DIAGNOSIS OF AIR HANDLING UNITS BASED ON ENGINEERING AND QUALITATIVE MODELS

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ABSTRACT

This paper presents a methodology for model-based fault detection and diagnosis underpinned by Modelica models and using a qualitative approach to diagnosis, which has been applied to diagnosis of an air handling unit based on data recorded by a building management system. The main steps from model development to component diagnosis are discussed and illustrated using a heating coil component.

KEYWORDS

Automated diagnosis, model-based diagnosis, Modelica models, qualitative models, air-handling units

1. INTRODUCTION

Heating Ventilation and Air conditioning (HVAC) systems are known for being very inefficient for different reasons, one of the most common causes being the presence of undetected failures in one or more of its components. Undetected faults can remain for long periods due to different factors: compensations made by the control algorithms of other elements belonging to the same system; lack of proper maintenance, improper timing of flow of energy to/from the building, etc. Even when systems are known to suboptimal operation, the presence of faults may be very difficult to manually localize and identify, making it a costly task for human operators who only act when indoor environmental conditions are not met. This lack of timely intervention raises the need for developing automated fault detection and diagnosis methods and technologies that assist the building operator (Katipamula, Michael, and Brambley, 2005).

The focus of this paper is on a model-based diagnostic solution that uses a **Modelica model of plant components**, a **qualitative diagnostic model** derived from it**, and consistency-based diagnosis** (Struss, 2008) for the part of the HVAC system corresponding to the **Air Handling Unit** (AHU). This solution is derived from a general first-principle Modelica model and exploits a general diagnosis algorithm that isolates and identifies faults that occur frequently and can cause significant loss of system performance in AHUs: passing heating- and cooling-coil valves, and stuck dampers. An application example using a heating coil model is presented and provisions are made for the extension to other components. The system has been applied to real data of several days of an AHU with different faults inserted and successfully evaluated.

The paper is structured as follows: section 2 presents the plant used in the case study. Section 3 outlines the targeted entire work flow, whose different steps are presented in section 4 and 5. Then we discuss the results of the evaluation of the system on real data.

2. THE AIR-HANDLING UNIT

The case study comprises a constant air volume air-handling unit (AHU) which schematic is shown in Figure 1. The AHU serves a facility consisting of an audio laboratory of around 50 m^2, where strict conditions of temperature and humidity should be met due to the presence of highly sensible music instruments. The building is located in Cork city in the Republic of Ireland.

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An Air Handling Unit (AHU) is a mode-switching hybrid system, that is, it is a system that will operate in multiple different modes depending on the prevailing external environmental conditions and the requirements of the area being served by the unit at a given time. Each different mode of operation utilizes the components in the AHU (heating- and cooling coils, dampers, etc.) in a different manner to satisfy required conditions in the rooms served by the unit under the given the environmental conditions.

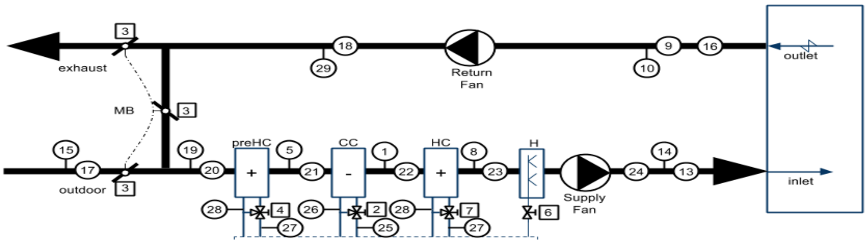

Figure 1. Air-handling unit

An AHU is composed of a number of individual components that function independently one of each other but are controlled by a central system. As a result, a fault in a component of the leading to a detriment in the indoor conditions may be compensated for by the overall control system by the use of another component, causing energy to be wasted.

The AHU presented in Figure 1 comprises the following components:

1. Mixing Box (MB): serves to recover heat from exhaust air by mixing a fraction of it with fresh air from outside;
2. pre-heat coil (preHC): is an emergency heat exchanger to prevent frost in the unit when outside air condition are below freezing point;
3. Cooling Coil (CC): is used to control both temperature and humidity by cooling the air;
4. Re-Heat Coil (HC): is used to control temperature by heating the air;
5. Humidifier (H): serves to control humidity by adding water vapor to in the air.

The data available for diagnosis are the actuator signals (controlling the mixing box and the coils).

6. SupplyFan and ReturnFan: produce the air flow.
7. Temperature sensors (circles 15, 19, 5, 1, 8, 14, 29) supply the input data to the diagnosis.

