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Versatile AHU fault detection – Design, field validation and practical application

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ABSTRACT

This paper describes a new tool developed for the detection of operating faults in ventilation units with heat recovery. In principle, the tool is based on the APAR (Air Handling Unit Performance Assessment Rules) method. By following the semantic data description in accordance with the BrickSchema and Project Haystack initiatives, the tool is portable. The executive part of the fault detection system consists of several dozen detection rules, which simultaneously seeks to estimate wasted energy, the threat to user comfort, or the risk of reduced device lifespan, so that the detected faults can be sorted according to their severity.The developed detection tool was validated on real devices incorporated in a pilot plant. For validation purposes, the method of fault induction on real HVAC (Heating, Ventilation and Air Conditioning system) units was used, with subsequent inspection of whether the faults were revealed or not. The results revealed a 90% detection rate. The data set created as a result of this pilot plant is published as an annex to this article.In addition, the ability of the detection tool to reveal faults was also verified on the basis of data sets of measurements taken during the standard operation of several dozen HVAC units. The elimination of the identified operating faults generated energy savings of several thousands of dollars per year.

Nomenclature

Abbreviations

Shortcut	Meaning
AFDD	Automated fault detection and diagnostics
AHU	Air Handling Unit
APAR	Air Handling Unit Performance Assessment Rules
BMS	Building Management System
ETA	Extract air
FDD	Fault detection and diagnostics
HRE	Heat recovery exchanger
HVAC	Heating, ventilation and air-conditioning
IAQ	Indoor Air Quality
IoT	Internet of Things
SCADA	Supervisory Control And Data Acquisition
SUP	Supply air
VAV	Variable Air volume

1. Introduction

It is widely known that buildings consume 20–40% of the total amount of consumed energy [13,31]. At the core of every building is the heating, ventilation and air conditioning (HVAC) system, the purpose of which is to make the internal environment comfortable for users. However, due to the increasing requirements being placed on the quality of the internal environment and the need to decrease energy

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consumption, these systems and those that control them are becoming more and more complex. For non-residential buildings, the running of HVAC systems accounts for almost 50% of the total consumed energy in a building and about 10–20% of the total energy consumption in developed countries [31,46]. It is estimated that fixing of existing problems in building infrastructure, which would improve the operating efficiency of such systems, could reduce annual energy consumption inside buildings by 29% on average [15]. According to Granderson et al. [17], failures in controlling HVAC systems waste 3–30% of the energy consumed by them. Research in the United Kingdom indicates that the extent of the energy wasted may be much higher, from 25 to 50%; with timely fault detection this could be reduced to under 15% [9]. According to a study by the International Energy Agency [22], it is possible to save 20–30% of the energy they consume through the re-commissioning of current HVAC systems, in particular air handling unit (AHU) operations. Another study on a set of more than 80 sample buildings proved that ongoing re-commissioning on average saves more than 20% of overall energy costs [33].

1.1. Failures in HVAC systems

Failures in HVAC systems may occur during the entire lifespan of the device. Surprisingly, failures may already occur in the project phase. It is not rare that commercial buildings are designed without knowledge of their future use and their operating conditions. For example, an administrative building in which offices will be leased to different end users. During the project phase, neither the future space occupancy nor specific requirements are known, so it is difficult to design the air handling system accordingly. Failures and excessive energy waste may also occur during the selection or installation of the equipment, or as a result of the inappropriate operation thereof. Unfortunately, these faults (including construction faults) may not reveal themselves during the entire operating period.

The most critical faults are those caused by the inappropriate operation of HVAC systems. Such faults may not only be caused by changes in building usage, but also by inadequately trained operators, a lack of regular servicing, control system faults, or just due to improperly defined requirements in the Building Management System (BMS). Some failures, for example fan failures, can be detected using the standard tools incorporated in BMSs. However, in more complex systems (e.g. the AHU), there are many faults that cannot be detected by typical BMS alarms. Faults may occur that can be compensated for directly by the AHU (e.g. non-optimal heat recovery is compensated with heating or cooling [25]. Information about the fault is still included in the operating data but is not directly visible.

1.2. Fault detection and diagnosis

The application of fault detection methods in buildings began in the 1970s, expanding rapidly in the 1990s [23]. In the 1990s, the International Energy Agency initiated a research project named Annex. The results of Annex are summarized in Hyvarinen and Karki [21] and Dexter and Pekanen [11]. The theme of the project centered on fault detection and diagnosis (FDD) methods for buildings. It covered several topics, each requiring a different degree of engineering knowledge. Particular attention was given to a comprehensive overview of typical HVAC system faults and the presentation of a wide range of fault detection methods.

Comprehensive literature review of artificial intelligence-based FDD methods for building energy systems in the past twenty years from 1998 to 2018 is provided in [55]. This article summarizes the strengths and shortcomings of the existing artificial intelligence-based methods and reveals the most important research tasks in the future. The authors point out that improvements in reliability, robustness and generalization of FDD methods are more valuable than the improvement of accuracy only. This finding agrees with the goals of this paper. Another comprehensive review was recently provided by [28] or [26].

There are various classifications of FFD methods, see for example the classifications in Katipamula and Brambley [23] and Yang et al. [51]. However, two main groups can be distinguished. First are data-driven methods such as artificial neural networks, pattern recognition techniques and statistical methods. The second group consists of methods based on a priori knowledge. This group includes first-principle methods, expert systems, physical model-based methods or simple limits and alarms. The method presented in this paper is an example of an expert system. A detailed review of the literature is provided in chapter 1.6.

1.3. Portability and testing of fault detection tools

An analysis of operating data may help reveal important operating faults. However, automatic analysis is complicated because AHU units vary, not only across different types of buildings and operations, but also across different configuration. Under current conditions, it is not economical to create an analytic tool tailored to a specific AHU. A more general approach covering various AHU schemes, dimensions and purposes is therefore more useful. However, this approach often leads to simplifications or the ignoring of certain problems during the operational data analysis because the specifications of the appropriate AHU are more difficult to follow. On the other hand, this method is considered progressive because the requirement to implement analytic functions decreases. The portability of the tool to other units requires the operating data to be machine readable. This can be achieved by use of semantic data description (metadata).

