Data-driven fault detection and diagnosis: research and applications for HVAC systems in buildings

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Editorial

Data-Driven Fault Detection and Diagnosis: Research and Applications for HVAC Systems in Buildings

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The main goal of Fault Detection and Diagnosis (FDD) processes is to identify faults, determine their sources, and recognize solutions before the system is further harmed or service is lost. Therefore, fully understanding an FDD process requires knowledge of the definition of "fault". Melgaard et al. [1] and Chen et al. [2] indicated that "a fault is an unpermitted deviation of at least one characteristic property (feature) of the system from the acceptable, usual, standard condition". Moreover, according to Chen et al. [2], the additional definitions of "malfunction" and "failure" have to be clarified and taken into account; a "failure" is defined as "a permanent interruption of a system's ability to perform a required function under specified operating conditions", whereas a "malfunction" is defined as "an intermittent irregularity in the fulfillment of a system's desired function". One system may malfunction due to a fault, which may ultimately result in the failure of that system.

Typically, FDD is characterized by three key processes: fault isolation, fault identification, and fault detection [1]. Fault diagnosis is the term used to describe fault isolation and fault identification. Without identifying the root cause of the defect, fault detection seeks to identify improper operation in a system (by merely indicating that something is not operating as intended). Contrarily, fault diagnostics seek to pinpoint the type of defect that occurred in a system, as well as its location, severity, and timing. Melgaard et al. [1] suggested that fault evaluation might come after fault detection and diagnosis, with the fault impact on a system that can be evaluated in terms of energy consumption, expenses, indoor comfort, equipment lifetime, etc. After evaluating the fault, a choice is made on whether or not to take actions in response to the fault occurrence. Detection, isolation, identification, and evaluation are the four phases that make up the procedure known as Automated Fault Detection and Diagnosis (AFDD).

This editorial provides an overview on the current research trends in the field of FDD, with specific reference to applications in heating, ventilation and air-conditioning (HVAC) systems. Key findings of several recent studies collected from scientific papers published in the journal *Energies* in the last 4 years are discussed. In particular, three main topics are analyzed: (i) FDD classification and taxonomy, (ii) approaches to data-driven FDD in HVAC systems, (iii) deployment of FDD strategies in buildings and related impact assessment.

According to Chen et al. [2], different FDD programs generally adopt inconsistent fault naming rules, with arbitrary fault names being used by multiple FDD tool vendors or even between different iterations of the same software tool. This issue makes the data more difficult to be analyzed and generates a clear mismatch across various FDD reports or software (with the risk that fault messages can only be interpreted by FDD tool developers). In order to combine the data from various sources into a coherent and shared knowledge framework, system and software outputs that present inconsistent naming conventions, hierarchical physical granularity of reporting, and descriptions of efficiency possibilities must be synthesized. To create data models and improve data

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Citation: Rosato, A.; Piscitelli, M.S.; Capozzoli, A. Data-Driven Fault Detection and Diagnosis: Research and Applications for HVAC Systems in Buildings. *Energies* **2023**, *16*, 854. https://doi.org/10.3390/en16020854

Received: 14 November 2022
Revised: 6 January 2023
Accepted: 6 January 2023
Published: 11 January 2023

representability and interoperability, two semantic techniques can be used: one type uses a taxonomy to define data terminology; the other uses an ontological frame to explain data structure and relations. Despite the fact that different methodologies were used to create a fault taxonomy in the HVAC industry, Chen et al. [2] highlighted that these methodologies rarely took the faults reported by FDD software into account; as a result, the developed taxonomy was insufficient to describe data obtained from different FDD tool reports. This is primarily because (i) the physical configuration elements of an HVAC system were not fully addressed by the majority of FDD tools, and (ii) the existing taxonomy does not effectively depict relationships between different types of defects. Because of this, Chen et al. [2] introduced a consistent taxonomy for HVAC system defects to permit effective comprehension and mining of the data from different FDD software reports. They created a taxonomy including a design schema made up of four components: (1) equipment physical configuration hierarchy, (2) controlled vocabularies for fault nature descriptions, (3) unified fault identification codes and fault library, and (4) fault relation models for locating condition-based faults and related behavior-based faults. The proposed taxonomy includes a library of 293 defects and covers three main types of HVAC systems (RoofTop Units (RTUs), Air-Handling Units (AHUs), and Air Terminal Units (ATUs)).