3. THE WORKFLOW

In this section, we present a complete workflow and system modules required to build a diagnostic solution for a class of plants (AHU) and to deploy it for a single plant and run it on-line, which is illustrated in Fig. 2. Here, we give only an overview of the steps and modules, the most important ones being discussed in more detail in the following sections.

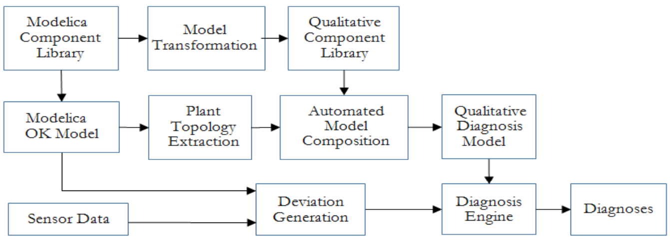

Figure 2. The workflow: from Modelica model to diagnosis.

1. Producing the general solution involves
   - the production of a library of Modelica models and
   - its transformation into a qualitative diagnostic model library.
2. Producing an application system based on the general solution, requires

- The configuration and calibration of a Modelica model of the correct behavior (named OK model and explained in section;
- the composition of the diagnostic model based on the diagnostic library and the component structure of the plant, which can be extracted from this Modelica system model. This composition step is part of the functionality of the tool used in this work, *Raz'r* (from OCC'M Software GmbH, OCC'M, 2014). The extraction of the component structure from Modelica has not yet been realized, but is expected to be straightforward, given that the models have been developed following certain requirements, which are stated in section 4.

3. For on-line diagnosis,
   - qualitative deviations are generated by computing the difference between the real data (currently for steady state only) and the predictions generated by the OK model of the plant (implemented in Modelica), and determining qualitative deviations based on given thresholds. A steady state filter is used to extract steady state data from the real operation data. The resulting qualitative deviations of dependent variables (and zero deviations for the exogenous variables) are processed by
   - the runtime diagnosis engine, which computes the set of all mode assignments containing minimal combinations of component faults that are consistent with the abstract observations (Struss, 2008).

4. MODELING FOR MODEL-BASED DIAGNOSIS

In order to support the model-based diagnosis approach as outlined above, the diagnosis models and, hence, also the numerical models to generate them from have to satisfy particular requirements:

1. 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.
2. **Fault models** should be represented (perhaps with a parameter characterizing the fault, such as the opening of a passing valve)
3. 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.

4.1 Model Development

Model development was driven by the specific application needs as specified in the previous section. These needs also encompass matching of the type of information interchanged between elements, reusability of the models, best use of manufacturer's data for setting up models and ease of use.

Ease of use and best use of manufacturer's data are closely related since the manufacturer's data is the first source of information a model developer will have in hand. In this regard, the developed model is such that this data is input into the parameters of the models corresponding this way to a first calibration step based on the manufacturer provided operation point.

The heating coil model calculates the outlet steady-state conditions in both, water and air sides, using equations derived from the conservation of energy and mass principles and the definition of effectiveness in the classical eff-NTU method which given by equations (1), (2) and (3) (ASHRAE, 2009):

$$Q = C_a * (T_{aO} - T_{aI}) \quad (1)$$

$$Q = C_w * (T_{wI} - T_{wO}) \quad (2)$$

$$Q = eff * min(C_a, C_w)*(T_{wI} - T_{aI}) \quad (3)$$

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The effectiveness 'eff', depends on the coil configuration (parallel flow, counter flow, or cross flow with both streams unmixed) (Wetter, 1999). These main equations transform almost directly into Modelica code.

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.

5. MODELING FOR MODEL-BASED DIAGNOSIS

Creating a diagnostic library, based on the Modelica library, requires its transformation into a diagnostic model library. The models used in our diagnostic approach are stated in relative, rather than absolute terms: they capture the deviation of variable values from the respective under nominal behavior.

Following (Struss, 2004) the qualitative deviation of a variable x is defined as:

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

Equation (4) 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 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). We use $\oplus$, $\ominus$ and $\otimes$, to denote addition, subtraction and multiplication on signs.

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

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

It is important to note that these equations do not contain and require values for the reference values xnom 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 finite relation.

In the following, we illustrate how this transformation can be done by manipulating the equations. According to energy balance equations (equations (1), (2) and, (3)), and assuming no losses, the energy balance in equation (7) can be reformulated in terms of deviations (Δ) as in equation (8).

