ten-minute settling periods until a valve position of 100% is achieved. The procedure is then reversed going from 100% back to the minimum position in steps of 10% with a 10-minute settling period between changes. The whole procedure is then repeated a second time giving two sweeps through the applicable valve positions to give sufficient data to enable the model calibration and diagnostics analysis on the heating coil, cooling coil components of the AHU. A similar procedure was performed also on the dampers of the mixing box.

4.3. Comparison of results

From the experiments (detailed in the previous section) four 24-hour data sets were compiled from real air handling unit data to compare the two diagnostics approaches namely, and the CMBD and QMBD approaches. A third technique, based on the traditional AHU performance assessment rules (APAR) rule set was also implemented to provide a base line of what is currently used in most cases in industry when fault detection and diagnosis is present.

The four data sets chosen included the following:

1. A nominal data set, where no faults are present;
2. A passing cooling coil data set, where the value of the coil control valve is reported as being 0% open when in fact it is modulated open (in steps of 10% every ten minutes up to 100% open), and then closed in steps of 10% every ten minutes.
3. A passing heating coil data set, where the value of the coil control valve is reported as being 0% open when in fact it is modulating open in steps of 10% every ten minutes up to 100% open and then closing in steps of 10% every ten minutes.
4. A stuck damper data set, where the value of the return air-damper valve being reported modulates between 20% and 100% depending on the system demand but in actuality the damper is 100% open the entire time.

Table 2 Diagnosis techniques results

Scenario	Fault	APAR	CMBD	QMBD	Comments
1	Nominal	No fault identified	No fault identified	No fault identified	No fault identified by each of the three approaches.
2	Passing Cooling Coil	No fault identified	1 fault identified during 7 separate time periods	2 possible faults identified during 5 separate time periods	No fault identified by APAR as the cooling coil being 0% made the engine think that the unit was in heating mode and therefore rules pertaining to the cooling coil were not applied. CMBD and QMBD both correctly identified an issue with the cooling coil.
3	Passing Heating Coil	6 possible faults identified during 3 separate time periods	1 fault identified during 6 separate time periods	4 possible faults identified during 3 separate time periods	APAR identified a number of possible faults including an issue with the heating coil. CMBD correctly identified a fault on the heating coil. QMBD correctly identified a fault on the heating coil and also correctly identified a fault in the mixing section of the AHU.
4	Stuck Mixing Damper	4 possible faults identified during 5 separate time periods	2 possible faults identified during 7 separate time periods	2 possible faults identified during 6 separate time periods	APAR identified a number of possible faults including an issue with the mixing dampers. CMBD correctly identified a fault on the mixing dampers but incorrectly identified an additional fault on the pre-heat coil. The pre-heat coil is the first component downstream of the mixing box. QMBD correctly identified a fault on the mixing dampers.

Table 1 details the results obtained from each of the three approaches. In the first scenario, the nominal data set, each of the three approaches reports that no fault has been identified as expected.

In the second scenario, the cooling coil passing, both the CMBD and QMBD approaches identify an issue with the cooling coil of the unit. However, the APAR approach does not identify any faults. APAR fails to identify the existing fault as the cooling coil being 0% open makes the rule set decide that the unit was in heating mode and therefore rules pertaining to the cooling coil were not applied. This is a shortcoming of the APAR rule set.

In the third scenario, the heating coil passing, each of the three approaches identifies a fault with the heating coil in the unit. However, the QMBD also determines that there is a fault in the mixing section of the AHU, which the other approaches do not identify. The mixing fault was occurring as a result of broken actuator arm connecting the control valve to the recirculating damper and so the QMBD identified simultaneous faults when the other approaches did not.

In the fourth scenario, the stuck mixing damper, each of the three approaches identifies a fault with the mixing section of the unit. However, the QMBD also identifies a fault with the pre-heat coil of the unit, which was not present at the time and is therefore giving a false positive reading.

It should be noted that for the APAR approach, a number of possible faults are identified for a given scenario of which one or two are related to the component in question. However, it does also give a number of other possible causes for the fault. In this regard, an amount of user knowledge is required to investigate the fault further before an accurate determination of the issue can be made.

5. Conclusions

The main advantages of the model-based approaches is the adaptability to different plants and to changes in the same plant. A brief description of the steps involved in adapting the qualitative (QMBD) and quantitative (CMBD) model based diagnosis is presented below.

- **Structural changes**: For QMBD, these changes will have to be reproduced in the model, which would need to be compiled and recalibrated. The diagnosis model structure is a 1:1 mapping of the model and as such only minor adaptation is needed. However, if the change involves variables considered for diagnosis, the variable mapping between model and diagnosis framework has to be modified and tested with new data sets. For CMBD, since this approach uses the Modelica model directly, any changes in the Modelica model will be reflected in updated diagnostics that can be computed;

- **Parameter changes**: recalibration of the models is in principle the only requirement. In the case these parameter changes impact the accuracy of the model, the QMBD tolerances of the diagnosis framework might have to be adjusted, and the CMBD residual analysis would need updating;
- **Sensor changes**: similar consideration to the case of structural changes should be taken in the case of adding new sensors or modifying position of existing ones. In the case that existing sensors are to be replaced with new ones with different precision, the steps described in the parameter changes are to be followed;
- **Changes in control:** plant model and diagnosis framework is, in principle, not affected by changes in the control strategy.

This adaptability makes model-based diagnosis a viable approach to fault detection and diagnosis in air handling units.

Both model based diagnostics approaches produced very similar results in terms of diagnostics power and robustness of the solutions. The main differentiator between both approaches is the time at which the highest amount of computational resources are needed. For the QMBD approach this is at set-up time in order to generate the qualitative diagnostic's models. In the case of the CMBD more power is needed during operation time as a higher amount of simulations are run for each diagnostics event.

6. Future Work

Next steps in this research are:

- Development and testing of models for other components of HVAC systems;
- Deployment and testing in a range of real units operating in normal environments;
- Automation of the steps linking model development, calibration, diagnostics generation and diagnostics inference aiming at an end-to-end tool.

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