An auto-deployed model-based fault detection and diagnosis approach for AHU using BIM and Modelica

Ando Andriamonjy^{a,1,*}, Dirk Saelens^{a,c}, Ralf Klein^b

^aKU Leuven, Department of Civil Engineering, Building Physics Section, Kasteelpark Arenberg 40 box 2447, BE-3001 Heverlee, Belgium

^bKU Leuven, Technology Cluster Construction, Technology Campus Ghent, Gebroeders De Smetstraat 1, BE-9000 Ghent, Belgium

^cEnergyVille, Thor Park 8310, BE-3600 Genk, Belgium

Abstract

The Air Handling Unit (AHU) is one of the most energy consuming devices in building systems. Fault Detection and Diagnosis (FDD) methods integrated into AHUs can help to ensure that they comply with the intended design, and their efficiency is maintained throughout the entire operational stage of the building. Nonetheless, the implementation and deployment of FDDs at the operational stage require an extensive effort. Especially, FDD approaches that rely on first principle models (model-based FDD) need to be manually implemented, and the information necessary for this process are scattered between several exchange formats and files, thus making it time-consuming, error-prone and subject to modellers' poor judgment.

This study aims at facilitating and partially automating the implementation and deployment of model-based FDD. An automated tool-chain that combines a BIM (Building Information Model)-to-BEPS (Building Energy Performance Simulation) tool with a model-based FDD approach is developed. The contribution of this paper lies in the extension of an existing BIM to Modelica BEPS method with an automated calibration approach and a novel model-based FDD. These three elements are integrated in a framework (implemented using Python) to reduce experts' involvement in FDD implementation and deployment. The developed model-based FDD combines a parity relation procedure for fault detection and profile identification for fault diagnosis. The latter uses the robust multi-objective optimisation algorithm NSGA-2. An error is detected when the difference between prediction and measured data over a specific time window is superior to a predefined threshold. The origin of the error is subsequently identified by estimating the profile of the different controllable components' control signal.

The developed tool-chain was applied to an actual AHU as well as on several numerical scenarios to identify typical AHU faults such as faulty dampers, valves and sensors. This study shows that the developed model-based FDD approach can identify some of the most common faults in AHUs, but more importantly that BIM can facilitate the deployment of model-based FDD in building systems.

Keywords: Fault Detection and Diagnosis (FDD), Building Information Model (BIM), Industry Foundation Class (IFC), Model based method, Modelica

1	Contents	10	8 Application	14
2	1 Introduction	11	8.1 Normal operation	14
3	2 Methodology outline	12	8.2 Synthetic scenarios	15
4	3 Description of the test facility used for the case study	4	9 Discussion	17
5	4 Preconditions	13	10 Conclusion	19
6	5 Automated system model generation	5		
7	6 Automated calibration	7	1. Introduction	
8	7 Automated model based fault detection and diagnosis	15		
9		16	Heating Ventilation and Air Conditioning (HVAC) systems	
		17	ensure the indoor air quality and thermal comfort within our	
		18	built environment but at the same time contribute to a significant	
		19	part of the energy use in buildings [1]. As a result, malfunctions	
		20	within the HVAC, due to improper installation, configuration,	
		21	lack of maintenance and equipment degradation might lead to a	
		22	noticeable discomfort and a substantial increase of energy use	
		23	(from 15% to 30%) [2, 3].	

*Corresponding author

Email address: ando.andriamonjy@kuleuven.be (Ando Andriamonjy)

The Air Handling Unit (AHU) is one of the critical components in an HVAC system. It provides appropriate comfort by controlling and conditioning the airflow to meet the actual cooling or heating demand. It is also one of the most energy consuming devices of the building system [4, 5]. Therefore, a fault within this equipment can significantly increase the overall energy use in a building.

A fault is a deviation of at least one AHU parameter from the normal operating condition. Typical faults in an AHU can be categorised as static (e.g. sensor with a constant offset), abrupt (e.g. mechanical failures: damper stuck) or degradation fault (e.g. the thermal efficiency of heat exchanger decreases over time) [2]. A comprehensive overview of the typical faults in VAV-AHU can be found in [4, 6].

Fault Detection and Diagnosis (FDD) methods are automated processes that detect and pinpoint the causes of faults for the purpose of limiting their impacts in terms of comfort and energy efficiency [7]. In the past decade, efforts have been undertaken to develop robust and efficient FDD methodologies for AHU. Kim et al. [8] observed that 42% of the recent studies on FDD focus on AHU; emphasising the importance of this equipment.

FDD methods can be categorised into four types [8] of approaches: process-history-based, qualitative, quantitative model and hybrid.

1. **Process history based** or data-driven methodologies include methods such as Artificial Neural Network (ANN), Principal Component Analysis (PCA), Support Vector Machine (SVM), Bayes Classifiers, or Fisher Discriminant Analysis (FDA). Although relatively easy to implement, these approaches require a significant amount of data to be adequately trained. Also, since they rely on past data, they perform poorly with unknown system operation. Furthermore, they cannot be directly applied on another system without being retrained with data specific to this system [8, 9, 10].
2. **Qualitative** approaches, on the other hand, require a priori knowledge of the system from which simplified relationships (e.g. the rule-based method [11]) are implemented. Such procedure is relatively simple but is also system specific and often requires a bespoke implementation which extensively relies on experts and developers' knowledge [8, 9, 10].
3. **Quantitative** or model-based approaches rely on first-principle models and are typically based on physical laws, such as mass and energy balance. The idea behind a model-based FDD is to analytically reconstruct the AHU system to mimic hardware redundancy through a modelling software (analytical redundancy). Residual analysis or the evaluation of the difference between measured and simulated values is the conventional approach in model-based FDD [10], in which, a disparity beyond an expert-defined threshold would indicate abnormalities. Model-based approaches do not rely on past data for training; consequently they are more efficient in detecting unknown abnormalities. They can be used at whole building level as well as for component level FDD. A further discussion

of the different model-based FDD techniques is provided later in the text.

4. **Hybrid** approaches aim at improving the overall performance in terms of reliability, accuracy and robustness by combining several of the aforementioned approaches. As an example, model-based FDD approaches present some limitations in diagnosing faults and are therefore often coupled with data-driven methods. An extensive overview of the different hybrid methods can be found in [8]

Model-based FDD approaches consist of three main techniques [12, 13]:

- **The observer based approach** is one of the most commonly used techniques in certain research fields, but has limited application in building systems due to its complexity. It relies on the generation of a set of residuals by utilising some observers. Each observer is sensitive to a specific fault but insensitive to others. As a result, if a fault occurs, only the observer sensitive to this fault deviates, resulting in significant residuals. This approach requires that the process' parameters, as well as the different faults, are defined and well characterised. This means that the faults must be modelled and introduced in the process' model; often requiring a complicated and extensive manual configuration [12, 14].
- **The parity relation approach**, on the other hand, is the direct implementation of the analytical redundancy. The residuals are computed from a simple comparison of the model output and measured data. Faults are detected if the residuals are beyond a given threshold. This approach has often been applied for fault detection in building system equipment. For instance, Cui et al. [15] used the parity relation on centrifugal chiller systems and concluded that it could detect the typical chiller faults. Also, Xu et al. [16] use different AHU equipment models to perform an automated functional performance testing and fault detection. They successfully detect multiple faults in the mixing box as well as in the AHU's fan. Later, a similar approach has been adopted by Wang et al. [17] to detect faults in a VAV-AHU. Beside of the application of the parity relation at the component level, O'Neill et al. [18] have applied a model-based fault detection at the whole building level resulting in a 30% energy savings during the first six months of its deployment. Nonetheless, parity relation methods are often coupled with other FDD methods such as rule-based classifiers [15, 17] to achieve an efficient fault diagnosis since a simple comparison between model outputs and measurements does not provide enough information to accurately pinpoint the origin of the fault.
- **Parameter estimation approaches** assume that faults can be reflected with some specific model parameters [19, 13]. The residuals are formed by differentiating the estimated parameters with the ones from the reference model, and faults are deduced from the significance of the disparity. Parameter estimation techniques include Kalman Filter based

approaches such as the Extended Kalman Filter (EKF) or the Unscented Kalman filter (UKF) [19]. For instance, Bonvini et al. [20] used the Unscented Kalman Filter to identify the typical faults in chiller systems. Another parameter estimation approach is the Prediction Error (PE) in which parameters are evaluated by minimising a given objective function. As an example, Jia and Reddy [21] proposed the "characteristic parameter approach" which consists of identifying some key parameters of the different components constituting a chiller system. They pinpoint the simplicity as well as the efficiency of their method in both fault detection and diagnosis. Moreover, Olson and Isakson in [22] propose a method that estimates the parameters of a physical model to identify faults in HVAC components (e.g. Coil and Control valve). They emphasise the capability of such an approach to identify multiple faults but also pinpoint the importance of limiting the number of parameters that need to be determined. Similarly, Madjid [22] proposes a procedure in which the characteristic curve of an HVAC component (e.g. centrifugal fans, coil) is estimated. A difference between the estimated characteristic curve and the actual one signifies a fault in the component.

Independently of the technique adopted, model-based FDD is the less investigated FDD approach and accounts for only 12% of the post-2004 FDD-related studies [8]. This lack of interest can be attributed to different reasons. The implementation and calibration of models require considerable efforts. Furthermore, a model is to a large extent manually implemented, and the required information is often scattered across several documents and different formats making the implementation process time-consuming, error prone and subject to modellers' poor judgment [23].

Recently, the use of Building Information Models (BIM) as an information source for simulation models has gained attention. BIM, an emerging technology [24] in the Architecture Engineering and Construction (AEC) industry, is a digital representation of physical and functional characteristics of a building project [25, 26]. It includes the 3D geometry, spatial relationships, geographic information and building element properties [27, 28, 29]. The open-BIM format Industry Foundation Classes (IFC), is used as input of the BIM to simulation interface in order to automatically instantiate a simulation model with information from the BIM. However, most of the developed methodologies focus on translating the geometry and material characteristics of the building envelope. They also rely on traditional energy simulation engines such as EnergyPlus. Among the approaches that include the translation of building systems, Bazjanac and Maile [30] designed the IFC HVAC to EnergyPlus utility which can generate an EnergyPlus HVAC input (IDF) from an IFC2x2. Later, O'Donnell et al. [31] developed SimModel to tackle the incompatibility between IFC and EnergyPlus input. SimModel is an intermediate data model (currently used in SimergyTM) designed to facilitate the data exchange for building energy simulation including building systems. Recently, under the umbrella of the IEA EBC Annex 60 project, SimModel has been coupled with the modelling language

Modelica to model HVAC systems [32, 33, 34].

Model-based FDD approaches are case specific and can not easily be adapted to other buildings. Among the likely reasons is the lack of modularity and flexibility of the traditional simulation engines (e.g. EnergyPlus) [35, 36]. Such limitations have led to the emergence of the open, object-oriented and modular modelling language Modelica for building energy simulation and FDD (e.g. see [37, 38]).

Modelica's features facilitate model reuse, exchange and extension and its modularity coupled with an appropriate BIM interface makes it possible to generate models for any building systems and AHU. Among the developed IFC to Modelica interfaces, the IEA EBC Annex 60 approach previously cited can be noted. Recently, Andriamamonjy et al. [39] have developed a rule-based tool-chain referred to as BII (BIM-IFC-IFC2MODELICA). BII is capable of generating the entire model for BEPS (Building Energy Performance Simulation) including the building envelope, HVAC and control directly from the IFC4 file, without the use of an intermediate format. This facilitates the use of FDD related information, included in the BIM, for the following steps of the tool-chain.

This study aims at facilitating and automating the deployment of model-based FDD in AHUs. It extends BII to achieve an automatically deployed model-based FDD for AHU. More specifically, the developed approach appends new FDD-specific rules to BII, as well as an automated calibration approach. The calibrated model is then used for model-based FDD. The contributions of this research are three-fold:

1. It presents a BIM-based automated calibration strategy that: (1) generates a model of the AHU, (2) links the model with a building monitoring system and (3) couples this model with an optimisation algorithm.
2. It proposes a novel, yet relatively straightforward model-based FDD approach that combines the parity relation for fault detection with profile estimation for fault diagnosis. The proposed FDD approach is designed to fit the aim of auto-deployed FDD and the coupling between FDD and BIM to BEPS interface. The different thresholds required for the FDD approach are automatically deduced from the automated calibration to reduce expert's involvement in its implementation and deployment.
3. Finally, this paper presents the application of the developed approach on both synthetic and real scenarios involving a Variable Air Volume Air Handling Unit (AHU).