The development of detection tools must not only overcome the variety of AHU units, but also the variety of communication protocols inside buildings and local hardware. This implies that any detection tool must be as universal and efficient as possible. Under such circumstances, it is therefore useful to create automatic diagnostics as a new analytic layer above the SCADA (Supervisory Control And Data Acquisition) server.

Although the analytic tool may be based on simple principles, the variety of available data elements, individual AHUs and various hardware or software devices makes automatic analysis a complicated task. It is therefore very desirable to test any detection tool on real data during its development to verify its detection and diagnostic abilities.

1.4. Severity of detected faults

When a fault is detected, it is necessary to be able to evaluate the severity and impact thereof. Such consequences can be divided into three basic categories – energy waste (electric, heating, cooling), reduction of device lifespan and impact on comfort in the operated area. This is a very complicated task because every operation has different priorities. One installation may place emphasis on the comfort and quality of the internal environment, whereas another may focus on energy consumption. The critical factor that determines the overall impact of the occurred fault is the size of the AHU. However, the size may not always be known in the SCADA. There are often devices in operation without proper documentation, on which the labels are illegible, etc. The severity of a fault with respect to all aspects of an operation can be evaluated by defining a severity index, which incorporates one or more indicators (e.g. for wasted energy, user comfort and device lifespan), so that the user can select the most suitable.

1.5. Business aspects

As analytic functions inside buildings are not very widespread yet, commercial models remain underdeveloped. Automated Fault Detection and Diagnostics (AFDD) may be delivered through various implementation models and may be used by the building operator or the energy manager, or it can be delivered on the basis of analysis-as-a-service contracts that do not require direct "internal" technologies to be used [17]. The commercial relations between the owner, lessee, building administrator and servicing companies concerning building operations are very specific and not standardized. It is therefore necessary to analyse the market delivery and find a place for detection tools with the highest value added. A good example of this is the Smart Energy Analytics Campaign [24] which focused on improving the use of practical diagnostics and the publication of many useful documents on the commercial aspects of this usage.

1.6. Related works

Several studies on AFDD of AHU have been undertaken in the past few years. Some authors focus on simulations involving specific AHU parts. For example, Pourarian et al. [35] used HVACSIM+ to simulate fan faults. The developed model showed satisfactory simulation results in comparison with experimental data. In a later work, Pourarian et al. [36] studied more than 20 fault scenarios for fan coil units (FCU). These scenarios combined various fault types and severities. Wen and Li [44], as well as Bushby et al. [5] and Montazeri and Kargar [29], used the same environment (HVACSIM+) to model certain parts of AHUs. Their work allows a better understanding of the individual parts, but it is hardly usable for detecting faults on the entire AHU.

In many cases, the diagnostics focus on a specific or specific type of AHU, using expert rules. The path of expert rules is simple but robust over tagged data sets. This technique, using common sense rather than complicated mathematics, was introduced in House et al. [20]. It is denoted as AHU performance assessment rules (APAR) and consists of 28 if-then rules that are evaluated according to the operational regime of an AHU. The APAR method received a lot of attention and was subsequently further elaborated by others (e.g. [39]). For example, Wang et al. [43] describe the online model-based AFDD method and the rule-based AFDD method in their study. They developed three rule-based fault classifiers that use 14 expert rules, including six expert rules from Schein et al. [39]. Trojanová et al. [42] presented a similar APAR-based tool and has achieved satisfactory results, but on only one specific AHU and concluded that the HVAC is too complex to create a general model-based solution. A fault detection technique for an AHU that combines expert rules and performance indexes is described in Qin and Wang [38].

Sterling et al. [41] analysed qualitative and quantitative models for AFDD and compared them with APAR. Their model-based diagnostics appear to be more efficient than APAR. However, this requires a great deal of expert work with each AHU and requires a lot of diagnostic sensors, so it would only be useful for really big devices. However, the advantage of this method is that it detects faults that APAR does not, as well as identifies the causes thereof more precisely. Bruton et al. [4] mentions the APAR extended ruleset – a set of 52 described faults [32]. InFO, which is based on Brutońs previous work [3], is able to detect each of these faults, but only in one type of HVAC unit (with circulation damper) without heat recovery. InFO is able to specify the severity of a fault in terms of financial costs calculated on the basis of wasted energy, but does not take into account the possible decrease in comfort or the shortened device lifespan. Desmukh et al. [10] also focused on one type of AHU and detected the two most common types of fault in which the impact on energy consumption may be critical. They considered faults involving circulation dampers to be the most critical. In their work, the authors state that their algorithms may also work in other buildings, although the data connection taxonomy is not included.

Some authors tried to develop ready-to-use tools for commissioning AHUs on cloud architecture, able to work with more types of AHU and with the ambition of mass expansion. Choiniere and Corsi [7] and Choiniere [6] present the DABO tool, which contains both SCADA server elements and diagnostic rules, as well as tools for data analysis. It focuses primarily on entire building, but also on HVAC units. It contains about 800 detection rules. Their work has been later validated in terms of fault detection with an 84% success rate, but only on artificially emulated data [16].

The lack of building datasets, with fault classification for validation of AFDD tools, is a persistent problem [26]. In most known studies [49,47,48,34,51], the authors use the ASHRAE Project 1312-RP [45] to develop and test their diagnostics. The 1312-RP project includes experimental data conducted at the Iowa Energy Center Energy Resource Station (ERS) test facility and a model using HVACSIM+. The project provides a collection of the fault-free and fault data that was experimentally simulated on two VAV (Variable Air Volume) AHU. These two systems had the same configuration of components (fans, coils, valves, dampers, and sensors) and were tested simultaneously – one with manually simulated faults and a second in the fault-free state. Although the project provides a large collection of experimental data as a dataset for comparison, the 1312-RP is only applicable for VAV AHU without heat recovery exchangers (HRE). This system rarely occurs in the European HVAC field since, according to European regulation, the AHUs must contain HRE. This makes the entire dataset of this project difficult to transfer. Lin et al. [27] proposed methodology for testing AFDD tools, using the data-set by Granderson and Lin [18], which is shorter than the ASHRAE RP-1312 dataset and contains the same type of AHU without HRE.