Assuming that the air flow and the water temperature (drop) are positive and not deviating and replacing the capacity flow by the mass flow $mflow_w$ (which differ only by a constant factor), we obtain equation (7) which applies to all modes of the coil.

$$0 \ = \ C_a*(T_{aO}-T_{aI}) - C_w*(T_{wI}-T_{wO}) \qquad (7)$$

$$0 \ = \ \Delta\,(C_a*(T_{aI}-T_{aO})) \oplus \Delta\,(C_w*(T_{wI}-T_{wO})) \qquad (8)$$

$$0 \ = \ \Delta T_{aI} \ominus \Delta\, T_{aO} \oplus \Delta mflow_w \qquad (9)$$

Following equation (4), each of the variables used for diagnostics (equation (9)) can have a deviation of the measured value from the simulated one as follows:

1. positively ('+'), when the actual (measured, predicted, or assumed) value is above the simulated plus a threshold;
2. negatively ('-'),when the actual value is below the simulated minus a threshold;
3. or not deviate ('0'), when the actual value is within the simulated value plus/minus the threshold.

Table 1 depicts the resulting relation on the three deviation variables, i.e. all solution tuples of equation (9). For instance, the first three rows of the table indicate the intuitive fact that, if the mass flow shows no deviation, a deviation of the incoming air temperature will simply be propagated to the output air temperature.

On the other hand, a positive deviation of the output air temperature in combination with no deviation in the input air temperature, is only consistent with a positive deviation in the mass flow rate of the water (last-but-one row).From the diagnostic perspective, this reveals a fault in the coil (e.g. a passing valve), because a correct coil will not produce a deviating water flow. A valve stuck closed may lead to a negative deviation "-", if the command Cmd to the valve is "open" (to some non-zero position, "+"). If the control commands the valve to be shut, anyway, a stuck-closed valve would cause no deviation in the water flow. This is captured by the model fragment in Table 3, which actually, is the complete fault model. Table 2 and Table 4 show the models of the OK mode and the passing valve, respectively. The table expresses that this mode may coincide with the nominal behavior for a certain range of opening commands, but deviate positively for smaller valve positions

With respect to their use for diagnosis, tables 2 – 4 jointly with table 1 capture which tuples of temperature and water flow deviations are consistent with which behavior modes. Note that this does not require that the deviations can be observed directly. They may also be **predicted** by the system model based on observations for a particular system health assignment.

Table 1. Relation on temperature deviations and water flow deviation.

$\Delta mflow_w$	ΔT_{aI}	ΔT_{aO}
0	-	-
0	0	0
0	+	+
-	-	-
-	0	-
-	+	*
+	-	*
+	0	+
+	+	+

Table 2. Qualitative representation of the OK mode.

Cmd	$\Delta mflow_w$
0	0
+	0

Table 3. Qualitative representation of the stuck closed valve mode

Cmd	$\Delta mflow_w$
0	0
+	-

Table 4. Qualitative representation of the passing valve mode

Cmd	$\Delta mflow_w$
0	+
+	0
+	+

Bear in mind that a qualitative representation of one mode does NOT exclude that any other mode can be reached with the same combination of inputs/outputs.

5.1 Runtime Deviation Generation

At runtime, the system will calculate deviations by following the steps:

1. Read each data vector corresponding to the sensor and actuator signals;
2. Extract the exogenous variables including (external temperature, damper, and valve commands);
3. Provide the exogenous variable values to the Modelica model of nominal behavior, compare the values predicted by this model with the actual sensor data, and compute the deviations. In the current solution, this is simply done by using a threshold (which can be different for different variables).

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For the example with the heating coil documented here, a threshold of 2°C was chosen in order to produce deviations in the domain of signs (‘+’,’-‘,’0’). In future solutions, different orders of magnitudes of the deviations could be generated by the abstraction module, which can take arbitrary sets of interval boundaries as an input.

For the example with the heating coil, Table 5 shows both the sensor data and the predicted values, highlighting the temperature before and after the heating coil. Using the 2°C threshold, the inflow air temperature is determined as nominal, while the outflow air temperature is higher than expected. This triggers a diagnosis event.

5.2 Diagnosis Inference

In our solution, we use Raz’r (OCC’M, 2014), a commercial tool that implements component-oriented consistency-based diagnosis (Struss, 2008). This is based on checking whether an assignment MA of behavior modes to components is consistent with the system description SD (i.e. the model library and a structural description of the plant) and the observations OBS:

$$SD \cup \{MA\} \cup OBS \not\models \perp$$

For detecting faults, it is first of all assumed that all components operate correctly: in the mode assignment MA_{OK}, OK modes are assigned to all components and the system behaves as intended. It then only has to be checked whether the model of the correctly behaving system is inconsistent with the observations:

$$SD \cup \{MA_{OK}\} \cup OBS \models \perp.$$

If faulty components should be localized, i.e. the separation of correctly operating components from faulty ones, it is often sufficient to restrict the modes of a component C to OK(C) and ¬OK(C). To perform fault identification and/or refine fault localization, fault modes of components and their respective behavior models can be defined, as previously mentioned. The combinations of fault models span an entire space of models.