The FDD approach which is hereafter referred to as the *tool-chain* allows achieving an automatically deployed FDD with limited or even no manual configuration.

Section 2 presents a general outline of the approach and the context for its use. The components included in the *tool-chain* are then developed in section 4 to 7. The *tool-chain* has been applied on the variable air volume AHU presented in section 3 and the achieved results are detailed in section 8. Discussion and conclusion end the paper.

Figure 1: Overview of the application of the *tool-chain* during a construction project. Section 4 defines the BIM requirements that need to be inserted in BIM during the design stage. The different elements constituting the *tool-chain* are developed in section 5 to 7. ⁽¹⁾: Building Monitoring System.

2. Methodology outline

Figure 1 illustrates how the workflow is integrated within the design and construction process. It also presents the different steps that need to be performed during the design and construction stages to ensure an automated deployment of the FDD approach in AHUs during the operational stage. This study assumes that BIM is adopted as information source for all stakeholders throughout the entire building life cycle. More specifically, the open-BIM standard format IFC4 (EN ISO 16739:2016) is used. The integration of BIM in a project requires an early agreement between all project partners. This agreement is initiated during the early stage of the project (see Figure 1, initiative) and is framed within a general approach as described in the upcoming EN ISO 19650-1 and -2. In the context of this study, the standard serves as a background to ensure that the service providers thoroughly apply the BIM modelling requirements during the design stage, as detailed in section 4. These requirements ensure that the BIM contains all the information necessary for the deployment of the *tool-chain*.

During the construction stage (see Figure 1, Construction), some information defined in section 4 and contained in the BIM is used to configure the building monitoring system. This BIM based configuration is necessary to automate the data acquisition for both the automated calibration and the fault detection and diagnosis.

During the operational stage, the BIM (IFC file) is used as an input (see figure 1, Building in use) to the *tool-chain*. The *tool-chain* comprises three elements:

1. A rule-based automated translation of IFC into a Modelica model. Section 5 gives a summary and the new rules added to adapt BII for FDD.
2. An automated calibration process (section 6). It converts the text-based Modelica model (.mo) into a Functional

Mockup Unit (FMU) and links the *tool-chain* with the monitoring system. The NSGA-2 algorithm is then used to calibrate the model.

3. A model-based automated FDD methodology (section 7).

An AHU is an assembly consisting of equipment required for cooling, heating, distributing, filtrating, mixing, humidifying and dehumidifying of air. It is composed of several moving devices such as fans, dampers, valves controlled by a central controller system (e.g. see figure 2). These devices are prone to failure due to their sophisticated design and embedded electronics [40]. Studies [41] concluded that defects in these moving devices constitute more than half of the most common faults in AHUs. A survey undertaken during the IEA Annex 25 [22], among designers and engineers, classifies the impacts of typical AHU faults in terms of environmental degradation, energy consumption, frequency of occurrence as well as repair time, cost of repair and difficulty of detection. The survey concludes that dampers and valves defects are among the ten most important faults regarding energy consumption (see [22]). They are also among the most difficult to detect. However, no clear figures are provided in term of the individual impact of such faults on the energy use. On the overall, the combination of good commissioning and fault detection and diagnosis can yield an average saving of 20% of the total energy cost. A study performed during the IEA Annex 47 shows a saving of 44% of electricity use and 78% of the gas use over a period of ten year [42, 43].

Dampers and (cooling) valves faults include defects such as blocked or broken damper linkage. When such faults occur, the components do not abide by the control signal and can go unnoticed until a total breakdown of the system, a dramatic increase of energy use or deterioration of the indoor comfort. Apart from these devices, detecting faults in sensors are also crucial since the different control decisions are based on the values supplied

by these devices. Biased sensors might misrepresent the condition of operation and mislead the controller.

The here-proposed model-based FDD focuses on identifying faults within AHU's dampers, valves and sensors. A fault is detected when the outputs (e.g. T_{SA} , T_{EA} in figure 2) of the actual AHU differs from those of the calibrated model. More specifically, the fault detection approach analyses the residuals or the difference between measurement and simulation. A significant residual beyond a predefined threshold indicates a fault. However, to identify the cause of the faults, an inverse modelling approach is adopted. The control profile of the moving components is estimated by minimising the difference between the measured and predicted outputs. A specific component is the cause of a fault if the characteristics of its estimated profile do not match those from the AHU's internal controller. A detailed explanation of the FDD process is provided in section 7.

Figure 2: (a): Scheme of the Air Handling Unit. (b): Main control modes of the AHU: (1) Heating, (2) Transition and (3) Cooling. HR: Heat Recovery, IEC: Evaporative Cooling, HC: Heating Coil, D: Damper, F: Filter, FN: Fan, T: Temperature sensor, SA: Supply Air, RA: Return Air, EA: Exhaust Air, BP: Bypass, R: Return, S: Supply

3. Description of the test facility used for the case study

The considered AHU (MenergaTM AdsSolair 56) ensures the indoor comfort and air quality of two lecture rooms that are part of the Technology Campus Ghent of KU Leuven (Belgium). Figure 2 shows the AHU's scheme including its internal elements and the sensors. The AHU is capable of delivering a maximum air flow rate of 5100 m³/h and an air flow of 4000 m³/h in normal conditions. The descriptions of its constituting devices are given in table 1.

The AHU has three main operation modes: heating, the transition mode and cooling:

1. During the heating mode (figure 2.b, Mode 1), the evaporative cooling system is disabled. The bypass dampers (D_{EABP} , D_{OABP}) and the recirculation damper (D_R) are closed. Both the exhaust air and outside air dampers (D_{EA} and D_{OA}) are open to enable the heat transfer between the warm return air stream and the cold outside air stream. The heating valves are activated during this mode.
2. During the transition mode (figure 2.b, Mode 2) both the evaporative cooling and the heating are disabled. The exhaust air damper (D_{EA}) and the recirculation damper (D_R) are respectively open and closed. The controller regulates the outside air dampers (D_{OA}) and the bypass dampers (D_{OABP} and D_{EABP}) to achieve the supply air temperature setpoint. Depending on the outside air temperature (T_{OA}), the controller may force the air flow through the bypass for free cooling, or drive the flow through the heat recovery unit (e.g. if $T_{OA} > T_{RA}$).
3. During the cooling mode (figure 2.b, Mode 3), the heating system is disabled, the bypass dampers and the recirculation damper are closed. Both the exhaust air and outside air dampers are kept open to redirect the air flow into the heat recovery unit in which water is sprayed to cool the return air flow which in turn cools down the supply air through the heat exchanger. This AHU does not possess a second cooling mode which provides mechanical cooling with minimum outside air but relies entirely on the combination of the heat exchanger and indirect adiabatic evaporative cooling which can induce a temperature difference of 14 K between the hot outside air and supply air.

The AHU has integrated temperature sensors placed at the air inlets and outlets and inside the heat recovery system (see figure 2 and table 1, T_{OA} , T_{SA} , T_{RA} , T_{EA} , T_{SAHC}). The controller of the AHU is connected through a BACnet interface with the building monitoring system. The modular, open-standard monitoring system is implemented with an industrial computer connected through Ethercat to different Input-Output units [44]. The data from the sensors is stored with a one-minute time interval in a Structured Query Language database and are accessible from the building monitoring system.

Independently of the operation mode, the exhaust air damper (D_{EA}) and the recirculation damper (D_R) are always respectively open and closed. Consequently, the FDD approach proposed in section 7 focuses more on ensuring that the bypass dampers (D_{EABP} , D_{OABP}), the outside air damper (D_{OA}) and the cooling system function correctly independently of the operation mode. Since a temperature sensor (T_{SA}) is placed at the inlet of the heating coil and another temperature sensor (T_{SAHC}) at its outlet, identifying faults in the heating coils becomes possible by comparing the values from both sensors. Therefore, faults in the heating coil are not considered in section 7. This AHU will serve as an example in the remaining sections.

4. Preconditions

This section lists the BIM modelling rules and requirements ensuring that the BIM contains the relevant data to generate

Table 1: Description the AHU's internal devices

Name	Description
<i>Internal devices</i>	
F_{OA}	Outside air filter
F_{SA}	Supply air filter
F_{RA}	Return air filter
FN_{SA}	Supply air variable speed fan
FN_{RA}	Return air variable speed fan
$HR + IEC$	Heat recovery unit equipped with two cross-flow heat exchangers (total efficiency superior to 75%) and an Indirect Evaporative Cooling (IEC) system
D_{OA}	Outside air damper
D_{EA}	Exhaust air damper
D_{OABP}	Outside air damper bypass
D_{EABP}	Exhaust air damper bypass
D_R	Recirculation damper
HC	Heating coils
<i>Sensors</i>	
T_{OA}	Outside air temperature sensor. Accuracy= ± 0.5 K
T_{SA}	Supply air temperature sensor. Accuracy= ± 0.4 K
T_{RA}	Return air temperature sensor. Accuracy= ± 0.4 K
T_{EA}	Exhaust air temperature sensor. Accuracy= ± 0.4 K
T_{SAHC}	Supply air temperature sensor after heating coil. Accuracy= ± 0.4 K

the AHU's simulation model and coupling this model with the monitoring system. The comprehensive list of the requirements can be found in [39]. However, the main rules relevant to AHU modelling and FDD are summarised within the following points:

1. The BIM of the AHU must be implemented down to its constituting components, i.e., the embedded components (e.g., fans, dampers, valves) must be represented, configured and connected according to the real physical interconnections between the actual devices. Also, these entities must be related to an IfcUnitaryEquipment entity through the Object Aggregation concept. Figure 3 presents the case study's AHU-BIM in which the internal components are represented by REVITTM Family objects.
2. The ports' flow direction must be either "SOURCE" or "SINK" and must follow the actual flow direction in the unit. In Autodesk REVITTM this condition is translated as: flow direction of the objects' connectors must be either *In* or *Out* depending on the actual flow direction in the AHU.
3. IFC property sets, especially those defined in table 2 must be provided.
4. Controllable elements such as fans, dampers or valves must be connected to an actuator object (IfcActuator)(e.g. see blue boxes in figure 3). Similarly, each sensor that will be installed on the building must be represented (e.g. figure 3.a, yellow object).
5. Each actuator (IfcActuator) and sensor (IfcSensor) shall be provided a unique name (done manually). For larger buildings and systems the use of the GUID as identifier is preferred, complemented with a chosen name for easier handling in the modelling tool.
6. An additional property set: Pset_AHUFDD is added to entities that are at the AHU's inlets or outlets. Pset_AHUFDD includes two data fields: *IN* and *TEMP*.

Table 2: IFC property sets required to instantiate the AHU

IfcDamper
Pset_DamperTypeCommon.NominalAirFlowRate
Pset_DamperTypeCommon.OpenPressureDrop
IfcFan
Pset_FanTypeCommon.NominalAirFlowRate
Pset_FanTypeCommon.NominalTotalPressure
IfcAirToAirHeatRecovery
Pset_AirToAirHeatRecoveryPHistory.TotalEffectiveness
Pset_AirToAirHeatRecovery.PrimaryAirFlowRate
Pset_AirToAirHeatRecovery.PrimaryNominalPressureDrop
Pset_AirToAirHeatRecovery.SecondaryAirFlowRate
Pset_AirToAirHeatRecovery.PrimaryNominalPressureDrop
IfcFilter
Pset_FilterTypeCommon.NominalFlowrate
Pset_FilterTypeCommon.NominalPressureDrop

IN is of the boolean data type (IfcBoolean), and its value is set to "True" for entities that are at the inlets of the AHU; otherwise, its value is set to "False". *TEMP* defines the identifier of the sensor entity corresponding to the thermodynamic state at these inlets or outlets (e.g. T_{RA} , T_{OA} or T_{SA} , T_{EA}). See figure 3.b, figure 3.c and figure 3.d as examples.

7. At the construction phase, the system integrator is mandated to use the names of the IfcSensor (or actuator) entities as identifiers of the corresponding actual sensor in the database. The system integrator should also integrate into the BIM the date of activation of the monitoring system.

