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Practical approach of an open Fault Detection and Diagnosis (FDD) method. Application to the HVAC system of a Near–Zero Energy university building.

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Abstract
For a wide application of fault detection and diagnosis in buildings, this work proposes an easy to implement method based on the use of generic tools. The approach combines a white box Modelica model for fault detection and classification methods for fault diagnosis. Based on the comparison between measured data and estimation, a set of simple rules is proposed to categorize the system status as fault free, unknown or faulty. Functional Mockup Unit (FMU) is used to facilitate the FDD integration into a BMS. The method was tested on a virtual scenario where miscellaneous types of faults (e.g: stuck dampers, valves and multiple faults) were introduced into a second simulation model of an Air Handling Unit which produces "synthetic" measured data. The proposed approach detected successfully the introduced errors. Although generic and easy to implement, the approach's robustness and effectiveness were emphasized by the performed tests.

Keywords – fault detection and diagnosis; Modelica; Classification

1. Introduction

Heating Ventilation and Air-Conditioning (HVAC) systems in buildings often do not meet the desired energy performance. In a non-exhaustive manner, this is due to improper equipment selection and installation, lack of commissioning, defect components, equipment degradation, non-qualified building management operator [1].

Fault detection and diagnosis (FDD) methods have the ability to determine the occurrence of a fault and its origin and thus avoiding increase of energy use.

Over the past few decades, a large effort has been provided to improve fault detection and diagnosis (FDD) methods in buildings. Nonetheless some major obstacles limit its generalized use: among others, the lack of standardized methods and awareness of its energy savings potential constitute major problems.

The goal of this paper is to contribute to the wide application of FDD methods by implementing and testing an approach where its intended features would be:

- easy to implement and to reproduce
- as generic as possible using only open concepts, tools and languages

The FDD method will be applied to a real-life case study to identify components failure in an Air Handling Unit (AHU) during the operational phase. It has been tested on a simulated scenario where faults in the components were introduced.

The paper consists of two major parts: A methodology part dedicated to the detailed practical implementation of the method and an experimentation part which presents the practical testing of the method. A discussion on the limitations and future works follows the two major parts.

2. Methodology

The proposed approach combines a calibrated white box model for fault detection and classifiers for fault diagnosis.

White box models are able to provide reliable estimators for Fault Detection [2], [3]. Nonetheless, studies agree that despite its qualities, they have some limitations. Firstly, they could be tedious and complex to implement and a large amount of input data is needed to describe the whole system. Secondly, they can be computationally intensive and not suitable for "near real-time" fault detection. Thirdly, they are generally difficult to embed in a standardized way into a Building Management Systems (BMS).

The present study overcomes these limitations by proposing a strategy based on the generic language and tool: Modelica [4] and Functional Mockup Unit (FMU) [5]. Modelica is used to facilitate model implementation whereas the FMU eases the embedding process of the model into the BMS.

This work relies on classification methods to detect the location and type of faults. This was motivated by their ease of implementation and ability to handle large scale systems. Furthermore, the efficiency and robustness of such method for fault diagnosis have already been demonstrated within the recent studies [2], [6].

2.a Fault Detection and Diagnosis Process

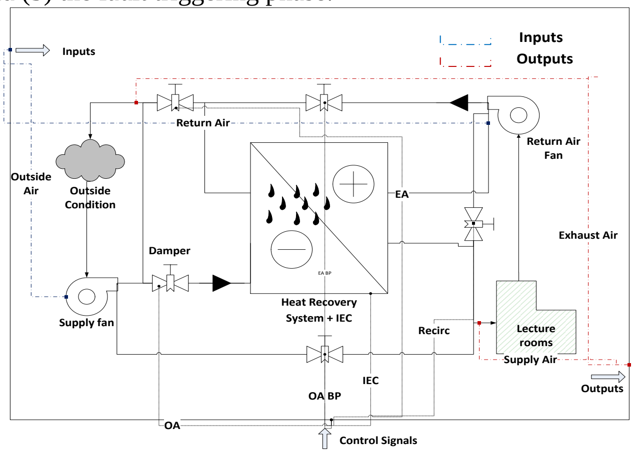
The current implementation is focused on FDD during operation. Consequently the followings assumptions and initial condition are made:

- A successful initial commissioning to create a "fault-free" reference situation

- Correct control command and no drift in sensors (focus on AHU components failure)
- Availability of a Building Management System within the building

The approach was tested to detect AHU's (fig.1) components failure having an impact on indoor comfort of an nZEB university building. The Supply Air (SA) temperature is the main surveyed output, while a correct airflow volume is assumed.

