IEA ANNEX 60 ACTIVITY 2.3: MODEL USE DURING OPERATION, APPROACH AND CASE STUDIES

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ABSTRACT

Annex 60 is developing and demonstrating new generation computational tools for building and community energy systems based on the non-proprietary Modelica modeling language and Functional Mockup Interface (FMI) standards. Demonstrations will include optimized design and operation of building and community energy systems. Within the Annex 60, Activity 2.3 focuses on the use of models to augment monitoring, control and fault detection and diagnostics methods. This promises to detect a degradation of equipment efficiency over time because measured performance can be compared to expected performance at the current operating conditions. Furthermore, use of models during operation allows operational sequences to be optimized in real-time to reduce energy or cost, subject to dynamic pricing.

This paper will offer an overview of the work carried out within this IEA Annex 60 Activity 2.3 both in terms of approach and case studies with a particular focus on model use during operation for fault detection and diagnosis.

INTRODUCTION

In general terms, a fault is considered as any issue or state that causes a reduction of the performance (Roth et al., 2005b), even if it is not perceived immediately by humans. Detecting a fault is the process by which, using available information, there is a realisation of this reduction of performance. Diagnosing a fault is determining the root(s) cause(s) of the loss of performance (Struss, 2008). Fault Detection and Diagnosis (FDD) is the field within control engineering that studies the automated detection and diagnosis of faults (Isermann, 1997).

Estimates give an average range of 15% to 30% for the energy waste in commercial buildings due to poorly maintained, degraded and improperly controlled buildings (Le et al., 2005; Bruton et al., 2012). These issues, apart from deriving in energy waste and reduction of equipment life, can also represent reduced performance and even health problems for the building's occupants (Mumma & Issues, 2003).

The building sector is just catching up with developments in FDD since operational optimisation of building operations is today becoming a requirement. It is estimated that FDD methodologies can reduce energy waste by 5% to 40% (Piette et al., 2001; Westphalen et al., 2003; Roth et al., 2005a) in particualr when faulty operations are timely rectified for the most frequent and high-impact fautls types (International Energy Agency, 2006; Heinemeier, 2012; Lee & Yik, 2010). However, in current practice faults are mostly identified manually during routine inspections, due to persistent alarms, or as a result of a noticeable degradation of performance. The problem with this approach is that many faults can be undetected for long periods of time thus leading to a considerable energy and monetary waste (Haves et al., 2009). Automated FDD can help with this problem by providing timely indications of the existence and root cause of the fault, and possibly also suggest correctives actions.

Automated FDD requires a-priori knowledge of the normal and faulty behaviour of the systems to be embedded in the methodology. In this sense, FDD techniques can be classified as rule-based or model-free methodologies (Donca, 2010), model-based methodologies and history-based methodologies (Sterling, 2015).

In the Annex 60 (Wetter et al., 2013), the focus lies specifically in using Modelica models for FDD benefitting from the extensive existing model libraries for buildings and HVAC&R systems and the various interfaces and coupling mechanisms provided for those models.

Modelica models can be used for FDD in two different aspects: directly, by using simulation results as a reference for the monitored data and indirectly, by using simulation data as training data for black box models. In the latter case, the results of the black box model are then used as a reference for the monitored data. The direct use of Modelica models for FDD, based on fault models, has been reported in (Bunus et al., 2009; Lunde et al., 2006; Cui et al., 2011).

In this paper we will present three case studies with relation to the use of Modelica models for FDD tasks as part of the IEA Annex 60 Activity 2.3: Model Use During Operations. In particular, the approaches

presented in this paper are applied to air handling units (AHUs).

Two approaches for model-based FDD are described in this paper:

- Qualitative model-based FDD, qualitative models describe the behaviour of a system only roughly. Instead of numerical values, qualitative models can deal with a symbolic representation of the system variables capturing deviations of variable values from their respective nominal behaviour.
- Quantitative model-based FDD, performs multiple simulations for various hypothesized states of the system, called health states based on monitored data. Then, the output of these multiple simulations is processed and combined into a single diagnostic output.

For both cases hold, that for Fault Detection (FD), nominal data that describes the faultless behaviour of the regarded system is needed. Fault Detection and Diagnosis (FDD) requires also fault models or faulty measurement data.