The rules 1 to 4 and 6 are similar to those defined in [39]. However, rules 5 and 7 are necessary to establish the link between the monitoring system and the *tool-chain*. As it will be explained in section 6 the unique naming adopted for the sensor

Figure 3: BIM view representing the HVAC system. (a): BIM object representing a sensor. (b): Boundary object (inlet) ($Pset_AHUFDD.IN=TRUE$, $TEMP=T_{OA}$). (c): Boundary object (inlet) ($Pset_AHUFDD.IN=TRUE$, $TEMP=T_{RA}$). (d): Boundary object (outlet) ($Pset_AHUFDD.IN=FALSE$, $TEMP=T_{SA}$). Brown objects: Filters. Green objects: Dampers. Orange object: Heat recovery system. Grey objects: Fans. Red objects: Heating coils.

and actuator entities will be used to retrieve the measurement data from the building monitoring system.

5. Automated system model generation

Assuming that the BIM contains the information defined in section 4, this step relies on the rule-based methodology (BII) developed in [39] to convert IFC into a Modelica model. The additional rules that adapt BII for FDD are presented in this section. BII consists of two main steps: the *topology generation* and the *mapping process*.

1. The *topology generation* simplifies BIM's data structure (e.g. see figure 4.a) into an interconnected set of nodes and edges referred to as a topology [39] (e.g. see figure 4.b). Each node represents an entity (e.g., IfcFan, IfcDamper, IfcAdiabaticCooling) but only the entities that are related to an IfcUnitaryEquipment entity are converted into nodes. The simplifications presented in [39] are also applied. For the entities that are associated with the $Pset_AHUFDD$ property set, those with $IN = TRUE$ are converted into "Inlet nodes" (*In*) while those with $IN = FALSE$ are converted into "Outlet nodes" (*out*). Figure 4.b shows the generated topology that corresponds to the BIM presented in figure 3.
2. The *mapping process* converts the topology into a Modelica model. It maps the edges into Modelica statements *Connect* and nodes into Modelica components. The reasons behind the use of Modelica as backend modelling language are extensively detailed in [39]. Also, the Modelica library used must be validated and in agreement with the constraints set in [39]. In this study, the Modelica components from the IDEAS library [45] were used.

IDEAS (Integrated District Energy Assessment by Simulation) allows dynamic simulation of buildings (single or multi zones), systems, controls and also electricity grids as described in Baetens et al. [45]. It is a validated Modelica library, already used in several other modelling studies [46]. Among the studies using IDEAS for HVAC modelling, Jorissen et al. [47] have recently published a validated model of an AHU using IDEAS components.

The mapping process relies on a *library template* [39] to define the Modelica component that corresponds to a specific node. A *library template* (e.g. see table 3) contains a set of *component templates* (each row in table 3). Each *component template* contains four types of information (table 3):

1. Node description (see table 3, first column)
2. Modelica component into which the node will be translated (see *function* in table 3).
3. Parameters required by the Modelica component expressed as IFC property sets (e.g. $\#Pset_AirToAirHeatRecovery$, $SecondaryAirFlowRate$ #)
4. Definition of the different Modelica connectors attached to the component.

Table 3 presents the *library template* used in this study and provides a brief description of the equations behind the components. For each node in the topology, the mapping process search within the *library template* its corresponding Modelica component and then instantiates this latter. For instance, a heat recovery node (**H**) (in figure 4.b) is mapped into a "IDEAS.Fluid.HeatExchangers.ConstantEffectiveness" component (see Table 3) which will be instantiated using BIM data. The information contained in the *edges* are then used to connect the different components.

Figure 5 presents the Modelica model of the considered AHU. It is a steady state model that can compute the thermodynamic state (temperature, humidity and pressure) of both supply and return air flows, as well as the electrical power used by the fans. For the present FDD approach, only the thermodynamical aspect of the model is considered. The model requires the outside air temperature (T_{OA}), the return air temperature (T_{RA}) and the different control signals (ζ_{DEA} , ζ_{DOA} , ζ_{DOA-BP} , ζ_{DEA-BP} , ζ_{DRC} , $\zeta_{Cooling}$, ζ_{FNRA} , and ζ_{FNSA}) as inputs. The supply air temperature (T_{SA}) and the exhaust air temperature (T_{EA}) are considered as outputs.

The performance (in term of accuracy and simulation time) of the generated model depends on the complexity of the components associated with the nodes. In this study, simple and generic IDEAS components were used, but more detailed components such as those defined in [47] can be used by changing the Modelica component corresponding to a node in the *library template*.

6. Automated calibration

BIM (IFC) contains the AHU's structure and design specifications that are extracted to create a numerical model of the

Nodes	Component	function, parameters, connectors	Description
(A)		function: Modelica.Blocks.Interfaces.RealInput(), Connectors: <i>signal</i>	Connector with one input signal of type Real.
(D)		function: IDEAS.Fluid.Actuators.Valves.TwoWayLinear(), parameter: $\dot{m}_{nom} = \#Pset_DamperTypeCommon.NominalAirFlowRate\#$, $\Delta P_{nom} = \#Pset_DamperTypeCommon.OpenPressureDrop\#$, Connectors: <i>fluid1</i> (air, source), <i>fluid2</i> (air, sink), <i>signal</i> (sink).	Linear opening valve with $\Delta P = (\frac{\dot{m}}{k})^2$ the pressure drop induced by the component, $\dot{m}$ the mass flow rate and k the flow coefficient. $k = (1 - y(1 - l)) \frac{\dot{m}_{nom}}{\sqrt{\Delta P_{nom}}}$ with $\dot{m}_{nom}$ and ΔP_{nom} respectively the nominal flow rate and the nominal pressure drop over the damper. y the actual position of the damper and l the leakage value ($l = 0.001$).
(FN)		function: IDEAS.Fluid.Movers.FlowControlled_m.flow(), parameter: $\dot{m}_{nom} = \#Pset_FanTypeCommon.NominalAirFlowRate\#$, $\Delta P_{nom} = \#Pset_FanTypeCommon.NominalTotalPressure\#$, Connectors: <i>fluid1</i> (air, source), <i>fluid2</i> (air, sink), <i>signal</i> (sink).	This model describes a fan or pump with prescribed mass flow rate (see [48]).
(H)		function: IDEAS.Fluid.HeatExchangers.ConstantEffectiveness(), parameter: $\epsilon = \#Pset_AirToAirHeatRecoveryPHistory.TotalEffectiveness\#$, $\dot{m}_{nom1} = \#Pset_AirToAirHeatRecovery.PrimaryAirFlowRate\#$, $\Delta P_{nom1} = \#Pset_AirToAirHeatRecovery.PrimaryNominalPressureDrop\#$, $\dot{m}_{nom2} = \#Pset_AirToAirHeatRecovery.SecondaryAirFlowRate\#$, $\Delta P_{nom2} = \#Pset_AirToAirHeatRecovery.PrimaryNominalPressureDrop\#$, Connectors: <i>fluid1</i> (air, source), <i>fluid2</i> (air, sink), <i>fluid3</i> (air, source), <i>fluid4</i> (air, sink).	Component for a heat exchanger with constant effectiveness where the amount of heat transferred is given by $Q = Q_{max}\epsilon$, where ϵ is a constant effectiveness and Q_{max} is the maximum heat that can be transferred.
(C)		User-defined, Connectors: <i>fluid1</i> (air, source), <i>fluid2</i> (air, sink), <i>signal</i> (sink)	Evaporative cooling component
(S)		function: IDEAS.Fluid.Sensors.Temperature(), Connectors: <i>fluid</i> (air, sink), <i>signal</i> (source)	This component computes the temperature of the fluid connected to its port. The sensor is ideal and does not influence the fluid.
(Out)		function: IDEAS.Fluid.Sources.FixedBoundary(), Connectors: <i>fluid</i> (air, sink)	Component providing boundary temperature.
(In)		function: IDEAS.Fluid.Sources.Boundary_pT(), Connectors: <i>fluid</i> (air, source), <i>signal</i> (sink)	Component providing a prescribed boundary temperature (use <i>T_in</i> = True).
(F)		function: IDEAS.Fluid.FixedResistances.PressureDrop(), parameters: $\dot{m}_{nom} = \#Pset_FilterTypeCommon.NominalFlowrate\#$, $\Delta P_{nom} = \#Pset_FilterTypeCommon.NominalPressureDrop\#$, Connectors: <i>fluid1</i> (air, source), <i>fluid2</i> (air, sink)	Component of a flow resistance with a fixed flow coefficient k ($\Delta P = (\frac{\dot{m}}{k})^2$) with $k = \frac{\dot{m}_{nom}}{\sqrt{\Delta P_{nom}}}$.

Table 3: Library template containing the corresponding Modelica component for each node. Details of implementation of these components can be found in the IDEAS library [46]

AHU. As briefly explained in section 5 and detailed in [39], BII maps the IFC entities into Modelica components. The *library template* contains the definition of the Modelica components that correspond to the different entities.

In an ideal case, the actual HVAC system including the AHU matches the exact specification in BIM; validated Modelica components with an adequate complexity are used and defined

in the *library template* and the sensors' noises are negligible. Under such conditions, the AHU model's prediction should match the measured data. However, in reality, poor workmanship and other uninformed decisions taken during the construction can alter the accuracy of BIM information [49]. Furthermore, the use of simplified Modelica components can impact the correctness and accuracy of the automated generated model.

Figure 4: a) IFC data structure b) The generated topology subsequent to the application of BII

Figure 5: Generated Modelica model of the AHU

For instance, in this study, the use of generic Modelica "fluid" components that simplify some physical effects can impact the accuracy of the final model. Such gap undermines the confidence in the model prediction [50, 49] and makes the generated model unsuitable for FDD. Consequently, to always ensure optimal prediction capabilities as well as a reliable FDD independently to the specific conditions of a specific AHU, the BIM-generated model of the AHU is always automatically calibrated using the subsequently described automated calibration approach.

This study does not investigate the actual reasons for the disparity between the model and the measured data but focusses on FDD at the operational phase. Consequently, the condition of the ventilation system after the initial commissioning is assumed to be its optimal condition.

Model calibration reduces the difference between measurements and simulations by identifying the optimal parameters that fit the simulations with observations. The calibration approaches can be either automated or manual [50]. The latter relies on iterative modellers' interventions and analyses to

⁽¹⁾ Building Monitoring System

⁽²⁾ Distributed Evolutionary Algorithms in Python

Figure 6: Automated model calibration: 1) conversion of the Modelica model into FMU, 2) automated data acquisition, 3) optimisation process, 4) automated generation of the thresholds for FDD

find the optimal set of parameters. A manual calibration is inherently resource-intensive, time-consuming, potentially error prone, dependent on the calibrator's skills and thus incompatible with an automated model-based fault detection and diagnosis approach. In contrast, automated calibration relies on mathematical optimisation algorithm coupled with a numerical model to routinely search out the optimal set of parameters. Nonetheless, modeller intervention is still necessary to (1) perform this coupling between Model and optimiser and (2) retrieve measurement data.

The *tool-chain* integrates an automated calibration process (figure 6) and includes a strategy which permits to remove the remaining manual configurations cited earlier. This automated calibration includes four steps that:

1. Compile the Modelica model into a Functional Mockup Unit (FMU) to facilitate its simulation from a PYTHON-based platform (figure 6.1).
2. Automate the acquisition of the measured data stored in the monitoring system (figure 6.2).
3. Couple the FMU with a multiobjective optimisation algorithm and perform the calibration automatically (figure 6.3).
4. Generate the thresholds used for the fault detection and diagnosis approach (figure 6.4).

Detailed explanations of these steps are provided in the remainder of this section.

FMU export. An FMU is a simulation component conforming to the Functional Mock-up Interface (FMI) standard. The latter is an open model interface standard developed by MODELISAR [51] to facilitate model reuse between various modelling tools and environments. The FMI standard defines how models are exported into a set of standardised C-codes and XML files to enable exchange and co-simulation between multiple software systems [52, 53, 54]. Therefore, an FMU is a software-independent and language-independent model that can be simulated from any platform compatible with the FMI standard. An FMU is a compressed file containing static information as well as differential, algebraic and discrete equations describing the physical system. Also, it includes a C-API for model management, i.e., setting, retrieving parameters

and simulations. The *tool-chain* relies on the FMI-compatible PYTHON library pyFMI [55] to compile the generated Modelica model into FMU. Also, pyFMI enables to run iterative simulations outside of the Modelica environment and provides access to parameters and simulation results.