In the past, FDD approaches have been categorized in a number of ways in the literature. According to Rafati et al. [3], there are two primary categories of FDD techniques used in buildings: knowledge-based and data-driven-based approaches. Knowledge-based approaches rely on the use of past information to construct rules or models for defect detection and diagnosis; expert engineers must put in a lot of effort to use knowledge-based approaches since they are very sophisticated, and the related models are difficult to be adapted to new systems and settings because they are tailored to specific ones [3]. On the other hand, data-driven approaches, which typically do not use physics-based laws, can automatically extract patterns for FDD based on the similarity of metrics. The main drawback of such methods is the requirement for separate datasets of both faulty and fault-free operations; as a result, training with unidentified faulty data can produce inaccurate FDD results, and may reduce the ability to detect and diagnose faults. Therefore, these FDD techniques cannot be used for newly installed systems or new operational situations due to the lack of data [3]. In recent decades, the majority of research on FDD has focused on data-driven methods as reported by Rafati et al. [3]. In particular, non-intrusive load monitoring has been developed to determine the power consumption of home appliances and equipment using an aggregated power measurement at power entry. Melgaard et al. [1] also made an effort to organize the classifications found in the literature they surveyed; they proposed a classification of FDD methods as either model-based or data-based in order to indicate whether or not historical measurements are required to develop the FDD process. In the case where model-based methodologies are adopted, professionals can develop the FDD tools by using only the building or system's metadata, while data-based methods require calibrated measurement training data. The FDD approaches mentioned above have been further classified into "qualitative" and "quantitative" methods [1]. While model-based quantitative methods focus more on using a reference model to be compared with measurements from the system, data-based quantitative methods use statistics or data-mining (data clustering, pattern recognition, and classification) to extract the knowledge from the data. Both model- and data-driven-based qualitative methods focus on rules and relationships between the parameters. Melgaard et al. [1] acknowledged that a number of the FDD approaches reported in the literature combine algorithms from both data-driven-and model-based methods. The most sophisticated FDD algorithms, according to Melgaard et al. [1], use machine learning (ML) techniques, including supervised or unsupervised learning. The adaptability of these algorithms in identifying patterns and trends from the gathered data offers significant potential for complex and practical applications. Despite this, these algorithms rely on system-specific data and this leads to customized models, which extends engineering time and costs.

Bezyan et al. [4] proposed a novel data-driven methodology for the detection and diagnosis of faults in the AHUs of HVAC systems. In particular, the authors developed a process for the detection and diagnosis of multiple dependent faults pertaining to the temperature sensors installed in an AHU (i.e., the mixed air temperature (T_{ma}) sensor and the air temperature sensor after the heating coil (T_{hac})). The process unfolds over different steps to address the detection and diagnosis task. Firstly, real data collected through a building automation system (BAS) are pre-processed to ensure the quality of the dataset, they are then segmented in training and testing datasets. At this stage a compound model, using two different but related models, is developed to obtain time step by time step the estimated values of T_{ma} and T_{hac} that represent the normal operation of the system. The following phase is aimed to perform a residual analysis, considering the bias between actual and predicted values through ML models. Eventually, in the case of the residual analysis suggests the occurrence of a fault symptom (i.e., the bias exceeds a defined threshold), the fault diagnosis module is triggered. Specifically, two groups of expert-based IF-THEN rules are used for conducting fault diagnosis based on whether a fault symptom is identified for T_{ma} or T_{hac}. This study demonstrated the effectiveness of the combination between ML-based detection models with rule-based diagnosis strategies for the implementation of FDD processes in AHUs. This kind of hybridization is essential to optimize the implementation time of data-driven FDD strategies (given the reduced need of pre-labelled data for the development of diagnosis models), increasing the robustness and generalizability of the approach. Another innovative aspect is related to the exploitation of information concerning the relationship and operation flow between sensors for the correct detection and diagnosis of dependent faults, often leading to misdetection and misdiagnosis issues.