Most relevant works published in the last few years are more focused on data mining and machine learning techniques. Zhang et al. [53] attempted to improve diagnostics using physical models, such as Energy Plus, in order to evaluate the impact of faults and thus their severity. Some authors are trying to use the latest possibilities of artificial intelligence to improve rule-based diagnostics. Dey and Dong [12], Zhao et al. [55], Shi et al. [40] and Hassanpour et al. [19] use rules to detect symptoms and perform diagnosis of these symptoms using data-driven methods such as Bayesian networks.

Hassanpour et al. [19] states that the purely data-driven method is not able to clearly distinguish faulty data from the normal. Yan et al. [50] used the SVM method, which in successive iterations includes data classified with a high degree of certainty in the training set, so that the training set grows in each iteration. In other works Douzas and Bacao [14], Yan et al. [47] and Yan et al. [46] tried to use a generative adversarial network to insert noise and aberrations into the classified data of the training set to enlarge and balance it.

Piscitelli et al. [34] tried to go the other way and with the help of complex methods of artificial intelligence such as decision trees and temporal association rule mining, tried to work out simple rules.

A drawback of machine learning methods is its need for large sets of classified data. The amount of data required increases with the number of faults to be detected. Efforts are being made to make use even of a smaller data set. However, the question is still whether artificial intelligence derived from a small dataset can ever detect faults that require deeper expertise. Zhou et al. [56] states that binary classification of faulty behaviour by data-driven methods works much better than multiple fault classification, but HVAC systems often contain multiple faults, and the type of fault must be clarified.

1.7. Novelty of proposed solution

The novelty of our solution lies in the portability and universality of the AFDD system, which we set as a main goal at an early stage of development. We decided to combine rule-based fault detection, semantic data description and cloud architecture, using them to create a universally applicable AFDD system.

Rule-based diagnostic systems are a universal and proven method of automatic fault detection and, unlike machine learning methods, can easily run on a fractional or varied set of data from measuring sensors, which we've found crucial for the portability of the entire system. The process also involves the use of semantic data for better transferability. The data is automatically converted to relevant units and if missing, key data points are automatically calculated by means of virtual sensors. The cloud architecture of the SCADA server allows us to directly connect our tool with operational data from hundreds of buildings.

2. Methods

The diagnostic system is built as a new analytical layer over a conventional SCADA system. This allows easy deployment on a large number of diagnosed devices. Fig. 1 is a schematic representation of the principle of the whole expert system. The first phase of the process involves the air handling units, the number of which is not limited. Each unit is equipped with sensors for control and visualization and is connected to the BMS which controls the unit. If some important sensors are missing in the unit, it can be equipped with IoT (Internet of Things) sensors, if necessary.

The APAR method by Schein et al. [39] was chosen for the construction of the detection system. The advantage of the APAR method is the low input data requirements, with a very good coverage of the range of possible malfunctions and failures. The cited article lists 28 different detection rules that are derived from only 11 data points. The idea of this detection method was also adopted in the construction of the presented tool, although the rules cannot be used strictly as is.

2.1. Portability

A key issue of the AFDD tool is its portability from one AHU to another. To deploy diagnostics on a larger number of devices, it is necessary to connect data points to the corresponding inputs of the diagnostic system. This is done by using the semantic description of data: Metadata (tags) assigned to the data points by human experts. To assign data point meaning to the diagnostic system, there are three tags that must be assigned to each point that enters the diagnostics. The data point is characterised by:

- the quantity it represents, such as "temperature", "logic", etc.,
- the location to which it relates, such as "supply air outlet", "heater valve", etc.,
- its role in regulation, such as "sensor", "required value", etc.

The combination of these pieces of information clearly determines the function of the data point in terms of diagnostics, while the tags are machine-readable. Unlike datapoint names, the tags are not world-unique, but follow the standard derived from the Haystack Project and BrickSchema [2] in order to maintain the maximum level of compatibility. It is not possible to comply with both standards, with neither proving sufficient for the semantic description of data in air conditioning. Current efforts by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) are focused on approximating both standards under the Unified Data Semantic Modelling Solution [1]. Within this context, it will be necessary to adapt the solution in line with developments in the world of semantic description of data. However, unambiguous translation from the suggested three dimensional tagging system and Haystack and BrickSchema ontology can be defined.

2.2. Mutual representation of signals and virtual sensors

Since the SCADA system contains only a list of data points without mutual links, it is necessary to add information about the unit type (basic unit, single unit with plate heat exchanger, etc.)[1] to each air handling unit involved in the AFDD system. Even within one type of unit, however, the air handling unit can be equipped with different types of data points. For example, fan power can be represented by a continuous signal of 0–100%, frequency of the inverter, air speed, etc. Therefore, the AFDD tool works with phenomena that can be expressed by multiple data points. According to an embodied substitution table, each phenomenon searches for appropriate data points from the most desired to the least. This means that for example, if we need to know the temperature in the outdoor air channel, we will rely on a signal, which represents the temperature measurement by the sensor in the channel. However, if such a sensor is not available, the temperature upstream of the inlet air filter may be utilized. If this information is not available, an outside air temperature sensor can still be used. If even this value is not available, it is possible to use information about the outside temperature from nearby surroundings (another building in the dispatching system or data from professional meteorological stations). Similarly, for each piece of information, we can find the entire list of possible representatives, sorted from the most suitable to the least suitable. In exceptional cases, when an important phenomenon is not measured or derivable from others, a real sensor can be added to the AHU.

There are also phenomena that cannot be simply replaced by another data point. A typical one is air temperature beyond the HRE. This value is very important, but rarely does a physical sensor exist for it. It is therefore usually calculated on the basis of the temperature conditions before the exchanger and the efficiency of the exchanger. This computationally acquired information is referred to as a virtual sensor, which can replace the missing physical sensor.

2.3. Fault detection rules

Most of the rules depend on the operating mode of the AHU. The heater, for example, has to be tested differently when an AHU heats or cools. The operating mode is therefore the most important virtual sensor, and on which the fault detection process strongly relies. Once the operating mode is known for a given timestamp, the appropriate set of rules can be activated. The rules themselves are not complicated and often rely on simple, straightforward calculations that cover a particular physical or regulatory phenomenon.