The computed deviation pattern (with a zero deviation of exogenous variables -input temperature, and valve commands-) forms the input to the diagnosis runtime system. The deviation patterns will be checked for consistency with the possible models. In the trivial example restricted to one component presented in Table 5, the input/output temperature deviations (0, +) match with only one row in Table 3 that holds for all behavior modes, which fixes $mflow_w$ to be positively deviating. This positive deviation is consistent with the valve passing mode (Table 4), but neither with the OK mode, not the stuck closed mode. Note, that this result can actually be concluded without information about the command to the valve.

What is illustrated here for a single component, is actually applied to the space of **plant** models covered by the system health assignments, which may yield alternative diagnosis hypotheses and also such that correspond to multiple component faults.

Table 5. Deviations between sensor data and model data

	T_{aI}(ºC)	T_{aO}(ºC)	T_{aI}(ºC)
Sensor Data	18.32	20.87	18.32
Model Prediction	18.44	18.44	18.44
Resulting Deviation	**0**	**+**	**0**

6. EVALUATION

In this section, we will present some results of testing the developed qualitative fault detection and diagnosis methodology in a real facility. First we will introduce the different experiment carried out, followed by a comparison of the results against the tradition APAR rule based approach (House, Vaezi-Nejad, Whitcomb, 2001).

Five experiments were developed, with the initial experiment having the objective of obtaining operational data for when humidity control on the unit has been disabled (Humidity control is not a focus of the research at the present time). Four further experiments then simulate faults with the mixing box, pre-heating coil, cooling coil, and heating coil. These experiments require the control valve of the individual component to be manipulated into a fault condition through the control system. Therefore, it was proposed to fix the damper/control valve position on the individual component for a set period of time, observe the system response and then adjust the position again. A brief outline of the procedure for one of these experiments is outlined below and the others follow a similar pattern.

In the experiment to simulate a stuck mixing box damper position, the damper is initially set at the minimum fresh air position and the reaction of the system is observed for ten minutes. The damper position is then opened by 10% 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 damper 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 damper positions to give sufficient data to enable the model calibration and diagnostics analysis on the mixing box component of the AHU.

As a result of the experiments, four 24-hour data sets were compiled from real AHU data and including each one of the experiment scenarios described before. In order to provide a baseline for comparison, the traditional APAR rule set was also applied to the data and results were used for comparison with the qualitative model-based diagnosis. The four data sets chosen for demonstrative purposes come from experiments 1 to 4. Table 6 presents and comments the comparison results obtained for each experiment.

Table 6. Evaluation results

Fault	*APAR*	*QMBD*	*Comments*
Nominal	No fault identified	No fault identified	No fault identified by each of the two approaches.
Passing Cooling Coil	No fault identified	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. QMBD both correctly identified an issue with the cooling coil.
Passing Heating Coil	6 possible faults identified during 3 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. QMBD correctly identified a fault on the heating coil and also correctly identified a fault in the mixing section of the AHU.
Stuck Mixing Damper	4 possible faults identified during 5 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. QMBD correctly identified a fault on the mixing dampers.

7. DISCUSSION

In this paper a tool chain from model development to fault detection in air handling units has been presented and discussed with an illustrative example of a heating coil. The development tool of choice for the model was Modelica since it provides all the necessary tools to comply with model requirement for model-based fault detection as shown in section 4. Furthermore, although in early stage, Modelica models bear the perspective to become the de-facto standard in energy modelling of building components as shown by the recently established International Energy Agency Annex 60.

One of the main advantages of the model-based approach is the adaptability to different plants and to changes in the same plant. A brief description of the steps involved in adapting the qualitative model based diagnosis is presented below.

1. **Structural changes**: 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.
2. **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 tolerances of the diagnosis framework might have to be adjusted.
3. **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.
4. **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. Since they have a fairly standard structure and comprise a small set of different component types, the current library of qualitative diagnostic models needs only limited extensions in order to be applicable to a broad class of AHUs.

In contrast to (Behrens, Provan, 2010), our solution is snapshot-based and does not require temporal reasoning. The work described in (Klenk et al., 2014) is closely related, but focuses on exploiting Modelica models for qualitative simulation.

Taking into account that heating ventilation and air conditioning systems are rarely critical systems, the benefits of model-based diagnosis in the building environment are more economically and environmentally relevant rather than being a safety issue and that hourly fault detection and diagnosis frequencies are more than acceptable in building applications; there is little scope for extending the models to include dynamic behavior at the moment.

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