Data acquisition. The manual integration of measurements data during the calibration process is another aspect limiting the full automation of the calibration. Measurements data provide both boundary conditions (e.g. weather data) and reference to model outputs (e.g. T_{SA} , T_{EA}). This study takes advantage of the rules 5 and 7 set in section 4 to automate the acquisition of data stored in a building monitoring system. Rule 5 mandates the BIM design team to (i) represent both sensors (IfcSensor) and actuators (IfcActuator) in the BIM and (ii) provide them with a unique naming. Subsequently, at the construction phase during the implementation of the building monitoring system, rule 7 requires the system integrator to use the sensors or actuators naming as identifiers for the monitoring system's data storage system. As an example, the supply air temperature sensor is named T_{SA} in the BIM. Therefore, its corresponding sample is stored in the SQL-database column bearing the same name (T_{SA}). The *tool-chain* needs to have a (remote or local) access to the database to enable the model calibration.

To automate the data acquisition during the operational phase, the *tool-chain* includes a code routine that (i) parses the IFC input and (ii) retrieves the name of the different sensor/actuator objects. These names are then used to perform queries on the database. The extracted data is then formatted to conduct simulations using FMUs.

Optimization. At this stage, the system model is represented by an FMU and the Model's inputs (e.g. T_{OA} , T_{RA} , ζ_{DEABP}) as well as output (e.g. T_{EA} , T_{SA}) are stored in the database. The *tool-chain* relies on the PYTHON library pyFMI to simulate and vary the FMU's parameters while SQL-dedicated PYTHON library such as MySQLdb can be used to access the database.

An optimization is the process combining numerical simulations (FMU) and mathematical methods to identify the set of model parameters (e.g. $\dot{m}_{nom}$, ΔP_{nom} , ϵ in table 3) that minimizes (or maximizes) the objective functions [56]. The Normalized Root Mean Square Error as defined in [57, 58] and indicated in equation 1 is set as the target for minimising.

$$NRMSE = \frac{100}{\max(M) - \min(M)} \sqrt{\frac{\sum_{i=1}^n (S_i - M_i)^2}{n}} \quad (1)$$

M_i and S_i are the respective measured and simulated data points, $\max(M) - \min(M)$ is the range of the measured dataset and n the number of measured data points.

In the remainder of this paper, the NRMSE between simulated and measured data of an output T_i will be referred to as $NRMSE(T_i)$.

In this study and as an illustration, the focus consists of ensuring the thermal behaviour of the AHU. Thus $NRMSE(T_{EA})$

and $NRMSE(T_{SA})$ are set as objective functions making the problem a multi-objective optimisation problem. A third objective function related to the energy use can also be added to monitor the different components influencing this index.

There are two methods to solve a multi-objective optimisation problem. The first approach consists of turning a multi-objective problem into a single objective problem by assigning weight factors to each objective and summing the weighted objectives (e.g. $f = w_i * NRMSE(T_{EA}) + w_j * NRMSE(T_{SA})$) [59, 56]. The likelihood that a particular objective function (e.g. $NRMSE(T_{SA})$) dominates the entire objective function constitutes a weakness since it could result in a model that accurately predicts one specific output and poorly estimates the others. This situation emphasises the importance of the weight factors (w_i , w_j) to counter-balance such effect. Nonetheless, methodologies that adequately identify the weight factors are not yet clearly defined. A conventional method is to test different weight factors which would increase the number of function runs and the optimisation time. Another approach is to identify by means of sensitivity analysis the parameters that have the highest impact on the objective function and then solely focus on these most influential parameters.

The second multi-objective optimisation approach which is used in this study relies on the concept of Pareto-optimality [59]. This method identifies a set of trade-off solutions referred to as Pareto optimal or non-dominated solutions. A solution is Pareto optimal or non dominated when there is not any other feasible solution that improves one objective function (e.g. $NRMSE(T_{EA})$) without deteriorating the others (e.g. $NRMSE(T_{SA})$). The set of non-dominated solutions is called Pareto frontier and is illustrated in figure 7 in the case of two objective functions. As pinpointed by Nguyen et al. [59], the selection of the "best" solution among the Pareto frontier solution constitutes one of the main challenges of this approach and often depends on the importance of the objective functions. As an example, if $NRMSE(T_{EA})$ is prioritised, the Pareto set (C) (see figure 7) should be chosen. On the contrary, the Pareto set (B) (see figure 7) must be selected. Since the goal is to obtain a calibrated model that provides a good prediction for all the objective functions, the Pareto set close to the ideal point (A) is automatically chosen as the "Best" Pareto set. More specifically, the Pareto set that minimises the difference between the objective functions is chosen ($\min(|NRMSE(T_{EA}) - NRMSE(T_{SA})|)$).

The Non dominated and crowded Sorting Genetic Algorithm-2 (NSGA-2) is one of the most popular and widely used multi-objective algorithms in building calibration [56, 59, 60]. NSGA-2 is a heuristic optimisation approach and belongs to the genetic algorithm (GA) family. It is based on an elitist, fast non-dominated sorting solution combined with a solution's diversity preservation process [61, 62, 60]. Deb et al [63] provide a detailed description of the algorithm. NSGA-2 is a derivative-free optimisation approach and can efficiently handle non-linear problems, discontinuities, local minima while being robust to high simulation failure rate and does not require an excellent initial parameter start [59]. These features are crucial since simulation failures may frequently occur while the derivatives of such an AHU model are not

Figure 7: Pareto front obtained during the model calibration. Point A: Optimal solution that ensures a trade-off between the objective functions. Point B: Solution that favours $NRMSE(T_{EA})$. Point C: Solution that favours $NRMSE(T_{SA})$.

always easy to extract. The PYTHON library DEAP 1.2.2 [64] was used to perform the optimisation.

As stated earlier, due to several factors, there is no guarantee that the Modelica model that is generated using BIM information will directly match the measurements. Consequently, the previously described automated calibration method is used to ensure that the generated AHU model provides an acceptable prediction for FDD purposes.

For the model to be assumed calibrated, a selected optimal Pareto set corresponding to a NRMSE inferior to 10% for each output considered (e.g. T_{EA} , T_{SA}) [65] is recommended. In the case where the model does not achieve a reasonable prediction accuracy, the modeller can increase the complexity of the Modelica components used, i.e. more complex and detailed components are used and defined in the *library template*. Also, the modeller should check whether the actual AHU corresponds to the BIM specification.

Figure 5 illustrates the Modelica model that has been created from the BIM presented in figure 3. The model parameters consist of the nominal flow rate $\dot{m}_{nom,i}$; the nominal pressure drops $\Delta P_{nom,i}$ of the different components i (dampers, filter) as well as the constant effectiveness ϵ of the heat recovery (see table 3). The objective is to identify their optimal values minimising the value of the NRMSE of both T_{SA} and T_{EA} .

During the optimisation process, The parameters' values were varied by 100% around their nominal values obtained from BIM. The NSGA-2 is configured with a population size $p = 200$ and a number of generation $g = 100$. A two-week, end-of-summer data that on average includes the different operation modes of the AHU presented in section 3 is used to calibrate the model. In real applications, it would be envisioned that data resulting from the initial commissioning is used. During that period (initial commissioning), various operating scenarios can be implemented to generate calibration data that equally represent the different operation modes of the AHU resulting in a more representative dataset. Figure 7 shows the Pareto Front

Table 4: Thresholds generated for the considered AHU

Output	Γ	δ	ψ_{ucn}
T_{SA}	1.3 K	4.5 K	24%
T_{EA}	1.5 K	5.2 K	19%

illustrating the Pareto optimal set of parameters and their corresponding objective function values. The point (A) illustrates the selected optimal parameter set which corresponds to a NRMSE of 7% and 7% respectively for T_{SA} and T_{EA} . It satisfies the condition previously set.

FDD thresholds. The performance of the FDD approach that will be developed in section 7 relies heavily on the accuracy of the calibrated model. The thresholds used in this FDD approach are deduced from the calibration process.

Assuming that $R^c = (R_1^c, R_2^c, \dots, R_i^c, \dots, R_n^c)$ is the vector of residuals deduced from the previous calibration with $R_i^c = M_i - S_i$. Three thresholds for each model output (here: T_{SA} and T_{EA}):

- Γ : the Root Mean Square Error (RMSE) of the calibrated model computed from the equation 2

$$\Gamma = \sqrt{\sum_{i=1}^n \frac{(R_i^c)^2}{n}} \quad (2)$$

- δ : the maximum residual ($\delta = \max(|R^c|)$).
- ψ_{ucn} : the *Uncertainty* threshold. It represents the percentage of residuals R_i^c superior to Γ and will be used during the FDD process to assess the performance of the actual AHU compared to the calibrated model. Assuming that $R^{c1} = (R_1^{c1}, R_2^{c1}, \dots, R_j^{c1}, \dots, R_m^{c1})$ is a vector of residuals in which $\Gamma < R_j^{c1}$. ψ_{ucn} is then derived from the equation 3.

$$\psi_{ucn} = \frac{m}{n} \cdot 100 [\%] \quad (3)$$

m is the length of the vector R^{c1} and n the length of the vector R^c .

Table 4 shows computed values of Γ , δ and ψ_{ucn} for the considered case study. These values are used in the next section to perform fault detection and diagnosis.

7. Automated model based fault detection and diagnosis

The proposed FDD approach ensures that the AHU functions correctly during daily operation. It aims at identifying any abnormalities that affect the AHU's response to the different excitations. More specifically, the focus is set on identifying defects in dampers, valves and sensors. The novelty of the proposed FDD approach lies in the association of two model-based techniques, i.e. a parity relation method for fault detection and a profile estimation for fault diagnosis. Especially, the robust-genetic algorithm- optimiser NSGA-2 is used to estimate the profile's characteristics. So far, this approach (the combination

of parity relation with parameter estimation and NSGA-2) has been deemed too computationally intensive and inappropriate for fault detection and diagnosis. However, regarding the current calculation power of computers together with the progress in Modelica modelling and the non life-threatening aspect of FDD in AHU, it can be applied for fault detection and diagnosis. Also, the proposed FDD approach has been designed to ease its automated deployment and to fit into the existing BIM to Modelica BEPS interface.

Figure 8: Definition of the time window T_w . T_w is the shortest period between two rising edges

The FDD analysis is performed daily (e.g. during the evening). In the remainder of this section, the time window (T_w) defines the interval at which the FDD is performed. The time window (T_w) is defined based on the actual control signal that has the shortest time period between two successive rising edges such as the signal presented in the last row of the Figure 8. The sampling interval (τ) represents the elapsed time (e.g., every minute) between two measurements or observations and a residual r_i is the absolute difference between an observation M_i and its respective estimated value S_i ($r_i = |M_i - S_i|$).

Furthermore, it is assumed that an initial commissioning has been performed and the AHU including its internal components work fault-free.

Fault detection. The forward fault detection uses the calibrated model of the AHU to compute the estimation of the outputs (T_{SA} , T_{EA}) and their residuals within the time window. It then categorizes each observation r_i as:

- *Non-faulty*
- *Uncertain*
- *Faulty*

A residual (or observation) is *Non-faulty* if it is below the threshold Γ (see table 4). As an example, figure 9 dark-green band indicates the *Non-faulty* region. In contrast, a residual is categorised as *Faulty* if its value is beyond the maximum residuals δ . In between these two thresholds, the residual is categorised as *Uncertain* (light-green band in figure 9). The *Uncertain* category serves as a buffer zone to cope with the different

Figure 9: Categorisation of the observations (r_i) into *Non-faulty*, *Uncertain* or *Faulty*. *Non-faulty*: $r_i < \Gamma$, *Uncertain*: $\Gamma < r_i < \delta$, *Faulty*: $\delta < r_i$. See section 6 for Γ and δ .

uncertainties that originate from sensors, model or calibration errors. Consequently, the *Uncertain* category considers these uncertainties and do not directly attribute an observation (represented by residual r_i) that is between Γ and δ ($\Gamma < r_i < \delta$) to a fault in the system since it could also be due to the under-performance of the calibrated model; requiring further analysis such as the fault diagnosis.

At the end of each time window, the percentage of *Faulty*, *Non-faulty* and *Uncertain* evaluations is computed. The forward fault detection identifies an error if the percentage of *Uncertain* is superior to ψ_{ucn} (see equation 3) or the percentage *Faulty* superior to 0%.