For example, checking the inlet damper position would throw up a fault if a fan was running while the position of the relevant damper is "closed". The logic of this rule is the same when the operating mode is "heating" or "cooling". However, when the regime is "off", the same damper should be tested in the "open" position while the fan is "off". Separate rules have therefore been created for each operating mode, whereby the rules that are focused on the same or closely related phenomenon have been associated into groups called "Tests". The relation-

[1] There are many air handling units and different terms are used for them in available sources. For clarification purposes, in this paper, a single-fan unit for fresh air is referred to as a "basic unit", and a single-duct unit for balanced ventilation with heat recovery of any type (plate, wheel or glycol loop) is called a "single unit".

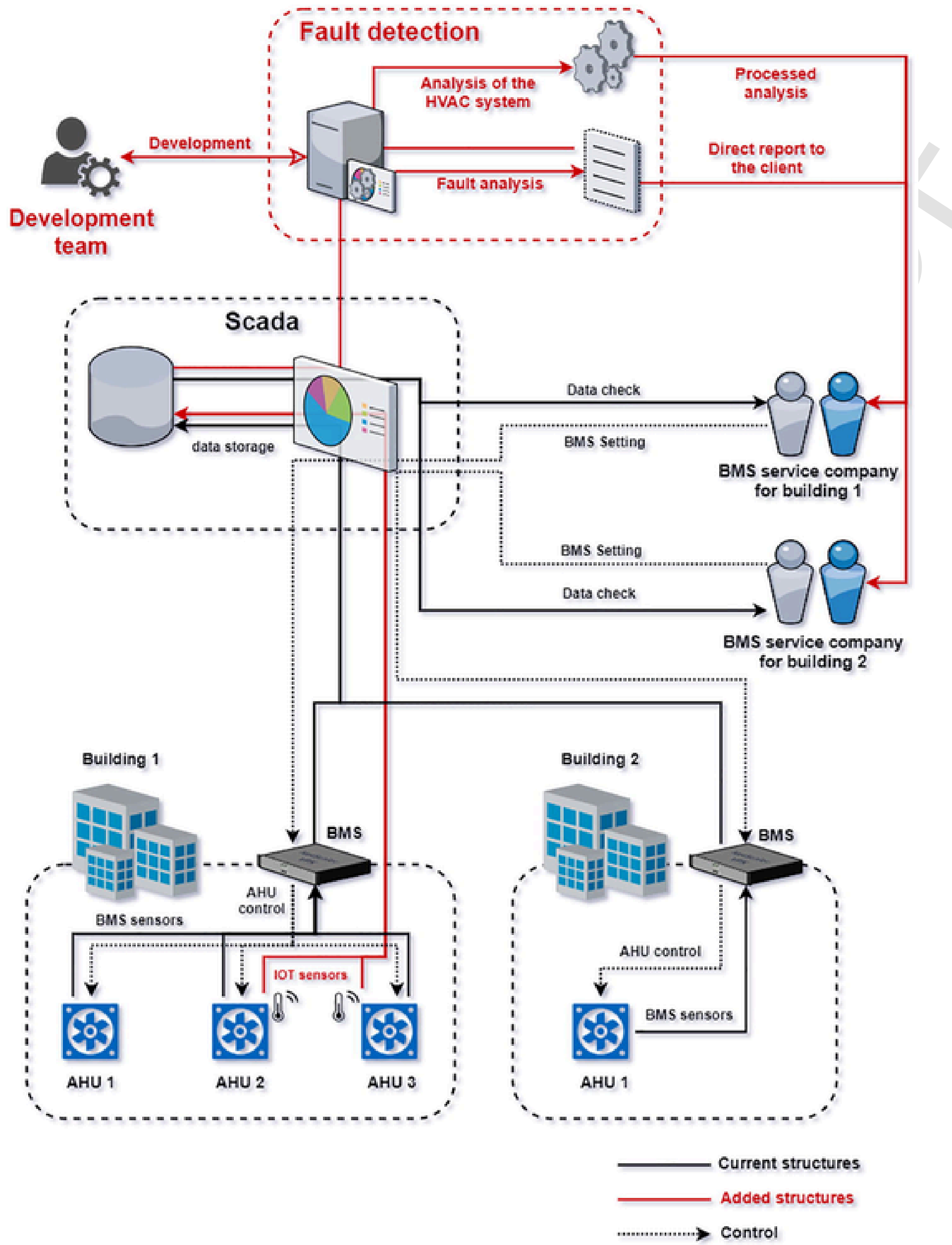

Fig. 1. Principle of expert system.

ships between the tests, rules and operating modes are presented in Table 1. The fault detection process is shown in Fig. 2.

2.4. Severity of the detected faults

When testing a large number of air handling units, a large number of faults are typically detected. It would be a waste of the operatoŕs time if they had to deal with all of these individually. The severity of a failure is therefore calculated for each fault detected. Severity is represented by a calculation that covers wasted electrical energy, heat, coolness, the threat to comfort in the ventilated area and the risk to the equipment operated. Five severity-indexes are therefore presented. The total of these signals the severity of the fault, thereby allowing the operator to prioritize the most important.

To calculate the amount of wasted energy it is necessary to know additional parameters of the AHU. The wasted energy can be satisfactorily estimated only if the nominal wattages of fans, pumps, heaters, and coolers are known. Unfortunately, SCADA usually does not contain information about the size of the AHU and obtaining this information can be complicated.

2.5. Long-term statistics & estimates

Machine evaluation of signals is dependent on threshold values. The presented system does not use impractical fixed constants, but determines threshold values directly from the aggregated history of the signal. Every signal is processed and statistical data – median, minimum, maximum, quantiles – are calculated. These values are used for thresholds calculation. For example, when calculating the volumetric air flow rate from the flow velocity, it is assumed that the nominal volumetric

Table 1
Relationships between the tests, rules (●) and operating modes.