Boahen et al. [5] developed an FDD methodology for detecting and diagnosing refrigerant charge faults on a water-to-water heat pump. Refrigerant charge faults have an adverse effect on the performance of heat pumps and their early identification is of great importance. In particular, authors performed a number of experiments under different boundary conditions (refrigerant undercharge/overcharge) to characterize the operational performance of a real water-to-water heat pump in both the heating and cooling modes. Experimental data have been then used to fit 2nd-and 3rd-order polynomial equations to estimate the refrigerant charge ratio (RCR) in the cooling and heating modes, respectively. Specifically, compressor discharge temperature, evaporating temperature, condensing temperature and degree of subcooling have been considered as input variables in the RCR estimation models. The estimated RCR is compared with the optimum refrigerant charge amount corresponding to the maximum coefficient of performance (COP) of the heat pump unit (the optimal RCR was identified during the experimental tests). At this stage a refrigerant fault is detected when the absolute difference between the predicted RCR and the optimum charge ratio exceeds a predetermined threshold error. After detecting a refrigerant fault, the diagnosis module is triggered. Additionally, in this case, the fault diagnosis is rule-based and exploits qualitative fault-symptom tables obtained through the experimental tests to diagnose the detected fault. The proposed FDD algorithm was able to detect refrigerant charge faults in the water-to-water heat pump within an error threshold of 4.5% and 1.1% in the cooling and heating modes, respectively, outperforming the results obtained in other studies especially concerning the fault sensitivity in the cooling mode.

Kim I. and Kim W. [6] presented a data-driven FDD approach that uses ML classification methods to detect and diagnose faults in a 90 ton (approximately 316 kW) centrifugal chiller system. Faulty and normal chiller operational data refer to the ASHRAE Project 1043-RP that collects experimental datasets about chiller faults with different severities. Six typical faults with four severity levels were investigated in this study, i.e., refrigerant overcharge (RO), refrigerant leakage (RL), reduced evaporator water flow (EWF), reduced condenser water flow (CWF), non-condensable in refrigerant (NC), and condenser fouling (CF). The proposed FDD process in this case is completely based on the use of ML techniques. Specifically, the detection and diagnosis tasks are simultaneously addressed by formulating the FDD process as a classification problem, where different ML and statistical models are used to classify the chiller operation as "normal" or affected by one of the six faults under analysis (i.e., RO, RL, EWF, CWF, NC and CF). The following classification models are employed in this study: logistic regression (LR), support vector machine (SVM), random forest (RF), and extreme gradient boosting (EGB). Eventually, when testing the robustness of the approach, different training scenarios for the classification models are considered by defining situations where the training data are sufficient and other situations affected by data-scarcity. The obtained results demonstrated that the RF and EGB methods achieved high-FDD accuracy for all the investigated scenarios, also in the case of insufficient training dataset. This is an important aspect for the implementation of fully ML-based FDD strategies in the real world in terms of both generalizability and robustness of the data-driven approach.

Building analytical tools, including fault detection and diagnostic tools, have emerged as key instruments in enhancing building energy performance during operation by supporting building operators to translate knowledge extracted from measured data into actionable energy-saving strategies. To promote the penetration of data analytics-based FDD tools and support technology innovation, building owners and technology developers need reliable evidence-based guidance on deployment practices. As a reference, Trothe et al. [7] reported that, in the United States, incorrect HVAC on/off modes are responsible for an over-cost of approximately $920 million per year, while inappropriate operational set-points contribute another $492 million per year.

From this perspective, Lin et al. [8] presented savings, costs, and the state of practice resulting from the implementation of FDD tools in analyzing data from the U.S. Department of Energy's Smart Energy Analytics Campaign from 2016–2020. In particular, it was found that organizations using FDD tools achieved 9% median energy savings considering a median base cost and annual recurring software cost for FDD equal to 0.65 $\$/m^2$ and 0.22 $\$/m^2$, respectively. The study also reported a two-year simple payback period associated with the implementation of FDD tools primarily aimed at improving HVAC scheduling, optimizing economizer operations, avoiding simultaneous heating and cooling, resetting setpoints, and adopting dozens of additional measures. Despite data analytics-based FDD tools demonstrated their high competitiveness as a profitable investment option in the building sector, their full penetration in the market has been thwarted by deployment issues.

