Barriers and drivers for implementation of automatic fault detection and diagnosis in buildings and HVAC systems

An outlook from industry experts

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Barriers and drivers for implementation of automatic fault detection and diagnosis in buildings and HVAC systems: An outlook from industry experts

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A B S T R A C T

This study aimed to assess the current status of Fault Detection and Diagnosis (FDD) implementation in building and Heating, Ventilation and Air Conditioning (HVAC) systems in the building industry. Semi-structured qualitative interviews were conducted with 29 experts from different HVAC company types in the building industry. In addition, a literature review was performed to investigate academic research on FDD implementation. The study identified barriers and drivers to implementing FDD systems, these included; technological and technical, economic and business, users, social and societal, and regulatory. An Automatic Fault Detection and Diagnosis (AFDD) implementation matrix was developed to evaluate FDD implementation in building systems, and all interviewed companies were classified based on their FDD knowledge, services, and type. Results show that expert-rule systems are still prevalent in the industry. The literature review revealed a scarcity of FDD implementation studies in academic research due to challenges in testing and validating results in actual building operation conditions. Lastly, this study discusses the key findings: 1) FDD does not sell, 2) Lack of actively engaging and promoting FDD services, 3) FDD seems to be an academic definition, 4) The bottlenecks: The fault handling process and user's mindset towards FDD, and 5) Governmental regulations and legislatives drive the implementation focus.

1. Introduction

The introduction is divided into three subsections, Motivations; background and motivations of this study, Definitions and concepts; definitions for the usage of specific terms in the context of this article and Contribution and structure of the article.

1.1. Motivations

The European Union (EU) has committed to cutting greenhouse gas emissions by at least 55 % before 2030 compared to 1990 [1]. As well known, the building sector is responsible for approximately 36 % of the greenhouse gas emissions in the EU, with 75 % of the building stock being deemed energy inefficient [1]. Hence, the building stock is a clear target for increasing energy efficiency. The latter can be reached through several initiatives, e.g., when renovating buildings, aiming for Nearly Zero-Energy Buildings (NZEB) [2]. Moreover, improving the energy efficiency of Heating, Ventilation, and Air Conditioning (HVAC) systems is another key initiative. However, the operational efficiency of these systems is often less than the nominal efficiency, which can be addressed through optimized building automation and technical system monitoring and control [2]. This can be achieved through several approaches, including Model Predictive Control (MPC) [3], Fault Detection and Diagnosis (FDD), and Occupant-Centric Controls (OCC) [4,5].

In this study, the focus will be on FDD, which has been the subject of extensive research but remains underutilized in real-world buildings [6]. While newer large buildings are equipped with integrated Building Management Systems (BMS), these systems are primarily designed for management and supervision rather than analytics or FDD. This is reflected in the basic form of FDD commonly used in the form of expert systems, where fixed boundaries are set by domain experts to trigger alarms based on thresholds. This approach often leads to many false alarms, making it difficult for building operators to prioritize significant faults amidst the numerous alarms. This highlights the need for effective fault detection and diagnosis in buildings. A study conducted in the United States of America (USA) found that 13 key faults identified in commercial buildings accounted for between 4 % and 18 % of energy

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Nomenclature

Abbreviation

AFDD	Automated Fault Detection and Diagnosis
AFD	Automated Fault Detection
AI	Artificial Intelligence
AHU	Air Handling Unit
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
APAR	Air-handling unit Performance Assessment Rules
BMS	Building Management Systems
EU	European Union
FDD	Fault Detection and Diagnosis
GDPR	General Data Protection Regulation
HVAC	Heating, Ventilation, and Air Conditioning
ID	Identifier
MPC	Model Predictive Control
MC-SVM	Multi-Class Support Vector Machine
NZEB	Nearly Zero-Energy Buildings
OCC	Occupant Centric Controls
PCA	Principal Component Analysis
TU	Terminal Units
UN	United Nations
USA	United States of America
VAV	Variable Air Volume

Company

B	Building Management System companies
C	Component companies
F	Fault detection and diagnosis companies
H	Heating and cooling companies
S	Software companies
V	Ventilation system companies

use for HVAC, lighting, and refrigeration [7]. Further research confirmed these findings and showed that most commissioning efforts in existing buildings had a payback period of fewer than two years. Additionally, monitoring-based commissioning (also known as FDD) was found to have the potential to decrease the annual energy use further [8].

Previous studies have explored the perspectives of various stakeholders in the building industry and the drivers and barriers to implementing FDD in buildings.