Tests and rules	Operating mode (regime)										
Test name	All regimes	Off	Ventilate	Ventilate-byp	Ventilate-hre	Heating	Cooling	Cooling-byp	Cooling-hre	Humidifying	Unknown
Working time	●										
Obedience to BMS	●										
Regimes cycling	●										
Dampers		●	●	●	●	●	●	●	●	●	
Heater/Cooler operation		●	●	●	●	●	●	●	●	●	
Regime suitability			●	●	●	●	●	●	●	●	
Conservation of energy			●	●	●	●	●	●	●	●	
Water dt on coil						●	●	●	●	●	
Air/water dt on coil						●	●	●	●	●	
Oscillation of signals	●										
Undersizing	●					●	●	●	●	●	
Fans											●
Missing data, out of range	●●										
Comfort	●										
Unknown oper. mode											●
Low air-flow			●	●	●	●	●	●	●	●	
Oversizing						●	●		●		
HRE operation						●			●		

air flow rate occurs at the 95% quantile of flow velocity. Using the maximum value is problematic, since it usually represents an outlier.

In addition to analysing the history of individual signals, long-term data on equipment for which there is no common data point, such as exchanger efficiency, is also evaluated. These characteristics, estimated from a long data section are then used, for example, in virtual sensors, where they help determine, for example, the air temperature beyond the exchanger. Changing the efficiency of the exchanger compared to the long-term average (e. g. clogging of the exchanger) is itself a diagnostic rule.

3. Validation

The control algorithms were validated on real devices incorporated in a pilot plant. In total, 25 operating faults on 6 AHU were intentionally caused in the Czech Technical University (CTU) building in Buštěhrad (Fig. 3) to be subsequently detected by an expert system. Some faults were invoked in all 6 units, some only in a few. In total, 105 incidents occurred, of which 94 faults were adequately detected. During the validation process, a set of operating data with corresponding faults schedule was created; this dataset is publicly available in the annex to this article.

3.1. Tested VAC units

A typical scheme (see Fig. 4) was used for the validation of the 6 single units in the CTU building in Buštěhrad. The tested units contained a plate exchanger for heat recovery, with bypass, heater and cooler, and on one unit an air humidifier. A more detailed specification of the units is given in Table 2.

3.2. Induced faults

On the whole, the operating faults were induced by writing the required value directly into the BMS control module for the building via the access interface Mervis IDE. This method allowed us, for example, to close a valve even if the information on the valve position required by the regulator still went to the SCADA system. As a result, the fault (stuck valve) would appear same as a real fault. However, in some cases, it was more useful to induce the faults using the SCADA server or to induce them mechanically, directly at the relevant AHU. All 25 faults are listed in Table 3.

3.3. Evaluation

For evaluation purposes, an analysis was made of how the diagnostic tool reacted to each fault and whether the fault was detected. The following options were possible:

1) Anticipated reaction: The tests for the detection of the specific fault give positive results for the critical period. If the reaction is anticipated, the fault is always detected. Out of 105 cases, an anticipated reaction occurred in 79.

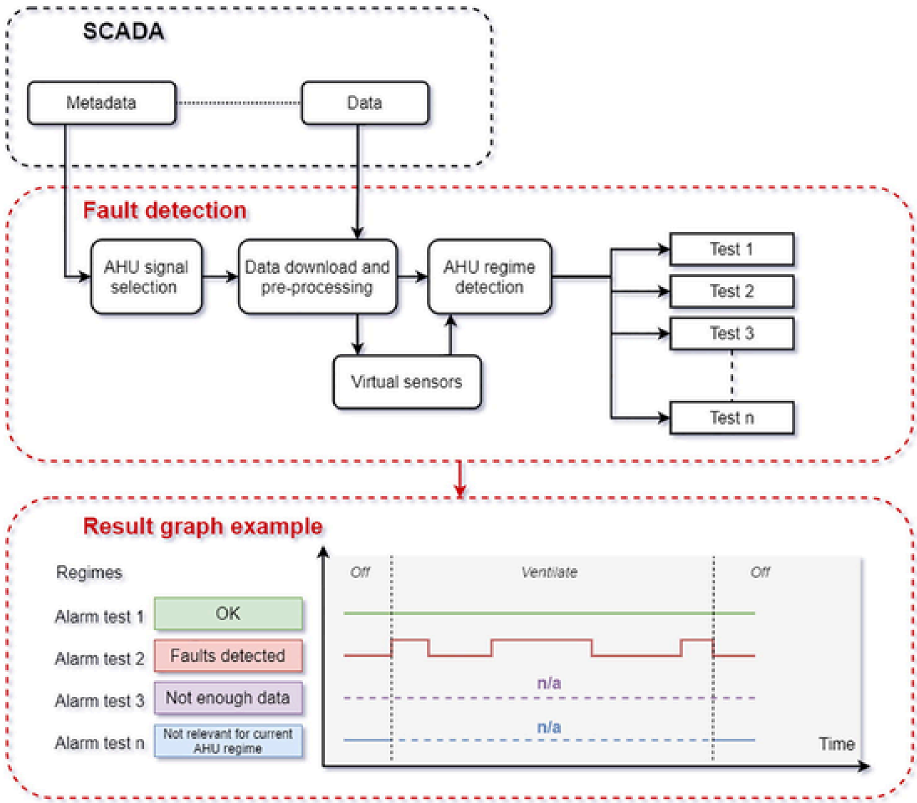

Fig. 2. Fault detection process.

Fig. 3. CTU-UCEEB building.

2) Other reaction: Some tests give positive results when reacting to the fault, but the set of positive tests does not clearly match with the set of anticipated tests. If the intersection of these sets is empty or almost empty, the resulting evaluation is that the fault was not detected. If the reaction of the diagnostic tool slightly differs from the anticipated reaction (e.g. one positive test is missing or false positive), the resulting evaluation is that the fault was detected, even though the reaction of the diagnostic tool did not fully meet the anticipated reaction. Out of 105 cases, an other reaction occurred in 21.
3) No reaction: If there is no positive test when reacting to the caused fault, the resulting evaluation is always that the fault was not detected. Out of 105 cases, the diagnostic tool did not detect 5 faults.