The first main deployment issue is related to the integration phase of analytical FDD tools. In fact, an accurate and effective collection and integration of data coming from different, heterogeneous sources is typically challenging and requires long configuration times. Operational variables measured in energy systems and typical faulty conditions often have inconsistent names, causing a complex interpretation of the data content, type, location, unit, and relationships to other equipment. With the aim of providing a contribution in this field, Chen et al. [2] proposed a unified taxonomy for HVAC system faults. The defined taxonomy allows the classification of HVAC faults according to their main features and causal relationships. The taxonomy includes fault categorization, physical hierarchy, a fault library, relation models, and a structured vocabulary library to increase data interpretability. The developed taxonomy can be used for FDD tool standardization, de facto increasing the degree of generalizability and reducing the need for extensive expertise and labor-intensive effort for their configuration.

Another topic area requiring further research to enhance FDD deployment pertains to the optimization of the information–intervention loop triggered by an FDD system. FDD tools are classified as decision support systems that include a human-in-the-loop paradigm to transform extracted knowledge in actionable energy conservation measures. However, building staff and technicians often do not have enough time to review the analytical tool reports and findings, and take actions to restore the normal operation of the system and obtain the consequent energy saving. In this perspective, automating the process of fixing faults could be a key solution for reducing costs and increasing savings of data-driven FDD systems. Lin et al. [9] contributed in this research area developing and implementing an automated fault-correction algorithm for HVAC systems in buildings. Starting from the assumption that it is not possible to automate the correction of mechanical faults, such as failed actuators, they identified a subset of faults that can be fixed automatically by closing the loop between diagnostics and control and then overwriting the control signal in the BAS with a corrected or improved one. The study introduced nine algorithms designed to correct faults in HVAC systems related to incorrectly programmed schedules, overriding manual controls, sensors bias, control hunting, rogue zones and setpoints or setpoints setbacks. The obtained results confirmed the efficacy of a subset of these algorithms, highlighting the high potential of such correction routines in improving operational and maintenance processes in buildings.

In conclusion, fault detection and diagnosis in HVAC systems currently represents one of the main solutions to enhance the energy performance of buildings during their operation. The literature provides evidence of the added value of a data-driven approach in this field; however, a research gap still exists between the theoretical FDD strategies and the real-world applications. Firstly, due to their dependency on training datasets, data-driven FDD tools are more sensitive to generalizability and transferability issues that are, conversely, the main strengths of knowledge-based methods. From this perspective, Rafati et al. [3] stated that the development of data-driven FDD strategies is hampered by the lack of public datasets, and additional research must be conducted to gather and make available to the public the real-world HVAC datasets for a variety of building types, including residential, industrial, commercial, and public buildings. In addition, Chen et al. [2] highlighted the need to extend current fault libraries so that they can cover novel faults when new equipment, physical configurations or additional components are used in HVAC systems. Eventually, Trothe et al. [7] also pointed out the importance of a well-configured monitoring infrastructure for effective, efficient and successful fault diagnosis. In this sense, further investigations are needed to generalize the optimal identification of sensor numbers and locations in buildings that keep FDD tools economically feasible while increasing their capabilities in reducing the operational and maintenance costs of HVAC systems during operation.

Author Contributions: Conceptualization, A.R., M.S.P. and A.C.; methodology, A.R., M.S.P. and A.C.; software, A.R., M.S.P. and A.C.; validation, A.R., M.S.P. and A.C.; formal analysis, A.R., M.S.P. and A.C.; investigation, A.R., M.S.P. and A.C.; resources, A.R., M.S.P. and A.C.; data curation, A.R., M.S.P. and A.C.; writing—original draft preparation, A.R., M.S.P. and A.C.; writing—review and editing, A.R., M.S.P. and A.C.; visualization, A.R., M.S.P. and A.C.; supervision, A.R., M.S.P. and A.C.; project administration, A.R., M.S.P. and A.C.; funding acquisition, A.R., M.S.P. and A.C. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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