CASE STUDIES

Fault detection through qualitative models of air handling unit components

Usually, qualitative models can be generated by an abstraction from a quantitative model or by stochastic qualitative identification. In this case study we will focus on the second method which has been developed by (Lichtenberg, 1998) which allows the generation of a qualitative model directly from measurement data or from simulation data.

The qualitative approach for fault detection shown here uses stochastic automata (SA) as qualitative models. Important work in this field has e.g. been done by (Lunze, 1994). (Lichtenberg & Steele, 1996) used a qualitative observer for FDD.

A common problem with SA is that complexity of the so-called behaviour relation of the SA increases rapidly with a rising number of inputs, outputs and state signals. Therefore, solutions for reducing the computational efforts and storage amounts are required. In addressing this issue, (Müller et al., 2015) have shown that the complexity of the behaviour relation of the SA can be reduced by exploiting the underlying tensor structure of the behaviour relation. Consequently, a non-negative canonical polyadic (CP) tensor decomposition is used to make qualitative models applicable to large discrete-time systems.

The basis for Fault Detection is the qualitative observer. The algorithm yields, for each time-step, a probability vector describing the possible behaviour of the system states depending on the measured qualitative input-output combination. If the probability vector contains only zeros, the measured input-output combination is inconsistent with the

qualitative model and a fault can be structurally detected, (Lichtenberg, 1998). For demonstrating FD with qualitative models, different faults have been simulated with the Modelica fault triggering library, developed by the German Aerospace Center (DLR), (Linden, 2014). In the following, an application example of a heat exchanger (HX) of a HVAC&R system shows the applicability of the qualitative modelling approach.

The following simulation results were generated during the project CASCADE of the European Union's Seventh Framework Programme FP7/2007-2013 under grant agreement no. 284920.

The considered heat exchanger (HX) is used as an air cooler and the signals shown in Figure 1 have been simulated with Modelica for nominal and faulty conditions.
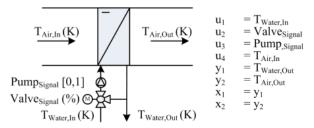

Figure 1. Generic HX scheme

The simulated fault describes a malfunction of the pump leading to a fully opened valve, because the controller tries to reach the regarded set point of the air outlet temperature. Figure 2 shows the faulty behaviour during the time interval $2420 \leq t \leq 2708$. As the figure shows, the air outlet temperature of the HX equals the air inlet temperature because no water circulates.
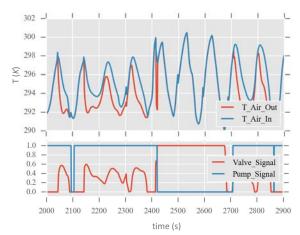

Figure 2. Simulation Data

Then, the qualitative model was trained by the nominal behaviour of the simulation data of the HX. Figure 3 illustrates the qualitative state trajectory of the state variable x_2 for a selected nominal time range. The state trajectory is a direct result of the qualitative observation algorithm and it shows the probability

distribution of the state signal for each discrete time step k. The different grey shades of the bars denote the probabilities. In the example, the state signal x_2 was quantised into five intervals that can be seen by the horizontal separation of the black and grey bars.
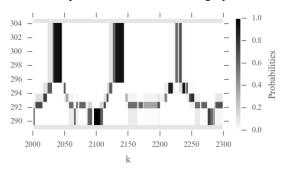

Figure 3. Qualitative state trajectory of the air outlet temperature x_2 (nominal condition)

Figure 4 shows the qualitative state trajectory for the faulty condition. During the faulty operation, the measured input-output pair is inconsistent with the qualitative model what leads to components of the probability vector tending to zero. This is visualized by the white space in the figure ($2420 \leq k \leq 2708$).

For a better interpretability, whether a fault occurred or not, a Boolean signal which will be 1 in nominal condition and 0 in faulty operation, can be displayed.
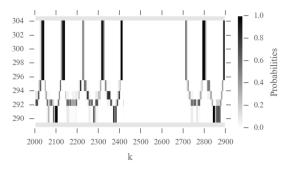

Figure 4. Qualitative state trajectory of the air outlet temperature x_2 (faulty condition)

While the example above shows how fault detection with qualitative models can be realized, fault diagnosis is also possible. To achieve this, a set of qualitative models, where each model is trained with a different faulty condition has to be generated.