In total, 105 faults were induced, of which 94 faults (90%) were detected. The remaining 11 faults were not detected. The reasons for this may have been the occurrence of another real operating fault that biased the results, or that the temperature differences during fault induc-

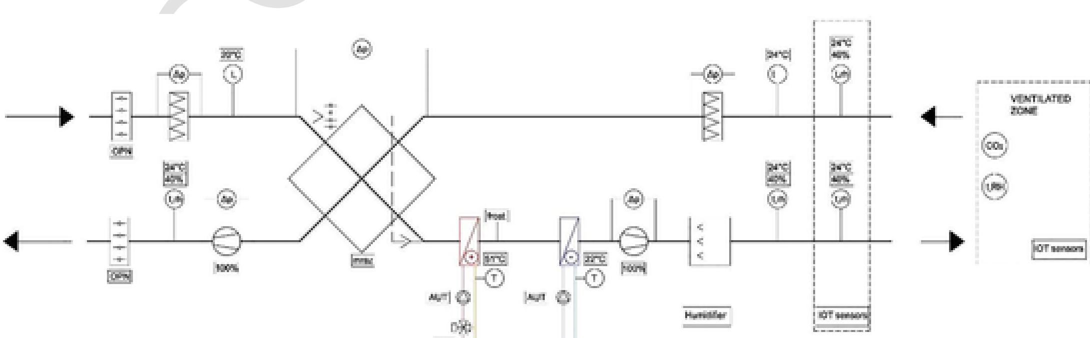

Fig. 4. Typical scheme for AHU testing.

Table 2
Specification of AHUs tested.

Label	Operated area	Air output [m ^{3}/h]	Components	Added IoT sensors
AHU1	Conference rooms, classroom	7850	HRE, heater, cooler	1x chamber SUP* 1x chamber ETA* 1x IAQ03 room 101 1x IAQ03 room 201
AHU2	Offices, passageways, kitchen, WC, cleaning room, changing room	4560	HRE, heater, cooler	1x chamber SUP* 1x chamber ETA* 2x IAQ03 Openspace
AHU8	ESEM microscope, laboratory	3680	HRE, heater, cooler, steam humidifier	1x intercooler and heater 1x chamber ETA*
AHU18	Laboratories, technical base	4420	HRE, heater, cooler	1x chamber SUP* 1x chamber ETA* 1x IAQ03 lab. 137
AHU23	Laboratories, solar simulator	4050	HRE, heater, cooler	1x chamber SUP* 1x chamber ETA*
AHU24	Firefighting room	2270	HRE, heater, cooler	1x chamber SUP* 1x chamber ETA*

* SUP – supplied air, ETA – exhaust air, IAQ – Indoor Air Quality.

Table 3
List of induced faults.

Fault		Method of causing failure	Detected	
No.	Description		YES	NO
1	Dampers are closed during heating regime	Mervis IDE	6x	–
2	Dampers are closed during cooling regime	Mervis IDE	4x	–
3	Dampers are closed during ventilate regime	Mervis IDE	3x	–
4	Heating valve is closed during heating regime	Mervis IDE	3x	1x
5	Cooling valve is closed during cooling regime	Mervis IDE	2x	2x
6	Heating pump is OFF during heating regime	Mervis IDE	2x	2x
7	Heating pump is ON during ventilate regime	Mervis IDE	2x	3x
8	Cooling pump is ON during heating regime	Mervis SCADA	4x	–
9	Heating valve is ON during ventilate regime	Mervis IDE	4x	–
10	Heating valve is stuck on 50% during heating regime	Mervis IDE	4x	–
11	Heating valve is open to the maximum level during heating regime	Mervis IDE	3x	–
12	Fans are OFF during heating regime	Mervis IDE	4x	–
13	Both tubes of differential pressure sensor disconnected	mechanically	6x	–
14	Tube of differential pressure sensor disconnected (negative pressure)	mechanically	5x	–
15	Quick regimes cycling	Mervis SCADA	6x	–
16	Heating pump is ON and valve is opened during ventilate regime	Mervis IDE	4x	–
17	Heating pump is OFF during humidifying regime	Mervis IDE	1x	–
18	Heating valve is OFF during humidifying regime	Mervis IDE	1x	–
19	Zone inlet temperature sensor reports −20 °C	Mervis IDE	6x	–
20	Zone inlet temperature sensor reports 150 °C	Mervis IDE	5x	–
21	Zone outlet temperature sensor reports −20° C	Mervis IDE	5x	–
22	Zone outlet temperature sensor reports 150 °C	Mervis IDE	6x	–
23	Heat exchanger is closed	Mervis IDE	3x	1x
24	Cooling valve is stuck on 50% during cooling regime	Mervis IDE	2x	1x
25	Cooling valve is open to the maximum level during cooling regime	Mervis IDE	3x	1x

tion were so small that the fault condition was within the range of tolerance of the sensors. In other words, not all the not-detections errors were caused by the diagnostic tool, some of them were due to unfavourable external conditions; in reality these conditions would disappear over time, so the fault could be detected.

Most of the results were anticipated reactions (79 out of a total 105 cases), whereby the detection was unambiguous. In five cases, the diagnostic tool did not detect the fault reliably. In the remaining 21 cases, the results were ambiguous. During the evaluation, some faults that ordinarily occur were also revealed, some of which arose during the construction of the building.

4. Testing in real buildings

4.1. Methods of testing

After successful validation, the diagnostic tool was applied to 124 air handling units (21 basic units and 103 single units) from several companies which were willing to make their data set available for testing of the expert system. The results of analysis were subsequently sent to them to enable them to revise their devices according to the faults detected, although their reactions to the detected faults were left to their discretion. The entire diagnostic process is presented in Fig. 5.

As the figure shows, the diagnostics starts with acquiring data sets and ideally ends with a well operating air handling unit with no faults detected. In most cases, the process was more complicated because not all participating companies were able or willing to optimise their HVAC with respect to the evaluation.

4.2. Categories of detected faults

To evaluate the results, the detected faults were divided into the following categories according to the verification level:

- Category I – faults with the highest verification level. These faults were detected by the automatic diagnostic system, confirmed by an expert and subsequently confirmed and eliminated by the participating company; in the next round of continuous commissioning they did not appear in detection anymore. From our point of view these faults are the most valuable ones because they present the ideal procedure during operation.