To detect and diagnose faults, the proposed approach relies on a three phase's process: (1) the categorization phase, (2) the fault identification phase and (3) the fault triggering phase.



IEC: Indirect Evaporative Cooling control signal
OA: Outside Air damper control signal
OA BP: Outside Air By-Pass damper control signal
EA: Exhaust Air damper control signal
Recirc: Recirculation damper control signal

Fig. 1 : Scheme of the considered system

Categorization phase

In this first phase, a comparison of the measured data Y and estimations $\hat{Y}$ is performed. In the next sections, thresholds are defined to categorize the operation status as fault free (*ff*), unknown (*ukn*) or faulty (*ft*).

Model based categorization: fault detection

Assuming that the residuals $\delta = Y - \hat{Y}$ (Y: measured value, $\hat{Y}$: estimation) are normally distributed, a current operation is supposed to be fault free (*ff*) if the operation's residual $\delta_{op} = Y_{op} - \hat{Y}_{op}$ falls into the 95% confidence interval of the residuals mean μ_{cal} (see equations 1 to 3). To increase the sensitivity of the fault detection, one could also use a lower confidence interval value.

In this work, (*op*) refers to a time step where an operation takes place and needs to be processed for FDD. A one minute time step has been chosen in this work.

μ_{cal} is the mean of the residuals obtained from the initial calibration of the white box model and the subscript (*cal*) refers to the set of measured data used for this calibration.

Due to various reasons ranging from sensor noise, integration error to inaccurate assumptions, the white-box model might fail to depict accurately the process. Such cases explain the 5% remaining points (such accuracy is achieved, as only the AHU is modelled) having a residual δ_{cal} with a great deviation towards the mean μ_{cal}. This might lead to a false categorization of δ_{op} during an operation and triggers a false alarm. These false alarms cannot be considered as fault free nor faulty status as it might be due to inaccuracy of the model itself. But it could be also due to a slight disturbance in the system. To take these effects into account, the unknown status (*ukn*) is used. This status is considered if δ_{op} does not satisfy the equation (1) but still falls into the 99% confidence interval of μ_{cal} (see eq 2).

These thresholds conditions are summarized within the followings equations (see figure 3 for illustration):

IF $Y \in [\hat{Y}+\mu_{cal}-z_{0.95}.\sigma(\delta_{cal}), \hat{Y}+\mu_{cal}+z_{0.95}.\sigma(\delta_{cal})]$ THEN $op=ff$ (1)

IF $Y \in [\hat{Y}+\mu_{cal}-z_{0.99}.\sigma(\delta_{cal}), \hat{Y}+\mu_{cal}-z_{0.95}.\sigma(\delta_{cal})]$
OR $[\hat{Y}+\mu_{cal}+z_{0.95}.\sigma(\delta_{cal}), \hat{Y}+\mu_{cal}+z_{0.99}.\sigma(\delta_{cal})]$ THEN $op = ukn$ (2)

IF $Y > \hat{Y}+\mu_{cal}+z_{0.99}.\sigma(\delta_{cal})$ *or* $Y < \hat{Y}+\mu_{cal}-z_{0.99}.\sigma(\delta_{cal})$ THEN $op= ft$ (3)

$z_{0.95}$, $z_{0.99}$ *and* $\sigma(\delta_{cal})$ represent the 95% , 99% confidence interval z-score and the standard deviation of the residual δ_{cal}. For the current case study, the observed output Y is the supply air temperature and the values of the aforementioned parameters are related in the Table 1.

Table 1. Fault detection parameters obtained from the initial calibration

RMSE	μ_{cal}	$\sigma(\delta_{cal})$	$z_{0.95}$	$z_{0.99}$
0.727	0.116	0.718	(-1.29, 1.52)	(-1.73, 1.96)

<u>Classifier based categorization: fault diagnosis</u>

To diagnose the origin of faults, classification methods were used. The classifiers estimate the control signal value of a component using measured inputs and outputs. The goal is to identify, considering the inputs and outputs, if the actual control signal value Z_{ci} of a component i (Dampers, valves, Adiabatic cooling,…) agrees with the estimated “correct” signal $\hat{Z}_{ci}$. A mismatch between the estimation and the actual signal value indicates a fault in the component.