Fault diagnosis. As stated earlier, moving components such as dampers or valves are prone to faults due to their complexities and embedded electronics. A valid assumption would be that an abrupt fault in the AHU would be due to a defect in these components. More specifically, stuck (open or close) or delayed dampers or valves are considered.

These components receive control signals (ζ_{DOA} , ζ_{DOABP} , ζ_{DEABP} , $\zeta_{DCooling}$ in figure 5) defining their rate of opening (e.g. open or close) and transition time τ (e.g. time of the day when a damper goes from open to close or vice versa). Assuming that the AHU controller operates correctly, a comparison between the actual control profiles and estimations (ζ_{DOA}^e , ζ_{DOABP}^e , ζ_{DEABP}^e and $\zeta_{DCooling}^e$) of these signals would provide valuable information on whether a specific component reacts correctly to the controller or not. A discrepancy between the actual control signal and the estimated one would indicate a defect in the specific component receiving the signal. Therefore, the inverse modelling fault diagnosis estimates the control signal profiles (ζ_{DOA}^e , ζ_{DOABP}^e , ζ_{DEABP}^e and $\zeta_{DCooling}^e$) and then compares them to the actual profiles (ζ_i , $i \in DOA, DOABP, DEABP, DCooling$) from the AHU's controller.

$$\zeta^e(t) = \begin{cases} 1, & \text{if } \theta - \omega < t < \theta + \omega. \\ 0, & \text{otherwise.} \end{cases} \quad (4)$$

To that end, during the fault diagnosis process, the input signals (ζ_i) of the model presented in figure 5 are fed by synthetic

signals (ζ_i^e) that are generated from the function $\zeta^e(t)$ (equation 4). $\zeta^e(t)$ represents a square wave signal as described in figure 10 and equation 4. It is characterized by two parameters: θ and ω . θ defines the line of symmetry of the pulse while ω represents the half width of the pulse. The function $\zeta^e(t)$ generates a signal which is characterized by its rising edge $\tau^{up} (= \theta - \omega)$ and falling edge $\tau^{down} (= \theta + \omega)$.

Figure 10: Control signal profile characterized by θ and ω . θ defines the line of symmetry of the pulse and ω the half width of the pulse. $\tau^{up} = \theta - \omega$ and $\tau^{down} = \theta + \omega$ define respectively rising and falling edge time of the signal.

Consequently, a control profile function ζ_i^e characterized by θ_i and ω_i is attributed to each controllable device i ($i \in D_{OA}, D_{OABP}, D_{EABP}, D_{Cooling}$). An optimisation technique identifies the values of the parameters θ_i and ω_i that minimize the objective functions (here: $NRMSE(T_{SA})$ and $NRMSE(T_{EA})$). The similar optimization approach as in section 6 is adopted. This choice is motivated by its robustness but also to the fact that NSGA-2 is robust towards random initial values (θ_i and ω_i).

Figure 11: Comparison of the actual control signal ζ_i of an AHU component (e.g. damper) with the estimated control signal ζ_i^e . a) *Non-faulty* component. b) *Acceptable*. c) *Faulty* component.

The estimated signals are subsequently compared with the actual signals from the AHU's controller. Figure 11 represents three examples of signal comparison. The (blue) signal (ζ_i) corresponds to the actual signal supplied by the AHU controller. It is characterised by its rising edge τ_{act}^{up} and its falling edge τ_{act}^{down} (*act* for actual signal). The (red) signal (ζ_i^e) represents the estimated one. The estimated signal corresponds to the selected Pareto set, i.e. the Pareto set that results in the minimum absolute difference between $NRMSE(T_{SA})$ and $NRMSE(T_{EA})$.

Each Pareto set belonging to the Pareto front consists of a set of (here: eight) parameters: θ_i and ω_i ($i \in [D_{OA}, D_{OABP}, D_{EABP}, D_{Cooling}]$). Consequently, a Pareto set provides an estimation of the rising edge ($\tau_i^{up} = \theta_i - \omega_i$) and falling edge ($\tau_i^{down} = \theta_i + \omega_i$) of the control signal of the different devices (i.e. $D_{OA}, D_{OABP}, D_{EABP}, D_{Cooling}$). Assuming that the Pareto front includes N Pareto sets, a set of population (ρ_i^d) of size N of τ_i^d can be drawn from the Pareto front ($i \in [D_{OA}, D_{OABP}, D_{EABP}, D_{Cooling}]$, $d \in [up, down]$). Subsequently, normal distributions $N(\mu(\rho_i^d), \sigma(\rho_i^d))$ are used to represent the different data set (ρ_i^d) as in figure 11. The potential location of the actual rising edge τ_i^{up} of a component i is then represented by $N(\mu(\rho_i^{up}), \sigma(\rho_i^{up}))$ while $N(\mu(\rho_i^{down}), \sigma(\rho_i^{down}))$ represents the potential location of the falling edge τ_i^{down} . $\mu(\rho_i^d)$ represents the population mean and $\sigma(\rho_i^d)$ its standard deviation ($d \in [up, down]$).

Finally, a device i ($i \in [D_{OA}, D_{OABP}, D_{EABP}, D_{Cooling}]$) of the AHU is diagnosed as *Non-faulty*, *Acceptable* or *Faulty* by considering the following rules:

- A device i is *Non-faulty* if the characteristics (τ_{act}^d) of the actual control signal profile (ζ_i) lie within the 68% confidence interval of the data set represented by $N(\mu(\rho_i^d), \sigma(\rho_i^d))$ (see equation 5). The dark green area in figure 11 represents the *Non-faulty* area. Figure 11.a depicts a fault free device since both the actual (ζ_i) and estimated (ζ_i^e) signals closely match and are included in the dark green area.

$$\begin{aligned} \mu(\rho_i^d) - \sigma(\rho_i^d) < \tau_{act}^d < \mu(\rho_i^d) + \sigma(\rho_i^d). \\ i \in [D_{OA}, D_{OABP}, D_{EABP}, D_{Cooling}] \\ d \in [up, down] \end{aligned} \quad (5)$$

- A device i is categorised as *Acceptable* if the actual control signal (τ_{act}) is located outside the 68% confidence interval but inside the 95% confidence interval (see equation 6). The light green area in figure 11 represents the *Acceptable* condition. Similarly to the fault detection, the *Acceptable* condition serves as a buffer zone to cope with uncertainties in the model and measurements. As an example, figure 11.b shows a device with a *Acceptable* status since the blue signals are located in the light green area.

$$\begin{aligned} \mu(\rho_i^d) - 2\sigma(\rho_i^d) < \tau_{act}^d < \mu(\rho_i^d) + \sigma(\rho_i^d) \\ \text{Or} \\ \mu(\rho_i^d) + \sigma(\rho_i^d) < \tau_{act}^d < \mu(\rho_i^d) + 2\sigma(\rho_i^d). \\ i \in [D_{OA}, D_{OABP}, D_{EABP}, D_{Cooling}] \\ d \in [up, down] \end{aligned} \quad (6)$$

- A device is assumed faulty if none of the two previous conditions is fulfilled. As an example, figure 11.c. shows a faulty component because a significant disparity exists between the two signals (ζ_i and ζ_i^e). More importantly, the actual signal is not included in the 95% confidence interval.

A fault is notified to the facility manager when the percentage of *Uncertain* (or *Faulty*) during the *fault detection* is higher than the threshold ψ_{ucn} , and at least one device is detected as *Faulty*. The approach can be extended to identify sensor bias by elimination i.e. if a fault is clearly detected but no origin among the different dampers are pinpointed, then the issue probably lies in the sensors. Lastly, the result of the FDD is always communicated to the facility manager independently of its outcome.

8. Application

In this section, the facility is considered as newly built, and its BIM representation implemented according to the preconditions defined in section 4. It is also assumed that the system integrator configured the building monitoring system according to the specifications described in section 6.

After the building's completion, an initial commissioning process [66] is performed to ensure that the system works as designed. It also permits to collect the initial data necessary for the calibration of the AHU model. After the initial commissioning, the *tool-chain* is deployed to ensure that the AHU continuously performs as designed during the entire operation stage.

The *tool-chain* generates the system model which is converted into a Functional Mockup Unit (FMU). For an automated model calibration and, auto-deployed FDD, the *tool-chain* establishes the link between the model (FMU) and the monitoring system (see section 6).

Section 8.1 presents the results of the *tool-chain*'s application during four consecutive days of normal operation while section 8.2 presents eight synthetic scenarios showing how the *tool-chain* would react in case of faults within the system.

8.1. Normal operation

Table 5: Results of the fault detection process for the 4 days considered

	<i>Non-faulty</i> (T_{SA} , T_{EA})	<i>Uncertain</i> (T_{SA} , T_{EA})	<i>Faulty</i> (T_{SA} , T_{EA})
Day 1	85%, 96%	14%, 3%	0%, 0%
Day 2	56%, 67%	42%, 31%	1%, 1%
Day 3	63%, 87%	35%, 12%	0%, 0%
Day 4	94%, 90%	5%, 9%	0%, 0%
$\psi_{ucnT_{SA}} = 24\%$, $\psi_{ucnT_{EA}} = 19\%$			

The FDD approach integrated into the *tool-chain* consists of fault detection and a fault diagnosis component. The fault detection component compares the model outputs (e.g. T_{SA} , T_{EA}) with actual measurements. The fault diagnosis component reconstructs the different control signals (ζ_{DOA} , ζ_{DOABP} , ζ_{DEABP} ,

$\zeta_{DCooling}$) of the AHU and identifies the signals that do not match the actual signals that come from the AHU controller. The device that corresponds to the deviating signal is likely faulty.

This section presents the application of the *tool-chain* during four consecutive days of normal real operation of the AHU. It is assumed that the fans (FN_{SA} and FN_{RA}), the AHU controller, the exhaust air damper (D_{EA}) and the recirculation damper (D_{RC}) operate correctly. This means that D_{EA} and D_{RC} being respectively closed and open. The goal is to identify faults in the Outside Air Damper (D_{OA}), the bypass dampers (D_{OABP} and D_{EABP}) and the cooling system.

Figure 12 shows the *tool-chain*'s report for the four days considered. The report includes a three-column chart. The first column represents the comparison of the measured outputs (T_{EA} , or T_{SA}) with the reference ones obtained from the simulation of the calibrated model (see *Fault Detection* in section 7). This comparison serves as a base to compute the percentage of *Faulty*, *Non-faulty* or *Uncertain* observation during the considered day (see table 5). A high percentage of *Uncertain* above the thresholds $\psi_{ucnT_{SA}}$ and $\psi_{ucnT_{EA}}$ (see table 4) or a percentage of *Faulty* above 0% would indicate an abnormality within the system. The two last columns show the characteristics of the estimated signal of the dampers (D_{OA} , D_{OABP} and D_{EABP}) and the cooling system (*Fault Diagnosis* in section 7). These schemas display both the signal sent by the AHU controller (blue) and the estimated one (red). The bell-shaped curves represent the distribution of the likely location of the rising edge (τ^{up}) and the falling edge (τ^{down}) that are obtained from the optimal Pareto sets.

For *day 1* and *day 4* the percentages of *Uncertain* observation for both supply air temperature and exhaust air temperature are below the defined thresholds ($\psi_{ucnT_{SA}}$ or $\psi_{ucnT_{EA}}$, see table 5) indicating that the system is fault free. As an example, for *day 1*, the percentage of *Uncertain* observation is 14% for T_{SA} and 3% for T_{EA} (see table 5). These figures are respectively inferior to $\psi_{ucnT_{SA}} = 24\%$ and $\psi_{ucnT_{EA}} = 19\%$ indicating a *Non-faulty* status. A similar outcome is obtained for *day 4*. The fault diagnosis (see figure 12, *day 1* and *day 4*) confirms this result since the estimations of D_{OA} , *Cooling* and D_{OABP} match the actual controller signal (fault-free component). More specifically, the actual control signals (blue) lie within the 68% confidence interval (dark green) of the estimated distributions. Only the control of the outside air damper (D_{OA}) of *day 4* is outside the 68% confidence interval but still lies within the 95% confidence interval and does not qualify as a *Faulty* component.