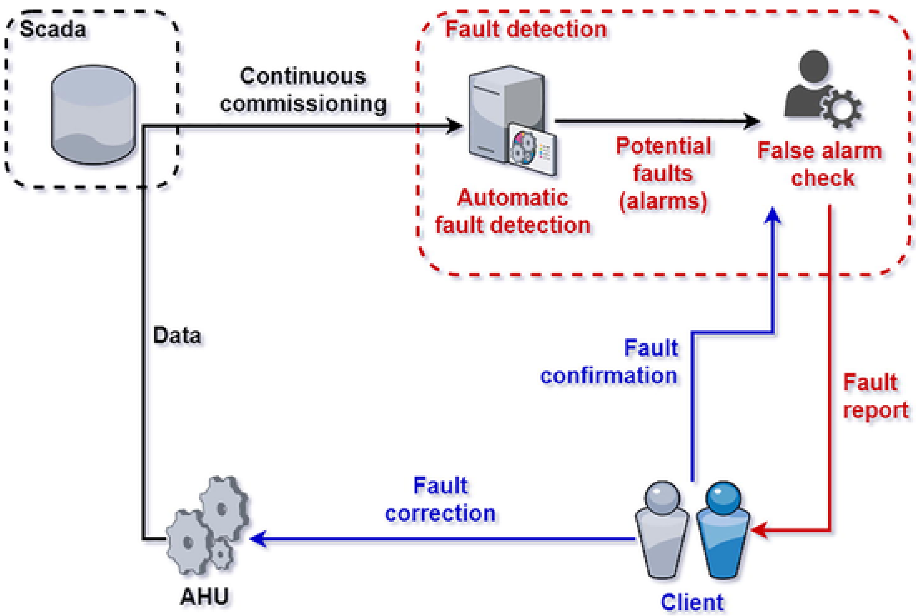

Fig. 5. Continuous commissioning.

- Category II – diagnosed faults confirmed by the client. However, these faults were intentionally induced by the client, so no remedial action was taken (e.g. flooding fault below).
- Category III – faults that were confirmed by the client, but which the participating company refused to deal with, and for which no remedial action was taken. Very often these faults occurred in the measurement and regulation system and could easily be verified in SCADA without inspecting the device physically. However, the resolution requires the adjustment of the current controlling algorithms, which may incur higher costs than the client is willing to accept.
- Category IV – faults that passed only the first two points of the defined course without any feedback from the participating company confirming the fault on the device. The fault was detected and subsequently verified by an expert, so it is very probably valid. For example, sensors may have been defective, setpoints not observed, etc.

Other faults with a lower verification level include faults detected by an automatic diagnostic, but not confirmed by experts for any reason.

5. Results

5.1. Detected faults by category

In total, 73 faults were detected in 58 AHUs during testing in real buildings. Of these, 60 were confirmed, of which 18 by the participating companies (categories I, II, III) and 42 through the analysis of the measured data (category IV). 10 faults were not resolved because the buildings, including the AHU, were going to be renovated. For the remaining 3 faults there were no responses from the participating companies.

Of the detected faults, 12 can be considered as confirmed and remedied; their occurrence and subsequent repair were confirmed by the participating company (category I). There were 4 faults detected of category II (faults with intentional switch into manual control), as well as 2 faults of category III, which were confirmed by the participating companies, but not resolved. For the other 42 detected faults, there was no feedback from the participating companies (category IV), only 2 were resolved as verified by continuous commissioning. The detected faults according to the categories are summarized in Table 4.

5.2. Causes and examples of detected faults

The most frequently detected fault related to when the AHU was in operation out of working hours, or on the contrary, when the AHU was switched off during working hours. This fault can be detected very easily and has a significant impact on energy waste and comfort inside buildings. Other quite frequently detected faults related to control logic of coolers and heaters or their operation during periods when they were supposed to be switched off, for example their concurrence or improperly defined controlling algorithms. A typical situation was when the AHU was in heating mode in the morning, which then had to switch to cooling or concurrent mode. In such situations it is desirable to set the dead band properly, so there is a suitable interval between switching from one mode to the other (e.g. 1 h). As predicted, faults were detected also at heat recovery control. In some cases, the heat recovery was launched under climatic conditions where the outdoor air was primarily cooled as it flowed through the HRE and then heated up to the required temperature. In other cases, the heat recovery capacity was not fully used and subsequently the air was heated up in the heater. Both variants lead to a waste of energy on heating. In the following sections, examples of some faults, including their subsequent solution, are illustrated.

Table 4
Detected faults by category.

Detected				
73				
Confirmed by participating company			Data-confirmed	Unconfirmed
18				
I	II	III	IV	
12	4	2	42	13

5.2.1. Recurring problems

AHU type: Single unit
Heat recovery exchanger: Plate without bypass
Heating: Yes
Cooling: Yes
Humidification: No

The diagnostic system detected that the fan would not respond to the running command. The problem was reported to the administrator. The fault was caused by a faulty differential pressure sensor. The problem was not resolved until nine months after the fault report. After its repair, the sensor reacted correctly. The repair enabled the activation of more detection rules, whereby continuous commissioning revealed another problem, namely simultaneous cooling and heating. According to the operator, the AHU was connected to the central source of cold and heat that is controlled manually by a technician. If the heating boiler is in operation, the cooling is shut down and vice versa. However, this represents a manual substitution of an automatic operation mode that should be used only as a temporary solution for the issue. This problem was reported 24 days after having resolved the previous situation. 4 days later the software of the BMS system was updated, resulting in the second fault also being resolved. However, at a later date the fault occurred again, which remains unresolved. Some personnel changes took place at the operator, which also affected the ability to take remedial action.

5.2.2. Excess humidification

AHU type: Single unit
Heat recovery exchanger: Wheel
Heating: Yes
Cooling: Yes
Humidification: Yes

Another example of a detected fault was the simultaneous humidification and cooling in two AHUs. In both cases, the humidification control should have followed the desired relative humidity (43% during working hours and 35% out of working hours). However, humidification was functioning even during cooling and even though the exterior humidity was higher than desired (dehumidification by cooler). The problem was reported to the administrator, who arranged for the humidifiers to be shut down manually. In the future, there are planned adjustments to the control system to ensure, among other things, that concurrent humidification and cooling will be blocked. There was a great deal of information available on this system, so in this case it was possible to calculate the financial savings after the fault repair, which were estimated at USD 16,000/year.