The estimation probability $\hat{Z}_{cpi}$ is also computed to identify the relevance of the estimation $\hat{Z}_{ci}$. A component i of the AHU is considered as fault free if the actual control value Z_{ci} and its estimation $\hat{Z}_{ci}$ belong to the same class along with a high estimation probability $\hat{Z}_{cpi}>0.75$. If the confidence in the estimation is weak $\hat{Z}_{cpi} < 0.75$, the operation is categorized automatically as "unknown" (*ukn*). The following equations summarize the classifier based fault diagnosis process (see figure 4 for illustration):

IF $Z_{ci} \epsilon$ *Class X* AND $\hat{Z}_{ci} \epsilon$ *Class X* AND $\hat{Z}_{cpi} > 0.75$ THEN *op = ff* (4)

IF $Z_{ci} \epsilon$ *Class X* OR $\hat{Z}_{ci} \epsilon$ *Class Y* AND $\hat{Z}_{ci} \epsilon$ *Class X*
AND $\hat{Z}_{cpi} < 0.75$ THEN *op=ukn* (5)

IF $Z_{ci} \epsilon$ *Class X* AND $\hat{Z}_{ci} \epsilon$ *Class Y* AND $\hat{Z}_{cpi} > 0.75$ THEN *op=ft* (6)

<u>Fault identification phase</u>

Based on the status (*ff*, *ft* or *ukn*) of the operations from the estimators (model for the surveyed output and classifiers for the components), this step defines the final status of the operation. A set of simple rules has been defined:

IF *Y = ff* AND *EXISTS ft IN Zci* THEN *op=ukn* ELSE *op=ff* (7)

IF *Y = ukn* AND *EXISTS ft IN Zci* THEN *op=ukn* ELSE *op=ff* (8)

IF *Y = ft* AND *EXISTS ft IN Zci* THEN *op=ft* ELSE *op=ukn* (9)

An operation is defined as fault-free or faulty if the two processes (white box model and classifiers) have the same status (both are fault-free or faulty), otherwise an unknown (*ukn*) case is triggered. The operation is identified as unknown if a fault is detected but the error origin is not diagnosed or a component is detected as faulty but the white box model fails to trigger an error. Thus, the "*ukn"* cases cannot be identified as fault-free or faulty and are labeled as "invalid operation" for fault detection.

<u>Fault triggering phase</u>

A fault is triggered and notified to the building manager if too many valid operations (i.e: not *ukn*) are faulty over a specific period (e.g: 2 days). In this study, a fault is triggered if faulty operations are over 75% of the valid operations along with a high rate of invalid operations (e.g: 50%). However, if too many invalid operations occur even if no errors are detected, a notification is sent to the BMS. This may indicate that due to changes in operation the model and the classifiers estimation are no more relevant and need to be re-calibrated and retrained.

2.b First implementation test

This section explains the implementation and calibration of the white box model and the classifiers using solely open tools (Modelica, Genopt [7], FMU) and easy to use libraries (Scikit-Learn library [8]).

The modelling language Modelica was chosen to build the physical model. The libraries used are developed under the umbrella of the IEA EBC Annex 60: Buildings library [9], Integrated District Energy Assessment Simulations library (IDEAS) [10] and AixLib [11]. They provide a generic and validated model for common components in buildings and systems (zones, walls, heaters,…).

Nonetheless, some specific components were still missing. Namely, the adiabatic cooling component was implemented using a simplified model based on the work presented by Erens et al [12].

Based on the scheme in figure 1, the AHU model was implemented with the Modelica Buildings Library. Besides the adiabatic cooling component, the generic components such as the constant effectiveness heat exchanger, damper, fan and pipe model present in the library were used.

To detect faults, the model needs to represent the "correct" behavior of the system and therefore needs to be calibrated with the initial "fault free" measured data. However, the model requires 38 parameters to be tuned to calibrate the model. This is computationally intensive and not suitable for a prospective online calibration and requires an initial sensitivity analysis to determine the most influential parameters towards the objective function (eq 10). The global sensitivity analysis method SOBOL [13] with the Saltelli-sampling method [14] was used. The initial parameters values were obtained from the as-built BIM (Building Information Model) of the HVAC while the dedicated Sensitivity Analysis Python package SAlib [15] was used along with a Modelica simulation engine to perform the analysis.