For *day 2* and *day 3* the percentages of *Uncertain* observation for both supply air temperature and exhaust air temperature are superior to $\psi_{ucnT_{SA}}$ and $\psi_{ucnT_{EA}}$. In addition, the outcome from *day 2* shows that 1% of the observations are categorised as *Faulty*. These results tend to show that the AHU can be defective during these days. However, the results of the fault diagnosis (see figure 12, *day 2* and *day 3*) contradict those from the fault detection since no *faulty* component has been identified. Consequently, the AHU is still assumed as *Non-faulty*.

This section shows the application of the developed FDD approach on the actual AHU. The robustness of the combination of parity relation and inverse modelling towards the un-

certainties in real conditions can be derived from the obtained results. The developed approach presents a potential to limit false alarms in FDD.

8.2. Synthetic scenarios

Table 6: Result of the fault detection process: percentage of *Non-faulty*, *Uncertain* and *Faulty* observations for each scenario

Scenario	Non faulty (T_{SA} , T_{EA})	Uncertain (T_{SA} , T_{EA})	Faulty (T_{SA} , T_{EA})
1	71%, 78%	28%, 21%	0%, 0%
2	49%, 74%	24%, 24%	26%, 0%
3	0%, 78%	49%, 21%	49%, 0%
4	42%, 57%	56%, 38%	0%, 3%
5	29%, 33%	30%, 23%	40%, 42%
6	42%, 57%	56%, 37%	0%, 4%
7	27%, 30%	26%, 30%	45%, 39%
8	73%, 49%	26%, 8%	0%, 42%
$\psi_{ucnT_{SA}} = 28\%$, $\psi_{ucnT_{EA}} = 22\%$			

Eight scenarios (or experiments) are considered to show how the *tool-chain* reacts in case of faults in the system. However, the fact that the current facility is an in-use building limits the possibility of introducing actual errors in the AHU. Consequently, numerical scenarios are considered instead. A calibrated model of the AHU is used to generate synthetic measured data. The synthetic measured data of a specific output (e.g. T_{EA} or T_{SA}) consists of simulation output to which two types of random noise are added. The first random noise is applied to all the observations and consists of a uniform noise that ranges between -0.5 to 0.5 °C. It simulates the general uncertainty of the model. The second random noise is applied to a limited amount of the observations (e.g. 10%). It consists of a uniform noise that ranges between -2 to 2 °C and represents the maximum possible deviation of the synthetic data compared to the reference. Therefore, the synthetic measured data consists of the model output with the two previously described random noise added to it.

The thresholds Γ , δ and ψ_{ucn} (see section 6) are computed by considering the comparison of two weeks of simulation with the corresponding synthetic measured data. As a result, the values of the thresholds used in this section are related in table 7.

The synthetic faults are added by using control signals corresponding to the faulty condition. As an example, to simulate a damper stuck in the open position, a signal with a constant value of one (e.g. $\zeta_{DOA} = 1$) is supplied to the system. The different scenarios considered are outlined below:

1. The first scenario represents a normal, *Non-faulty* AHU operation and will serve as a reference to the other situations.

2. The second scenario portrays a faulty AHU unit in which the activation of the dampers (D_{OA} , D_{OABP} and D_{EABP}) is delayed by several hours compared to the actual control signals sent by the controller.
3. In the third scenario, a constant offset of 2°C is applied to the supply air temperature sensor (T_{SA}).
4. In the fourth scenario, D_{OA} is stuck in the *open* position.
5. In the fifth scenario, the outside air damper bypass (D_{OABP}) is continuously open throughout the considered day.
6. In the sixth scenario, both the exhaust air damper bypass (D_{EABP}) and the outside air damper bypass (D_{OABP}) are stuck in the *closed* position.
7. In the seventh scenario, the exhaust air bypass damper (D_{EABP}) is stuck on the open position
8. Finally, the cooling system is continuously turned on.

Figure 13 and 14 show the FDD results for all the considered scenarios during one day of operation of the AHU. The considered day combines cooling mode with transition mode (see section 3). Table 6 displays the percentage of *faulty*, *Non-faulty* and *Uncertain* observations for the different experiments. A detailed explanation of the FDD results is provided in the remainder of this section.

Scenario 1: Non-faulty. The fault detection process (figure 13, first column) showed that most of the observations are comprised in the *Non-faulty* zone (dark green) and therefore considered as non-faulty. This is confirmed by the results of the categorisation displayed in table 6 since 71% of T_{SA} observations and 78% of T_{EA} observations are *Non-faulty*. The percentage of *Uncertain* observation for T_{EA} is below the defined threshold $\psi_{ucnT_{EA}}$, while the percentage of *Uncertain* observation for T_{SA} is equal to $\psi_{ucnT_{SA}}$. The latter might indicate that the system is faulty. However, as shown in figure 13 (scenario 1), the estimations of the different control signals closely match the actual signals sent by the controller (i.e. the actual signals lie within the 95% confidence interval). Since a fault is identified if it is both detected and diagnosed, this first scenario is categorised as *Non-faulty*.

Scenario 2: Delayed signal. The impact of the delay can be seen on the supply air temperature (T_{SA} in the figure 13, scenario 2). The percentage of *Faulty* T_{SA} observation is 26% indicating that a fault is present in the system. The fault diagnosis process (column 2 and 3) shows that the issue is within the dampers (D_{OA} , D_{OABP} and D_{EABP}) since it estimates (red signal) a delay in the activation of the different dampers. The outside air damper takes several more hours to open compared to the reference signal (blue) while the closing of both D_{OABP} and D_{EABP} is also delayed. In addition, the reference signals (blue) for these components (D_{OABP} , D_{EABP} , D_{OA}) are not comprised in the 95% confidence interval of the estimated distributions. As a result, the AHU can be categorised as faulty and the faults are localised within the dampers (D_{OABP} , D_{EABP} , D_{OA}).

Table 7: Thresholds used for the synthetic scenarios

Output	Γ	δ	ψ_{ucn}
T_{SA}	0.35 K	1.98 K	28%
T_{EA}	0.43 K	1.94 K	22%

Figure 12: FDD report generated by the *tool-chain*. 1st column: categorisation of the different observations. 2nd column: comparison of the estimated D_{OA} and cooling signals with the actual ones. 3rd column: comparison of the estimated D_{OABP} and D_{EABP} signals with the actual ones.

Scenario 3 Constant offset. As shown in table 6, the percent-ages of *Uncertain* T_{SA} observation and *Faulty* T_{SA} observation are both equal to 49% indicating that a fault is present in the system. Considering the fault diagnosis (figure 13, scenario 3), the estimated signals of D_{OA} and D_{EABP} deviate from the AHU controller signal. Moreover, the distribution curve has an important standard deviation; indicating that there is no optimal combination of the dampers' positions that can provide a similar output as the faulty AHU. This shows that the fault is not within the considered dampers and by elimination can point to other devices such as sensors.

Scenario 4: D_{OA} open. As it can be seen in table 6, the *Uncertain* observations for both T_{SA} and T_{EA} are above the thresholds $\psi_{uncT_{SA}}$ and $\psi_{uncT_{EA}}$; indicating that the system is likely faulty. The estimations of the cooling signal, D_{OABP} and D_{EABP} correspond to the signal supplied by the controller (see figure 13 (scenario 4)). However, the estimation of D_{OA} shows that the

outside air damper was open since the AHU was turned on at the beginning of the day, pinpointing exactly the error that has been introduced.

Scenario 5: D_{OABP} open. Similarly to the previous scenario, significant percentages of *Uncertain* observations indicate an abnormality in the AHU. D_{OA} , D_{OABP} estimation match the control signal from the controller while D_{EABP} estimation presents some uncertainties as shown in figure 14 (scenario 5). However, the distribution curve has a large standard deviation including the correct control signal from the controller. The estimation of D_{OABP} indicates that the damper was always open throughout the entire day which confirms that D_{OABP} is faulty.

Scenario 6: D_{OABP} and D_{EABP} closed. The percentages of *Uncertain* observations for both supply air temperature and exhaust air temperature are superior to the defined thresholds ($\psi_{uncT_{SA}}$ or $\psi_{uncT_{EA}}$, see table 6) indicating that the system is

Figure 13: Application of the FDD approach on the scenarios 1 to 4

Faulty. This result is confirmed by the fault diagnosis process¹¹⁷ represented in figure 14 (scenario 6). The estimated signals of¹¹⁸ both D_{OABP} and D_{EABP} do not match the reference signals. The¹¹⁹ rising edge of the reference signal of D_{OABP} is largely outside of¹²⁰ the 95% confidence interval of the estimated distribution while both rising and falling edges are outside of the acceptable confidence interval for D_{EABP} . The profile of the estimated signals¹²¹ tends to show that both dampers (D_{OABP} and D_{EABP}) are closed,¹²² as it has been introduced in the scenario. However, the result,¹²³ also shows that D_{OA} might have a slight delay.

Scenario 7: D_{EABP} open. Similarly to the previous scenarios,¹²⁸ the introduced fault has been detected (see 6). The fault origin¹²⁹ is correctly identified since the estimated control signal shows¹³⁰ that D_{EABP} is constantly open. In addition the signal from the¹³¹ controller (blue) is outside the 95% confidence interval of the¹³² different distributions.

Scenario 8: Cooling. In this last scenario, the defect component is defined as being the cooling system as shown in figure 14 (scenario 8). The error introduced has been clearly identified.

9. Discussion

On the model-based approach. A successful application of the proposed model-based approach requires a reliable and accurate numerical model of the AHU. It is essential to ensure that the preconditions set in section 4 are rigorously applied, and the different parameters properly inserted in BIM. Also, a validated Modelica library such as IDEAS is required. These two conditions combined with the automated calibration reduce the risk of obtaining an inadequate AHU model. However, the model calibration requires that the data used for this purpose is fault free and represents the optimal behaviour of the system. Consequently, an initial commissioning process is essential. In addition to that, the parameters estimated during the calibration

Figure 14: Application of the FDD approach on the scenarios 5 to 8

can be updated in the BIM and used to identify the discrepancy between the actual performance and the design specifications. However, the physical validity of the estimated parameters should be taken with care since it depends on their identifiability.

Analysing one day of AHU operation (e.g. 8h to 18h) takes about six (6) hours. This result is obtained by setting NSGA-2's population number to 200 and the number of generations to 100; knowing that an FMU run lasts about one second on an average computer with an Intel Core™ i5 CPU with eight (8) gigabytes of memory. This duration of the FDD analysis means that the facility manager obtains the results of the FDD the next day which is considered to still qualify as satisfactory. The facility manager can use the results from the previous day for daily routine checks.

Section 8.1 demonstrates that the *tool-chain* can identify non-faulty conditions, and consequently is robust to model uncertainties and noise. Also, a certain number of conditions must be satisfied before considering an AHU as faulty. Firstly, an

abnormality is considered as a fault when the detection process can clearly identify a fault and its origin. Secondly, the dispersion of the optimal set of solutions from the Pareto front is provided as a normal density function. This information makes it possible to identify whether the actual signal is among the potential optimal results or not. Despite a possible discrepancy with the estimation, if the actual signal is still comprised within the range of the likely result (i.e. within the 95% confidence interval), no fault will be triggered. The combination of both parity relation and profile estimation ensures an FDD approach that is robust towards false alarms.

As demonstrated in section 8.2, the developed model-based FDD approach can diagnose faults in dampers, valves as well as in sensors by elimination. Also, it has the potential to identify combined faults as presented in experiments 2 and 6. However, additional studies are needed to pinpoint the simultaneous errors that could accurately be identified. Furthermore, the extension of the approach to reliably identify faulty-fans and filters is one of the logical next steps to the current study and can be

achieved by adding the energy use as one of the objective function since the fans and filters have a significant impact on this index.

As presented in section 7, the fault diagnosis approach relies on the reconstruction of the different control signals through an inverse modelling process. An arbitrary control signal function (e.g. equation 4) is used to automatically generate signals. The goal is then to identify the optimal values of the control signal function's parameters (e.g. θ and ω) that minimise the objective functions. This study investigates the use of a simple binary control signal profile (equation 4 and figure 10). However, more complex profiles with more features can be used. As an example, a square wave signal with a variable amplitude can be used instead of a simple binary signal. This will potentially enable to identify the different intermediate opening states (not only open or closed) but will also increase the number of parameters that needs to be estimated. This parameter increase has an impact on the computation time as well as on the identifiability of the control signals. Therefore, a balance should be found between the complexity of the control profile function and identifiability. A thorough identifiability analysis can also be performed. However, it is out of the scope of the current study. As a general recommendation, it is preferable to use simple control function with few parameters.