5.2.3. Heated up plant (Heating up)

AHU type: Single unit
Heat recovery exchanger: Wheel
Heating: Yes
Cooling: Yes
Humidification: No

The automatic detection system recognized running outside of the buildinǵs working hours (the inlet and outlet fans were constantly running) and identified the fact that the temperature of the intake air was very high. It appeared that this was caused by the need to heat up two floors in the building to dry out rooms after flooding. Heating up the rooms took place one morning, but from that day on, the VAC ran nonstop in manual mode for 49 days. After being switched back to standard mode, continuous commissioning revealed that the fans did not operate in accordance with their commands. As a consequence, the differential pressure sensors were changed and everything returned to normal.

6. Discussion

6.1. Comparison with existing methods

The FDD tool presented in this paper is rule-based. The goal of Závorka [52] was to use the same validation data set from UCEEB buildings using an alternative approach, namely artificial intelligence. Various types of decision trees were used in order to train a set of FDD rules. Oblique decision trees provided the best results compared to basic decision trees and random forest algorithms.

However, the results were not satisfactory due to the small amount of faulty training data. The decision trees overfit the data, resulting in rules that were irrelevant to the particular faults and worked only on the training and validation data sets. Similar findings related to over-fitting also discussed Zhao et al. [54]. However, the authors do not draw any general conclusions about rule-based and data-driven FDD methods based on these results.

The goal of this study is not the maximum success of fault detection for a particular AHU, but a satisfactory detection rate for the maximum amount of AHU. Authors agree with Lin et al. [27], saying that it is difficult to draw comparisons or understand the overall state of technology, as each study uses different datasets, test conditions, and metrics. We can add that the tool presented by us shows a success rate of 90%, which we consider sufficient due to the breadth of coverage. Pena et al. [30] presented FDD tool for entire building, which goes into larger entities in less detail and shows a specificity of 90% as well as a sensitivity of 95%. Another similar tool DABO [6], proved a success rate of about 84% [16].

6.2. Practical issues and complications

In the set of tested units there were basic units for only fresh air supply, single units with plate HRE, with and without bypass, units with a heat wheel, and units with heat recovery through glycol circuits, all of them with or without heater, cooler or humidifier. The detection system is not yet able to detect faults in units with a mixing air damper.

In addition to fault detection, estimating the wasted energy was also given consideration. This turned out to be much more complex than the fault detection itself. The calculation is complicated by the fact that the size of the relevant AHU is usually unknown. During the work, these basic parameters proved to be difficult to determine. Usually the owners operate AHUs without detailed knowledge thereof because the documentation either does not exist, is not available, or nobody is willing to find it. Even if detailed AHU parameters were available, the calculation of wasted energy can only be an approximation. For example, the performance of a heater running unnecessarily could be calculated from air temperature differences and air flow or from water temperature differences and water flow. However, all three crucial parameters are usually not available. Generally, only one of the three parameters is available and the two remaining parameters have to be estimated with the help of virtual sensors, so they are inaccurate. The final calculation of wasted energy can therefore only really be used for comparative purposes with regards to establishing fault severity in relation to other faults. However, the absolute value needed, for example for invoicing purposes, is lacking. As a result, and for development purposes, this will not be quantified in kilowatt-hours of wasted energy in the future, but as a dimensionless severity index.

6.3. Practical applicability

This article deals with AHU fault detection method design. However, in practice, effective cooperation with local technicians and managers is crucial for fixing detected faults. We were surprised by the high level of resistance from many technicians, resulting in unfixed faults. In general, technicians were sceptical that someone without detailed knowledge of the current HVAC could give advice on how to operate it. In almost all cases, the local staff were in a hurry and did not have time to deal with analytical findings. We had the best experience with those companies that own (or operate) several buildings. In these companies, there is usually a manager responsible for HVAC operations who is willing to fully exploit the added value of automated fault detection.

Another major practical problem was that none of the participating companies were in a position to a priori estimate the potential savings that could be generated through the application of fault detection methods (in contrast to conventional energy savings methods like insulation). The reliable automated estimation of energy and cost savings is a far more complicated task than fault detection. Expert knowledge is needed for fault diagnostics and the estimation of monetary consequences.

6.4. Market readiness

HVAC fault detection methods have been widely investigated since the 1980s. Despite this, fault detection still does not form part of common HVAC operations today. This is mainly due to the low level of portability of fault detection methods and therefore the high cost of fault detection applications. As mentioned previously, we are seeking to address this issue through the design of a versatile AHU fault detection system that can be applied to a wide range of AHUs. More importantly, the increasing importance of semantic data in building management systems will play an important role in making fault detection methods more widespread. Major companies such as Siemens and Johnson Controls are acknowledging this [8]. The expectation is that semantic data will become a common part of BMS within a few years. As a result, the application of fault detection methods should then become surprisingly simple, cheap and a common part of BMS.

7. Conclusions

The system of automatic fault detection in AHUs, as presented in this paper, proved to be functional and useful. The system shows a high success rate with a relatively wide range of detected faults. It covers several types of AHU. The main advantage of the presented tool is the fact that it covers the full range of issues: the authors not only present algorithms for fault detection, but also address data sources, semantic description of data, portability, and the application of the tool to a wide range of AHUs. Portability of the tool is the key to expanding fault detection in the market and its adoption as a common component of BMS or SCADA. As part of the development, many dozens of AHUs were automatically commissioned, while data point tagging and connection to the detection system was handled by one person in a few working days, despite the fact that this involved AHUs of various types in dozens of buildings across the country.

The effectiveness of the detection algorithms was demonstrated in a controlled environment on the basis of artificially induced faults. Authors note, that the data set created for the validation of algorithms is a part of this paper. This verification produced a 90% fault detection rate. In addition, some natural faults were detected that occurred when the AHU was taken into operation or which occurred during operation and were not detected (e.g. burnt bypass damper drive in AHU used for ventilation of a fire laboratory).

Fault detection has proven to be useful and provides high added value not only in a controlled environment, but also in practice. Dozens of faults were confirmed and the savings achieved by their elimination ranged from zero to about USD 16,000/year. The costs of continuous commissioning of one AHU are not precisely quantified and may vary from case to case, but are in the order of hundreds of USD/year. In some cases, banal faults in information sensors were found – seemingly without any impact on the economics of operation. However, their removal made it possible to detect hitherto hidden fundamental faults, such as simultaneous heating and cooling.

Uncited reference

[37].

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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