A sensitivity analysis (figure 2.a), shows that only 4 parameters have a significant effect on the surveyed output. These influential parameters are related to the exchangers efficiencies and the adiabatic cooling parameters.

$$f(x)= \sum_I \sum_K (Y_k - \hat{Y}_k)^2 \quad (10)$$

An optimization based calibration approach was then performed to estimate the influent parameters values and calibrate the model. The generic optimization tool Genopt with the pattern search Hook-Jeeves algorithm was used [7]. For the AHU model calibration, k=2, Y_1=Supply Air Temperature and Y_2=Exhaust Air Temperature were chosen.

A calibration loop process was carried out, an initial model based on data from the as-built BIM is used. If a non-satisfactory final RMSE is obtained, a manual re-check of the model structure is performed. The loop is stopped when an acceptable RMSE is achieved (e.g: between 0 and 1). Figure 2.b shows the comparison between the calibrated AHU model and the initial calibration data. The RMSE and the parameters required for fault detection are obtained from this calibration process and are presented in the table 1.

To illustrate the classifiers implementation, let us consider the AHU dampers. The control signal command the dampers opening range which has a value between 0% and 100% (closed-open). This range is then divided into classes. The challenge is to find the right number of classes which avoids overfitting but allows to represent accurately the process. In this study, a simple analysis of the initial control signal data pattern support the use of ten classes. Nonetheless, further study is required to identify the optimal number of classes.

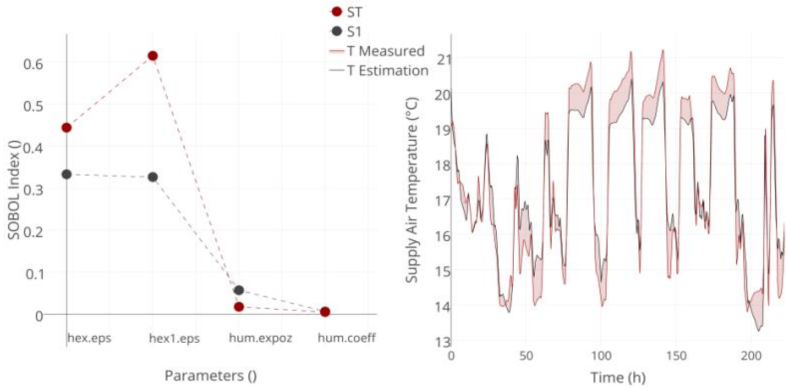


Fig. 2 (a) Sensitivity analysis results, (b): Physical model calibration

The classifiers are trained using machine learning algorithms [8] (k-nearest neighbors, random forests,…) and used to estimate the class of a signal using new set of inputs and outputs. To facilitate the implementation of the classifiers, the dedicated Python package Scikit-Learn has been used. It provides a set of ready to use supervised multiclass classifiers such as the K-nearest neighbors, the random forest classifiers and the gradient boosting classifiers. In this study, the focus was set on the K-nearest neighbors classifiers while other methods will be tested in future experiments.

3. Experimentation part: virtual scenarios

The virtual scenarios use synthetic data from a numerical model to simulate AHU real behavior. However, results from real testing on the AHU is ongoing and will be presented in a future work.

These virtual scenarios show how the method performs to detect and classify faults. For this purpose, four (1 to 4) scenarios were considered (figure 3):

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

The figures 3 and 4 represent respectively the model-based and the classifiers-based categorization. In these figures, the comparison between estimated and measured value are presented alongside with the operation status (red area) calculated by equations (1)-(6).