Note that even for this simple example the behaviour relation of the SA contains over $3.9 \cdot 10^6$ values, what leads to a significant calculation amount for each discrete time step k. Especially for the case, that the qualitative model should be implemented on a building automation system (BAS) with limited computing capacity, the CP-decomposition is needed. In the case at hand, the size of the behaviour relation of the SA could be reduced by a factor of more than 3200, down to 1200 values to be stored, making it transferable to BAS with real-time application.

Fault diagnosis using qualitative models of air gnadling units

This case study, which results can be found in (Sterling et al., 2014), comprises a constant air volume AHU which schematic is shown in Figure 5. The AHU serves a facility consisting of an audio laboratory of around 50 m². In this audio laboratory, strict conditions of temperature and humidity should be maintained due to the presence of highly sensitive music instruments (e.g. Steinway grand pianos). The building is located in Cork city in the Republic of Ireland.

The AHU presented in Figure 5 comprises the following components:

- Mixing Box (MB): serves to recover heat from exhaust air by mixing a fraction of it with fresh air from outside;
- Cooling Coil (CC): is used to control both temperature and humidity by cooling and dehumidifying the air;
- Heat Coil (HC): is used to control temperature by heating the air;
- Humidifier (H): serves to control humidity by adding water vapour to the air.

Coils and humidifier are operated by controlling the respective valves that increase, decrease, or block the flow of hot or cold water through them. The mixing box is operated by means of dampers that regulate the mixture between outdoor fresh air and recirculation air that passes though the unit.

The unit under study is a reasonably well instrumented AHU making it suitable for research purposes. The available sensors can be seen in Figure 5, where 'T' stands for temperature (°C) sensor, 'RH' for relative humidity (%) sensor, 'AV' for air volumetric flow rate (m³/s) sensor and '%' represents the opening of valves and dampers. The signals and sensors data is recorded with a frequency of one minute. The current application exploits only the control signals and the data from the temperature sensors. Technical manufacturer data for each of the components of the unit is available.

The approach of this case study is shown in Figure 6. System specific information was gathered from the facility's maintenance and operation manuals. Domain specific information corresponds to model developed in Modelica modelling language (Elmqvist, 1978) and representing first-principles of energy and mass transfer between the components of the AHU. Finally the task specific information is provided by OCC'M Raz'r diagnosis engine (OCC'M, 2014). The diagnosis approach is based on the development presented in (Struss & Fraracci, 2012).
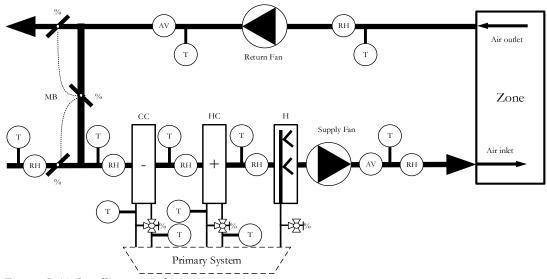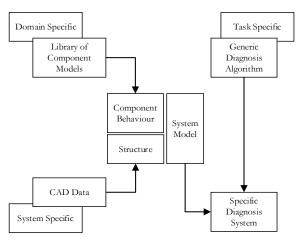
Figure 6. Air handling unit schematic.

Figure 5. Generating diagnostic systems

In order to support the diagnosis in this case study, numerical models used to generate diagnostics model needed to satisfy particular requirements:

- The modelling approach needs to be strictly component-oriented: 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 (coils), mass exchanger (humidifier, mixing box), mass movers (fans), etc.;
- For fault identification, fault models must 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 artifacts that link certain variables that are not really interacting directly via a physical connection;
- The models in the library have to be formulated in a context-independent manner and must not rely on implicit assumptions

about a specific control regime, operation mode, or 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.

Modelica is a very adequate tool for developing models that support the diagnosis approach presented in this case study as it aligns with the above items. Eventually, models need callibration which was performed following the approach in (Febres et al., 2013).

A number of experiments were conducted in a systematic manner with faults introduced to the system by modifying a single component and observing the reaction. In the experiments, while one of the components is being tested, the rest of the system is left to operate normally (e.g. control will compensate for any disturbance in order to maintain set point conditions in the zone). As a result of the experiments, four 24-hour data sets were compiled from real AHU data, one for a nominal working scenario and three for the three components under study namely mixing box, heating and cooling coils. Results from the experiments can be seen in Table 1.