Torabi et al. [9] focused on the impact and causes of human errors in Variable Air Volume (VAV) Air Handling Unit (AHU) control systems made by technical professionals during the design, construction and operation phase. One of the main findings were that the FDD methods had difficulties in detecting sequencing logic faults, resulting from poor programming of the control systems. Another main finding was the lack of training for the engineers creating the control system logic, resulting in either poor or unfinished control sequences and the operational personnel, causing a lack of understanding for how to properly operate the systems. Andersen et al. [10] identified barriers for increasing the smartness in the Norwegian building stock by interviewing experts within digitalization and building management and operation. The categories of the identified barriers were infrastructure, data sharing and security, psychosocial factors among end-users, implementation and business models. The study identified that psychological factors in end-users represent the most challenging barrier to overcome, according to several interview participants. They suggested that this barrier could take up to 20 years to be resolved. The main driver identified was the desire to use the digitalizing of their building to increase its energy efficiency and thus strived towards the United Nations (UN) sustainability goals and the Paris agreement [11]. Frank et al. [12] conducted a study covering both technical and economic barriers focusing on small commercial buildings (less than 1000 m^2). For the building owners and operators some of the most common barriers were cash flow, lack of time and knowledge, resources and available technologies. On the technical barriers, the lack of data collection and monitoring equipment was found to be the most significant barrier. In terms of cost and market barriers, it was found that most Automated Fault Detection and Diagnosis (AFDD) products have difficulties scaling down to smaller buildings, as the potential savings decrease, while the costs remain similar to the larger buildings, this is due to the implementation and tuning process of mainly rule-based methods. Some of the solutions to increase the implementation of AFDD systems in smaller commercial buildings were focused on providing a product that is simpler to use, requires less customization and changes the business model from a fixed monthly fee to a savings related fee. Granderson et al. [13] mainly focused on the different FDD companies and their software. It was found that most companies provide products with similar capabilities, with most focusing on rule-based methodologies, with a shift towards historical data driven slowly happening. Some of the barriers mentioned were related to the integration between different systems, uncertainty in the value added and a lack of common standards in data, metadata and semantic representation. Katipamula and Brambley [14] and Bruton et al. [15] specifically examined technical barriers to implementing FDD systems, such as selection of detection thresholds, the ability of a system to diagnose without immense prior training and the ability to handle simultaneous faults. Mills [8] identified four key barriers to the commissioning process, which can also be applied to the FDD process: training and communication among commissioning personnel, low awareness and incentives among building owners, a lack of standardization in methods and definitions, and fragmentation in the field into various small groups and certifications. Zhao et al. [16] investigated the advantages and challenges of using Artificial Intelligence (AI)-based FDD methods in building energy systems and identified seven tasks for future research, with the most relevant for this article being 1) the distinction between sensor faults and component faults, 2) balancing accuracy and reliability, and 3) transferring knowledge between systems. The first two tasks relate to the difference between the goals in academia and industry, where academia typically aims for maximum accuracy, while industry prioritizes lower accuracy for increased reliability with fewer false positives. The last task deals with data availability, where academia often has access to highly detailed labeled datasets for training FDD models. The opposite is true for industry, where such labeled datasets with ground truth on faults are rare and expensive to create, meaning that most companies does not have any experience in creating them. Thus, industry-suitable methods focus on low or no dependence on labeled datasets for a specific system or transferring models between similar systems.

Given the rapidly evolving nature of technology and the building industry, it is necessary to update and expand upon the previous findings to gain a current understanding of the barriers and drivers in implementing FDD. The authors of this study aim to build upon the existing research and provide an updated perspective on the challenges that lie ahead in the near future. To the best of the author's knowledge, such a comprehensive study has not been performed to date.

1.2. Definitions and concepts

The terms “AFDD” and “implementation” are employed in this article. Prior academic research has reported varying definitions for these terms. Hence, this section provides a specific definition for the usage of these terms in the context of this article.

1.2.1. When is fault detection and diagnosis an Automated process?

Melgaard et al. [6] identified multiple variations of FDD and its associated subprocesses. To eliminate ambiguity in discussions of these different FDD terms, an ontology was developed and utilized in this article. The term "FDD" encompasses scenarios where the fault detection and diagnosis process lack an integrated FDD mechanism within the component or system, or is solely based on expert rule-based alarm systems. Conversely, the term "AFDD" defines situations where the component or system has a built-in algorithm capable of adapting to the system, thereby accommodating a wider range of operating conditions than typically accounted for in traditional FDD methods.

1.2.2. How can we determine when fault detection and diagnosis tools are Implemented?

In a similar manner to the definition provided for FDD and AFDD, it is also necessary to clearly define the term "implementation". In this article, the term implementation is defined by the following three broad criteria:

- Continuous operation in real-time or near real-time.
- Operation within a building during normal/typical operation without the introduction of artificially induced faults.
- Provider of either FDD- or AFDD-type feedback, either in the form of information to operational personnel or as a direct control signal to the system.

Fig. 1 shows the key components required for a building to be considered to have implemented an FDD or an AFDD system based on the main criteria outlined above. These requirements only represent the highest-level considerations for classifying implementation. In practice, implementing FDD or AFDD methods requires addressing a multitude of additional considerations, some of which will be discussed in subsequent sections.