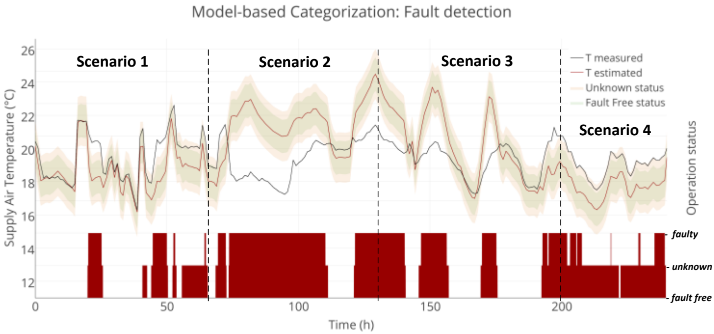


Fig. 3 categorization phase: fault detection using white box modelling

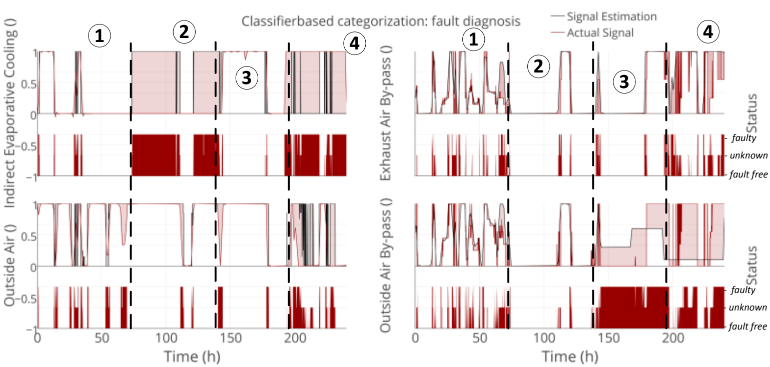


Fig. 4 Component control classification

The figure 5 presents the fault identification phase which is obtained by applying the equations (7)-(9) to the previous results. These results are stored into a database and analyzed to trigger faults.

From figure 5, by calculating the percentage of fault free operations over the valid operations in the scenario 1, a rate of 96% fault free and 4% “faulty” operation is obtained. This indicates a normal, “fault free” operation of the system during this period. In the scenario 2, 76.16% of the operations of the adiabatic cooling system is detected as “faulty” while other components are fault free (see fig. 4). Furthermore, a rate of 87.51% of “faulty” operations over the valid operations has been obtained which emphasized the faulty status of the system during this period (see fig. 5). For the scenario 3, the approach detected 100% of faulty operation within the outside air bypass (fig. 4) while 98.37% of the valid operations of the AHU are categorized as “faulty” (fig. 5). Nevertheless, this third scenario shows a high rate of invalid operation (67.98 %, fig. 5) and requires further investigation. The multiple errors introduced in the scenario 4 are also detected and diagnosed correctly: 83% of faulty operations in the IEC system, 61.54% of errors in the outside air bypass dampers and 76% of introduced errors were detected during this last period (fig. 5).

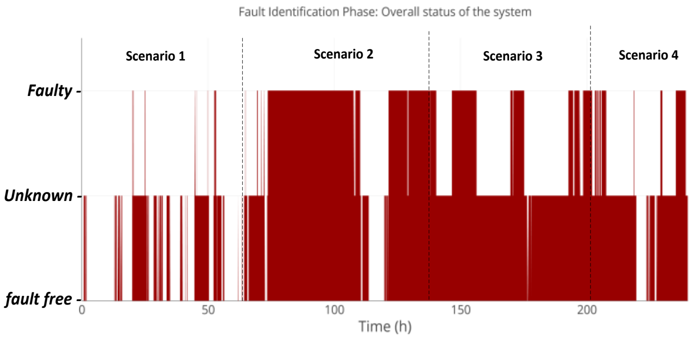


Fig. 5 Fault identification phase: Overall status of the system

These results shows that all the introduced errors were detected and well diagnosed. This outlines that in the current case the approach is effective and robust, despite its implementation simplicity.

4. Limitations and future works

The current study focuses on the component failure in the AHU, therefore a logic continuation of the present work is the implementation for the entire system of a building (HVAC).

The need of numerous inputs to run the model-based fault detection outlines the necessity of a highly monitored facility. A subject for future work is the implementation of a FDD tool with a “reduced BMS” system.

The detailed model implementation might be also further improved by using BIM to automatize the model generation. The IEA EBC Annex 60 focuses on this concept to facilitate BEPS model implementation.

5. Conclusions

This research focused on the use of a combination of robust existing FDD approaches where only open, generic, well-known proven tools and language has been used. The goal is to increase the “customizability and reproducibility” of FDD methods.

An easy to use and to implement fault detection and diagnosis approach which relies on white box modelling for fault detection and classifiers for fault diagnosis was proposed. Modelica has been chosen to build the model due to its specific features (standardized language and availability of open source libraries for buildings and systems). Genopt along with a Modelica simulation engine were used to calibrate the model. The origins of faults have been also diagnosed using classifiers generated by the python package Scikit-learn. To ease the FDD tool integration into a real life BMS, the model was translated into a FMU.

The approach was successfully tested for virtual scenarios where the method was able to detect and diagnose the introduced errors.

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