Beside of that, this study assumes that the AHU controller is fault free. The approach can be extended to identify a control fault. However, an additional method is required to distinguish between faults due to the controller and mechanical defects.

Another aspect that could be considered is the identification of long-term degradation (e.g. clogged filter). Regular parameter estimation can be performed where a change over time of a specific parameter can signify a slow degradation of the device. Stringent conditions on the parameters' boundary are required to ensure that the estimated parameters are physically meaningful. However, this approach raises the issue of non-identifiability in which it is unlikely that a specific behaviour of the model is the result of a unique set of parameters.

In the fault diagnosis approach, although some devices might provide a feedback signal, signals from the controller are only considered as the 'actual control profile' for the comparison between estimation and measurement. A direct comparison of the feedback and the controller's signal might provide insight on the different issues in the AHU. However, if the device is faulty, such feedback signal is not reliable, emphasising the need of FDD methods as presented in this paper.

Sensors sense the values of the parameters of interest and their accuracy is crucial for efficient fault detection and diagnosis. The levels of accuracy of the different sensors used in this study are presented in table 1. Consequently, developing a method that is robust towards the built-in sources of uncertainties in sensors is critical. The good results obtained in section 8.1 is an indication that the developed FDD approach is robust towards the accuracy of the sensors presented in table 1. This outcome is comforted by the results obtained in section 8.2 since the method is capable of identifying the introduced errors despite the noise purposely introduced in the synthetic data. However, further research and application of the *tool-chain* is

required to draw a definite conclusion.

On the tool-chain. The *tool-chain*'s advantages and limitations have been identified based on FDD's desirable characteristics presented by Yu et al. [7]: quick detection and diagnosis, computational requirements, isolability, robustness, novelty identifiability, classification error estimate, adaptability, explanation facility, modelling requirements, and multiple fault identifiability.

The *tool-chain* performs the analysis after a predefined time window (e.g. a day) and provides the results after several hours (profile identification). Consequently, it cannot be applied for faults that require real-time, quick fault detection and diagnosis but is more suitable for non-critical faults that are difficult to identify. However and as demonstrated earlier, the *tool-chain* is robust towards model uncertainties and false alarms and can identify multiple defects. Also, as shown in figure 13 and 14, the *tool-chain* displays the results while pinpointing the exact causes of an error. Moreover, the *tool-chain* is based on first-principle equations model which makes it suitable for detecting novel faults.

The *tool-chain*'s adaptability and the need for minimal modelling requirement constitute its main strength. The approach behind the *tool-chain* can be used on any AHU as long as the building project's BIM is implemented according to the preconditions set in section 4, and all AHU's internal devices have a corresponding Modelica component in the *library template*. Modelica is an open language, and most of its existing libraries are publicly available (e.g. IDEAS). Modellers and manufacturers can therefore implement and integrate their components within these libraries and enrich the current *library template* to include new components or improve existing ones.

In addition to implementing and calibrating the model internally, the *tool-chain* automatically establishes the connection with the building monitoring system and performs the model-based FDD. Its deployment would require the installation of the *tool-chain* on a computerized device with access to the monitoring's database. BIM is then used as an input to the *tool-chain*. This study demonstrates the potential of BIM for a significant reduction of the manual configuration required to deploy model-based FDDs.

10. Conclusion

Model-based FDD is the least investigated FDD approach because of the extensive effort required for its implementation.

This study proposes a BIM-based strategy that aims at automating the implementation and the deployment of model-based FDD in AHUs. A *tool-chain* that combines the use of a BIM to BEPS interface with a novel model-based FDD approach was developed.

The methodology takes advantage of BIM as a tool for information management and exchange between the tasks in different life cycle stages. Preconditions are set to ensure that the relevant information is inserted in the BIM during the design stage. After hand-over, the information contained in the BIM related to the description of sensors and actuators is used as a

link between BIM and the building monitoring system. This BIM-monitoring link enables to automatically retrieve the data stored in the building monitoring system. At the operational phase, BIM is used as input to the *tool-chain* which is a combination of several interconnected PYTHON tools including a BIM to BEPS tool (BII). BII creates a numerical Modelica model of the AHU from BIM. Subsequently, to minimise the impact of the different factors that might induce a gap between the prediction and the measurement, the generated model is automatically calibrated. The calibrated model is then integrated into an FDD approach that combines parity relation for fault detection and profile identification for fault diagnosis. A fault is detected when a certain number of observations obtained during a defined time window is superior to a threshold. The cause of the fault is subsequently identified by estimating the profile of the different controllable components' control signals. A difference between the estimated and the actual controller's signal signifies that the considered component is faulty. The different thresholds used during the FDD process are derived from the calibration process limiting FDD experts' involvement.

The method has been applied to an AHU of a test facility under normal conditions of operation as well as on several numerical scenarios depicting the typical faults in AHU: stuck dampers and valves as well as sensor faults. As a result, both normal conditions, as well as the different faults introduced, were correctly detected and identified demonstrating the pertinence of the developed approach regarding its robustness and its fault identification capacity.

This study highlights BIM capabilities for facility management and more specifically for the automation of the implementation of model-based fault detection and diagnosis. The coupling between BIM to simulation model and FDD methodologies alleviates the limitations and the main weakness of a model-based approach making it potentially one of the most straightforward methods to implement and to deploy in AHUs. Also, despite its relative simplicity, the proposed model-based approach presents promising results in the detection of the typical AHU faults. The combination of forward modelling with inverse modelling increases the robustness of the FDD towards false alarms. Further investigations are however necessary to obtain a fully mature and industry-grade FDD strategy that can be applied to all devices of the building systems.

Acknowledgments

This project received funding from KU Leuven, the European Union, the European Regional Development Fund ERDF, Flanders Innovation & Entrepreneurship and the Province of Limburg.

References

- [1] D. Li, G. Hu, C. J. Spanos, A data-driven strategy for detection and diagnosis of building chiller faults using linear discriminant analysis, *Energy & Buildings* 128 (2016) 519–529. doi:10.1016/j.enbuild.2016.07.014.

- [2] R. Zhang, T. Hong, Modeling of HVAC operational faults in building performance simulation, *Applied Energy* 202 (2017) 178–188. doi:10.1016/j.apenergy.2017.05.153.
- [3] A. Beghi, R. Brignoli, L. Cecchinato, G. Menegazzo, M. Rampazzo, F. Simmini, Control Engineering Practice Data-driven Fault Detection and Diagnosis for HVAC water chillers, *Control Engineering Practice* 53 (2016) 79–91. doi:10.1016/j.conengprac.2016.04.018.
- [4] Y. Zhao, J. Wen, F. Xiao, X. Yang, S. Wang, Diagnostic Bayesian networks for diagnosing air handling units faults part I: Faults in dampers, fans, filters and sensors, *Applied Thermal Engineering* 111 (2017) 1272–1286. doi:10.1016/j.applthermaleng.2015.09.121.
- [5] K. Bruton, P. Raftery, B. Kennedy, M. M. Keane, D. T. J. O'Sullivan, Review of automated fault detection and diagnostic tools in air handling units, *Energy Efficiency* 7 (2) (2014) 335–351, ISBN: 10.1007/s12053-013-9238-2. doi:10.1007/s12053-013-9238-2.
- [6] H. Wang, Y. Chen, A robust fault detection and diagnosis strategy for multiple faults of VAV air handling units, *Energy & Buildings* 127 (2016) 442–451. doi:10.1016/j.enbuild.2016.06.013.
- [7] Y. Yu, D. Woradachjumbo, D. Yu, A review of fault detection and diagnosis methodologies on air-handling units, *Energy and Buildings* 82 (2014) 550–562. doi:10.1016/j.enbuild.2014.06.042.
- [8] W. Kim, S. Katipamula, A review of fault detection and diagnostics methods for building systems, *Science and Technology for the Built Environment* 24 (1) (2017) 3–21. doi:10.1080/23744731.2017.1318008.
- [9] S. Katipamula, M. Brambley, Review Article: Methods for Fault Detection, Diagnostics, and Prognostics for Building Systems A Review, Part I, *HVAC&R Research* 11 (1) (2005) 3–25. doi:10.1080/10789669.2005.10391123.
- [10] S. Katipamula, M. Brambley, Review Article: Methods for Fault Detection, Diagnostics, and Prognostics for Building Systems A Review, Part II, *HVAC&R Research* 11 (2) (2005) 169–187, ISBN: 1078-9669. doi:10.1080/10789669.2005.10391133.
- [11] J. Schein, S. T. Bushby, N. S. Castro, J. M. House, A rule-based fault detection method for air handling units, *Energy and Buildings* 38 (12) (2006) 1485–1492. doi:10.1016/j.enbuild.2006.04.014.
- [12] V. Venkatasubramanian, R. Rengaswamy, K. Yin, A review of process fault detection and diagnosis Part I: Quantitative model-based methods, *Computers and Chemical Engineering* 27 (2003) 293–311, ISBN: 1315268442. doi:10.1016/S0098-1354(02)00160-6.
- [13] E. C. Mid, V. Dua, Model-Based Parameter Estimation for Fault Detection Using Multiparametric Programming, *Industrial & Engineering Chemistry Research* 56 (2017) 8000–8015. doi:10.1021/acs.iecr.7b00722.
- [14] R. Isermann, Model-based fault-detection and diagnosis status and applications, *Annual Reviews in Control* 29 (2005) 71–85. doi:10.1016/j.arcontrol.2004.12.002.
- [15] J. Cui, S. Wang, A model-based online fault detection and diagnosis strategy for centrifugal chiller systems, *International Journal of Thermal Sciences* 44 (2005) 986–999. doi:10.1016/j.ijthermalsci.2005.03.004.
- [16] P. Xu, P. Haves, M. Kim, *Model-Based Automated Functional Testing-Methodology and Application to Air-Handling Units*, in: ASHRAE Transactions: Symposia, 2005, pp. 979–989 [Accessed on: 2018-08-14]. <https://pubarchive.lbl.gov/islandora/object/ir%7D3A123665>
- [17] H. Wang, Y. Chen, C. W. H. Chan, J. Qin, J. Wang, Online model-based fault detection and diagnosis strategy for VAV air handling units, *Energy & Buildings* 55 (2012) 252–263. doi:10.1016/j.enbuild.2012.08.016.
- [18] Z. O. Neill, X. Pang, M. Shashanka, P. Haves, Model-based real-time whole building energy performance monitoring and diagnostics, *Journal of Building Performance Simulation* 7 (2) (2014) 83–99. doi:10.1080/19401493.2013.777118.
- [19] S. Garatti, S. Bittanti, A new paradigm for parameter estimation in system modeling, *International Journal of adaptive control and signal processing* 27 (2013) 667–687. doi:10.1002/acs.
- [20] M. Bonvini, M. D. Sohn, J. Granderson, M. Wetter, M. Ann, Robust online fault detection diagnosis for HVAC components based on nonlinear state estimation techniques, *Applied Energy* 124 (2014) 156–166. doi:10.1016/j.apenergy.2014.03.009.
- [21] Y. Jia, T. A. Reddy, Approach to Modeling Chillers Suitable for Fault