Table 1. Diagnosis results summary

Experiment	Results	Comments
Nominal	No fault identified	No fault identified.
Passing Cooling Coil	2 possible faults identified during 5 separate time periods	Correctly identified an issue with the cooling coil.
Passing Heating Coil	4 possible faults identified during 3 separate time periods	Correctly identified a fault on the heating coil and also correctly identified a fault in

		the mixing section of the AHU.
Stuck Mixing Damper	2 possible faults identified during 6 separate time periods	Correctly identified a fault on the mixing dampers.

Quantitiative model-based diagnosis of AHUs

This case study focuses on the application of an open and easy to replicate FDD method. A more detailed description of this method can be found in (Andriamamonjy et al., 2016).

The method was used for component failure detection in an AHU, focussing on a prospective malfunction of the dampers, the heat recovery system and the fans.

The AHU is part of a comprehensive test facility located on the KU Leuven Technologycampus Ghent in Belgium. It is constructed on the top of an existing university building and has four "zones" which are two lecture rooms, a staircase and a technical room where the AHU and the monitoring system are located. The lecture rooms form two parallelepiped insulated volumes, where one room has massive brick walls with insulation on its exterior face and the other room has a timber frame structure. The indoor parameters such as the temperature, the humidity and the CO_2 within the lecture rooms are continuously monitored. The facility is also equipped with its own weather station measuring global solar irradiation, relative humidity, temperature, precipitation, wind speed and wind direction.

In addition, a set of embedded sensors keep track of the AHU parameters such as the air volume flow (VF), air temperature (T) and relative humidity in the suplly air and in the return air circuit. The damper position (%) signal (γ_i) (see Figure 7 are also monitored.

The monitored data (e.g. the outputs σ_i, the inputs μ_i, the control signals γ_i) are centralized and stored with a one minute frequency in a Soft-PLC based monitoring system where the BMS and the FDD algorithm is integrated on the same industry PC hardware (Andriamamonjy & Klein, 2015).

The FDD method consists of analyzing the received data (operation) each minute. Figure 8 schematizes the FDD process, which is based on a combination of a model-based fault detection and history based fault diagnosis.
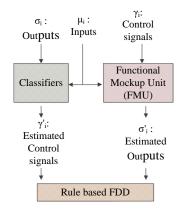

Figure 8. FDD method schema

A calibrated Modelica model evaluates the outputs σ_i from the inputs (μ_i) and the control signal γ_i. A discrepancy superior to a predefined threshold between the measured value σ_i and the estimation σ'_i might be sign of malfunction within the AHU. In this scope, the use of Modelica was motivated by its ability to model dynamic behaviour of the components of the AHU. In addition, as an open language and considering the availability of open-source and validated libraries dedicated to buildings, Modelica fits especially well the aim of developing an open FDD method.

The Modelica model was exported into a FMU to be integrated into the BMS for a near-real time estimation of the outputs σ'_i. A Python based approach which relies on the pyFMi library was used for this purpose.

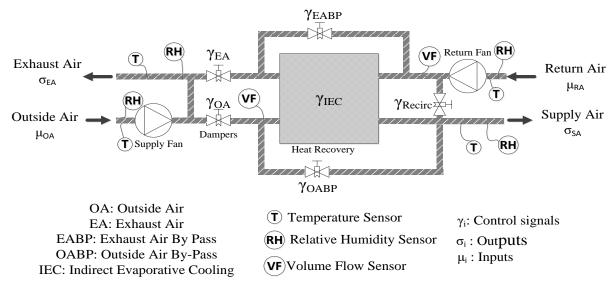For fault diagnosis, machine learning classification methods estimate the class of a control signal γ_i (i ϵ

OA: Outside Air
EA: Exhaust Air
EABP: Exhaust Air By Pass
OABP: Outside Air By-Pass
IEC: Indirect Evaporative Cooling

T Temperature Sensor
RH Relative Humidity Sensor
VF Volume Flow Sensor

γ_i: Control signals
σ_i : Outputs
μ_i : Inputs

Figure 7. Air Handling Unit schema

[OA, EA, EABP, OABP, IEC, RECIRC]) based on the input and output values. If the estimation γ'_i of the component i does not belong to the same class as the actual signal γ_i, a fault is assumed within this specific components.

These classifiers are trained from a combination of synthetic data generated from a calibrated model and initial commissioning data which are assumed to be fault free.

In a third step, a rule based strategy analyzes the results from the aforementionned steps to categorize an operation as fault free (*ff*), faulty (*ft*) or unknown (*ukn*). An unknown status is obtained if the two first steps do not agree. For instance, if the model based fault detection triggers a fault while the fault diagnosis process fails to isolate the cause(s) of the errors or vice versa.

The method has been tested on a virtual scenario where synthetic "measured" data was used to simulate the AHU. The following four scenarios were investigated:

1) No error introduced.
2) The Indirect Evaporative Cooling (IEC) keeps running despite a stop signal.
3) The Outside Air damper bypass (OA BP) is stuck on the closed status.
4) Multiple errors introduced (faulty OA BP and IEC).

Table 2 shows the results from 8 days of data, which represents about 12000 operations (or 12000 min). Each scenario was simulated for an average of 3000 operations each. The table 2 reflects the percentage of fault free, faulty and unknown operation detected throughout each scenario and for each component of the AHU. The *ff* and *ft* were taken out of the valid operations (not unknown). One can observe that all the introduced faults were identified within the considered scenarios, in addition the causes were identified. For instance, for the scenario 2, 87.5% were correctly classified as faulty and 76.1% of the faulty operation of the IEC was detected.

Table 2. FDD results

category	FD	EA BP	IEC	OA	OA BP	FDD results
Scenario 1						
ff	78.4%	89.8%	92.3%	81.7%	87.6%	96%
ft	21.5%	10.1%	7.7%	18.2%	12.4%	4%
ukn	20.1%	14%	2.1%	8.5%	19.9%	37.3%
Scenario 2						
ff	19.8%	92.5%	23.8%	89%	96.3%	12.4%
ft	80.1%	7.4%	76.1%	10.9%	3.6%	87.5%
ukn	4%	7.7%	2.3%	1.4%	11.7%	16.9%
Scenario 3						
ff	66.4%	96.9%	98.6%	96.2%	0%	1.7%
ft	33.5%	3%	1.3%	3.7%	100%	98.3%
ukn	5.3%	0.8%	1.3%	0.2%	4.2%	67.9%
Scenario 4						
ff	6.9%	75.2%	17%	73.1%	38.4%	24%
ft	93%	24.7%	83%	26.8%	61.5%	76%
ukn	59.7%	25%	8.1%	19.7%	28%	55.8%

CONCLUSIONS

In this paper we presented three different approaches by which Modelica can support the implementation of fault detection and diagnosis systems in air handling units. Direct implementation of modelica models embedded in the BAS is still not foreseen due to different constrains associated with model complexity and hardware restrictions. However, if we take into account that, unlike other sectors, FDD in airhandling units is not necessary for safety issues but its implementation follows rather economic and environmental contrains; it becomes clear that FDD in AHUs can be performed with a lower frequency than the data collection and control which, together with the simplicity and versatility of the language, allows for different FDD approaches to bebased on Modelica models with different levels of complexity.

Some clear advantages in the use of Modelica for supporting FDD include:

- Possiblity to integrate hybrid modelling processes in the same model. Modellica allows for mechanical, electrical, thermodynamic modellign, control algorithms, etc., all to be integrated in the same model;
- Object-orientiation not only enhances reusability of the models but also allow models to be developed following the physical system structure which makes them easier to understand;
- The open source characteristic combined with the existince of several freeley available Modelica libraries (Baetens et al., 2012; Lauster et al., 2014; Nytsch-Geusen et al., 2013; Wetter et al., 2014) allows for models to be modified and extended depending on the necesities;
- The possibility to import and export Modelica models as Functional Mock-up Units (FMUs) enables the integration of models using a standardized, tool-independent API into existing FDD routines or the development of integral solutions that couple tools for data analysis, simulation, FDD and optimization in one single environment. An integral solution can be realized, for example, using the Building Controls Virtual Test Bed (BCVTB) (Wetter, 2011) or JModelica with the python module PyFMI (Åkesson et al., 2010).

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