- Detection, Diagnosis, and Evaluation, Transactions of the ASME 125 (2018) 258–265. doi:10.1115/1.1567317.
- [22] IEA ANNEX 25, Building optimization and fault diagnosis source book, 1996, ISBN: 9525004104.
- [23] S. Imam, D. A. Coley, I. Walker, The building performance gap : Are modellers literate ?, Building Services Engineering Research & Technology 38 (3) (2017) 351–375. doi:10.1177/0143624416684641.
- [24] D. Ilter, E. Ergen, BIM for building refurbishment and maintenance : current status and research directions, Structural Survey 33 (3) (2015) 228–256. doi:10.1108/SS-02-2015-0008.
- [25] X. Zhao, A scientometric review of global BIM research : Analysis and visualization, Automation in Construction 80 (2017) 37–47. doi:10.1016/j.autcon.2017.04.002.
- [26] T. El-diraby, T. Krijnen, M. Papagelis, BIM-based collaborative design and socio-technical analytics of green buildings, Automation in Construction 82 (2017) 59–74. doi:10.1016/j.autcon.2017.06.004.
- [27] Y. Liu, S. V. Nederveen, M. Hertogh, Understanding effects of BIM on collaborative design and construction : An empirical study in China, International Journal of Project Management 35 (2017) 686–698. doi:10.1016/j.ijproman.2016.06.007.
- [28] A. Ghaarianhoseini, J. Tookey, A. Ghaarianhoseini, N. Naismith, S. Azhar, O. Emova, K. Raahemifar, Building Information Modelling (BIM) uptake : Clear benefits, understanding its implementation, risks and challenges, Renewable and Sustainable Energy Reviews 75 (2017) 1046–1053. doi:10.1016/j.rser.2016.11.083.
- [29] H.-y. Chong, C.-y. Lee, X. Wang, A mixed review of the adoption of Building Information Modelling (BIM) for sustainability, Journal of Cleaner Production 142 (2017) 4114–4126. doi:10.1016/j.jclepro.2016.09.222.
- [30] V. Bazjanac, T. Maile, IFC HVAC interface to EnergyPlus - A case of expanded interoperability for energy simulation, in: IBPSA-USA National Conference, SimBuild 2004, 2004 [Accessed on: 2018-08-14]. <http://escholarship.org/uc/item/5zb4j9nb>
- [31] J. O'Donnell, R. See, C. Rose, T. Maile, V. Bazjanac, P. Haves, SIMMODEL: a domain data model for whole building energy simulation, in: 12th International Conference of the International Building Performance Simulation Association (IBPSA), BS2011, no. 1223, 2011 [Accessed on: 2018-08-14]. http://www.ibpsa.org/proceedings/BS2011/P_1223.pdf
- [32] P. Remmen, J. Cao, S. Ebertshäuser, J. Frisch, M. Lauster, T. Maile, D. Müller, C. V. Treeck, An open framework for integrated BIM-based building performance simulation using Modelica, in: 14th International Conference of the International Building Performance Simulation Association (IBPSA), BS2015, no. 2384, 2015 [Accessed on: 2018-08-14]. <http://www.ibpsa.org/proceedings/BS2015/p2384.pdf>
- [33] M. Thorade, J. Rädler, P. Remmen, T. Maile, R. Wimmer, J. Cao, M. Lauster, D. Müller, C. Nytsch-geusen, C. Van Treeck, An open toolchain for generating Modelica code from Building Information Models, in: Proceedings of the 11th International Modelica Conference September 21–23, 2015, Versailles, France, 2015. doi:10.3384/ecp15118383.
- [34] R. Wimmer, J. Cao, P. Remmen, T. Maile, J. O. Donnell, J. Frisch, R. Streblow, D. Müller, C. V. Treeck, Implementation of advanced BIM-based mapping rules for automated conversions to Modelica, in: 14th International Conference of the International Building Performance Simulation Association (IBPSA), BS2015, no. 2424, 2015 [Accessed on: 2018-08-14]. <http://www.ibpsa.org/proceedings/BS2015/p2424.pdf>
- [35] M. Wetter, Modelica-based modelling and simulation to support research and development in building energy and control systems, Journal of Building Performance Simulation 2 (2009) 143–161, ISBN: 1940149090281. doi:10.1080/19401490902818259.
- [36] J. L. M. Hensen, R. Lamberts, Building performance simulation for design and operation, Spon Press, 2011, ISBN: 9780415474146.
- [37] T. Müller, T. Rist, A qualitative modeling approach for fault detection and diagnosis on HVAC systems, in: Proceedings of the 13th International Conference for Enhanced Building Operations, Montreal, Quebec, 2013, pp. 11–14 [Accessed on: 2018-08-14]. http://www.cascade-eu.org/cms/fileadmin/_migrated/content_uploads/TCEBO_2013_Final_Paper_1_-_Thorsten_Mueller_-_Fraunhofer_ISE.pdf
- [38] R. Sterling, G. Provan, J. Febres, D. O. Sullivan, P. Struss, M. Keane, Model-based fault detection and diagnosis of air handling units : A comparison of methodologies, Energy Procedia 62 (0) (2014) 686–693. doi:10.1016/j.egypro.2014.12.432.
- [39] A. Andriamamonjy, D. Saelens, R. Klein, An automated IFC-based workflow for building energy performance simulation with Modelica, Automation in Construction 91 (2018) 166–181. doi:10.1016/j.autcon.2018.03.019.
- [40] T. Darure, J. J. Yamé, F. Hamelin, Fault-Adaptive Control of VAV damper stuck in a Multizone Building, in: 3rd Conference on Control and Fault-Tolerant Systems, Barcelona, Spain, Sept. 7–9, 2016, 2016, pp. 170–176. doi:10.1109/SYSTOL.2016.7739746.
- [41] T. Mulumba, A. Afshari, K. Yan, W. Shen, L. K. Norford, Robust model-based fault diagnosis for air handling units, Energy and Buildings 86 (2015) 698–707. doi:10.1016/j.enbuild.2014.10.069.
- [42] K. Bruton, P. Raftery, P. O. Donovan, N. Aughney, M. M. Keane, D. T. J. O. Sullivan, Development and alpha testing of a cloud based automated fault detection and diagnosis tool for Air Handling Units, Automation in Construction 39 (2014) 70–83. doi:10.1016/j.autcon.2013.12.006.
- [43] K. Bruton, D. Coakley, P. Raftery, D. O. Cusack, M. M. Keane, D. T. J. O. Sullivan, Comparative analysis of the AHU InFO fault detection and diagnostic expert tool for AHUs with APAR, Energy Efficiency 8 (2015) 299–322. doi:10.1007/s12053-014-9289-z.
- [44] A. Andriamamonjy, R. Klein, A modular, open system for testing ventilation and cooling strategies in extremely low energy lecture rooms, in: 36th AIVC- 5th TightVent- 3rd venticool 2015, 2015 [Accessed on: 2018-08-14]. https://lirias.kuleuven.be/bitstream/123456789/602970/1/AIVC_AndriamamonjyKlein.pdf
- [45] R. Baetens, R. De Coninck, F. Jorissen, D. Picard, L. Helsen, D. Saelens, OpenIDEAS - An Open Framework for Integrated District Energy Assessment, in: 14th International Conference of the International Building Performance Simulation Association (IBPSA), BS2015, no. 2243, 2015 [Accessed on: 2018-08-14]. <http://www.ibpsa.org/proceedings/BS2015/p2243.pdf>
- [46] F. Jorissen, G. Reynders, R. Baetens, D. Picard, D. Saelens, L. Helsen, Implementation and verification of the IDEAS building energy simulation library, Journal of Building Performance Simulation doi:10.1080/19401493.2018.1428361.
- [47] F. Jorissen, W. Boydens, L. Helsen, Validated air handling unit model using indirect evaporative cooling, Journal of Building Performance Simulation (2017) 1–20 doi:10.1080/19401493.2016.1273391.
- [48] M. Wetter, Fan and pump model that has a unique solution for any pressure boundary condition and control signal, in: 13th Conference of International Building Performance Simulation Association, Chambéry, France, August 26–28, 2013 [Accessed on: 2018-08-14]. http://www.ibpsa.org/proceedings/BS2013/p_1040.pdf
- [49] G. Chaudhary, J. New, J. Sanyal, P. Im, Z. O. Neill, V. Garg, Evaluation of Autotune calibration against manual calibration of building energy models, Applied Energy 182 (2016) 115–134. doi:10.1016/j.apenergy.2016.08.073.
- [50] D. Coakley, P. Raftery, M. Keane, A review of methods to match building energy simulation models to measured data, Renewable and Sustainable Energy Reviews 37 (2014) 123–141, ISBN: 1364-0321. doi:10.1016/j.rser.2014.05.007.
- [51] MODELISAR, Functional Mock-up Interface for Model Exchange and Co-Simulation 2.0, Tech. rep. (2014) [Accessed on: 2018-08-14]. https://svn.modelica.org/fmi/branches/public/specifications/v2.0/FMI_for_ModelExchange_and_CoSimulation_v2.0.pdf
- [52] A. Aljarbouh, B. Caillaud, Chattering-Free Simulation of Hybrid Dynamical Systems with the Functional Mock-Up Interface 2.0, Proceedings of the 1st Japanese Modelica Conference May 23–24, 2016, Tokyo, Japan doi:10.3384/ecp1612495.
- [53] F. Yilmaz, U. Durak, K. Taylan, Adapting Functional Mockup Units for HLA-compliant Distributed Simulation, in: Proceedings of the 10th International Modelica Conference March 10–12, 2014, Lund, Sweden, 2014, pp. 247–257. doi:10.3384/ECP14096247.
- [54] T. Noudui, M. Wetter, W. Zuo, Functional mock-up unit for co-simulation import in EnergyPlus, Journal of Building Performance Simulation

- lation 7 (3) (2014) 192–202. doi:10.1080/19401493.2013.808265.
- [55] J. Åkesson, M. Gäfvert, H. Tummescheit, *JModelica - An Open Source Platform for Optimization of Modelica Models*, MATHMOD 2009 - 6th Vienna International Conference on Mathematical Modelling (2009) 8 [Accessed on: 2018-08-14].
<http://www.control.lth.se/documents/2009/ake+09mathmod.pdf>
- [56] V. Machairas, A. Tsangrassoulis, K. Axarli, Algorithms for optimization of building design : A review, *Renewable and Sustainable Energy Reviews* 31 (2014) 101–112. doi:10.1016/j.rser.2013.11.036.
- [57] D. Chakraborty, H. Elzarka, Performance testing of energy models : are we using the right statistical metrics ?, *Journal of Building Performance Simulation* 11 (4) (2018) 433–448. doi:10.1080/19401493.2017.1387607.
- [58] C. Cui, T. Wu, M. Hu, J. D. Weir, X. Li, Short-term building energy model recommendation system : A meta-learning approach, *Applied Energy* 172 (2016) 251–263. doi:10.1016/j.apenergy.2016.03.112.
- [59] A.-t. Nguyen, S. Reiter, P. Rigo, A review on simulation-based optimization methods applied to building performance analysis, *Applied Energy* 113 (2014) 1043–1058. doi:10.1016/j.apenergy.2013.08.061.
- [60] Y. Yusoff, M. S. Ngadiman, A. M. Zain, Overview of NSGA-II for Optimizing Machining Process Parameters, *Procedia Engineering* 15 (2011) 3978–3983. doi:10.1016/j.proeng.2011.08.745.
- [61] G. Ramos, C. Fernández, T. G.-a. Temes, A. S.-o. Gutierrez, Genetic algorithm for building envelope calibration, *Applied Energy* 168 (2016) 691–705. doi:10.1016/j.apenergy.2016.01.075.
- [62] G. Campos, C. Fr. R. Kelly, F. Yalaoui, R. Kelly, A NSGA-II and NSGA-III comparison for solving an open shop scheduling problem with resource constraints, *IFAC-PapersOnLine* 49 (12) (2016) 1272–1277. doi:10.1016/j.ifacol.2016.07.690.
- [63] K. Deb, A. Member, A. Pratap, S. Agarwal, T. Meyarivan, A Fast and Elitist Multiobjective Genetic Algorithm : NSGA-II, *IEEE transaction on evolutionary computation* 6 (2) (2002) 182–197. doi:10.1109/4235.996017.
- [64] F.-A. Fortin, F.-M. De Rainville, M.-A. Gardner, M. Parizeau, C. Gagné, *DEAP : Evolutionary Algorithms Made Easy*, *Journal of Machine Learning Research* 13 (12) (2012) 2171–2175 [Accessed on: 2018-08-14].
<http://www.jmlr.org/papers/volume13/fortin12a/fortin12a.pdf>
- [65] B. V. Ruijven, J. P. van der Sluijs, D. P. van Vuuren, P. Janssen, P. S. C. Heuberger, B. de Vries, Uncertainty from Model Calibration : Applying a New Method to Transport Energy Demand Modelling Intergovernmental Panel on Climate Change, *Environmental Modeling & Assessment* 15 (2010) 175–188. doi:10.1007/s10666-009-9200-z.
- [66] F. Xiao, S. Wang, Progress and methodologies of lifecycle commissioning of HVAC systems to enhance building sustainability, *Renewable and Sustainable Energy Reviews* 13 (2009) 1144–1149. doi:10.1016/j.rser.2008.03.006.