1.3. Contribution and structure of the article

This article seeks to provide valuable insights into the challenges and opportunities related to implementing FDD and AFDD in the building industry, highlighting academia's role in addressing these challenges. This study focuses on the perspective of HVAC companies supplying a range of products utilized in the building industry, including BMS and software companies, as well as component companies. A comprehensive, holistic approach is adopted to gain a thorough understanding of the topic, combining semi-structured qualitative interviews and a literature study.

The objectives of this article are to:

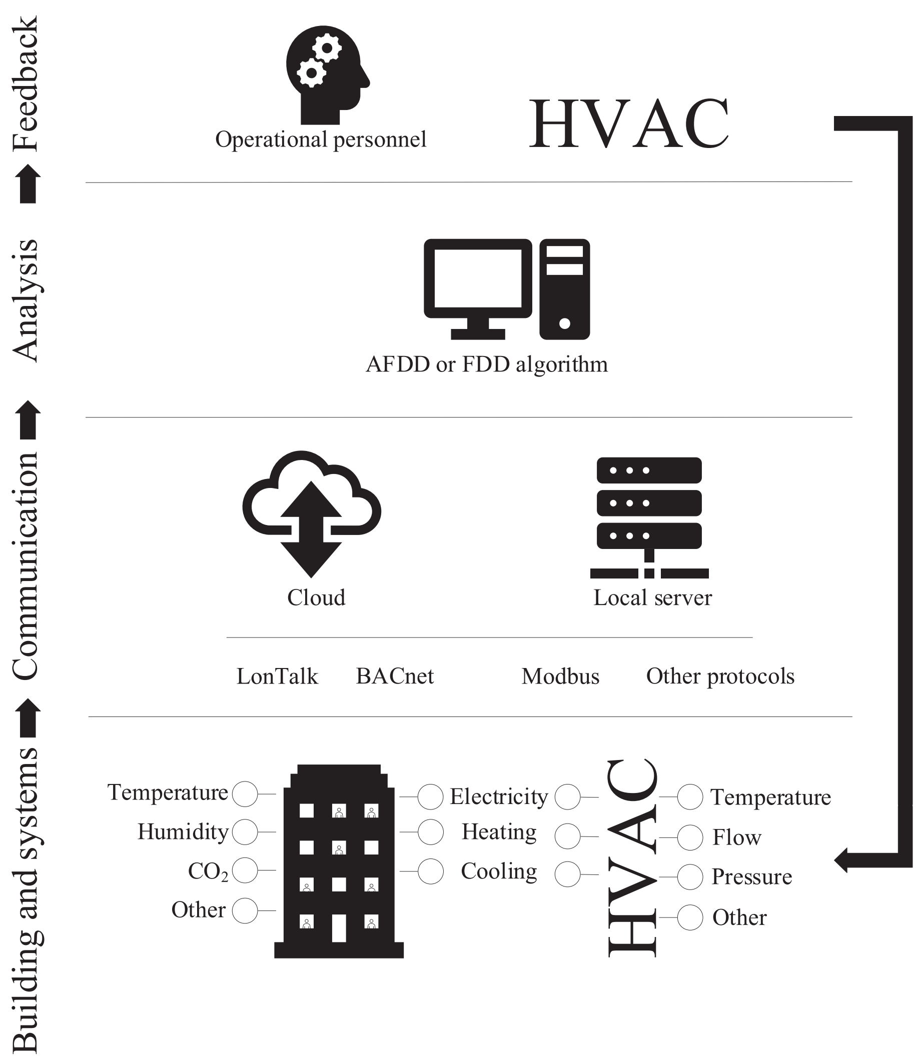

Fig. 1. Overview of the key elements that are involved in defining implementation of AFDD.

1. Assess the current state of FDD and AFDD implementation in the building industry.
2. Examine the barriers and drivers identified by the industry for implementing FDD or AFDD in building systems.

The article is structured as follows:

1. Introduction: This section provides an overview of the motivation behind the review and the definitions and concepts used in this study.
2. State-of-the-art: Implementation of fault detection and diagnosis in building systems: This section presents the results of a comprehensive literature review on the current status of FDD and AFDD in academic research.
3. Methodology: This section describes the methodology and the implementation of the semi-structured qualitative interviews conducted in this study.
4. Results: This section presents the key-findings from the interviews with the different companies in the building industry.
5. Discussion of key-findings: This section provides a discussion of the key-findings, discussing the different perspectives of the stakeholders and identified categories.
6. Conclusions and Outlook: This section makes concluding remarks and presents the future outlook for FDD and AFDD in building systems, both from the perspective of the interview participants and the findings from the literature review.

2. State-of-the-art: Implementation of fault detection and diagnosis in building systems

This section is based on the found literature in a literature review conducted by Melgaard et al. [6] which covered the existing literature on FDD in building systems from 1980 to April 2021. In addition, an updated literature search was conducted to include peer-reviewed research articles published between April 2021 and November 2022, increasing the total number of included articles to 281, thus ensuring that the article presents a comprehensive and up-to-date overview of the field of FDD in building systems.

2.1. Classification of study types

In order to understand the focus of academic research in advancing the field of FDD and AFDD for practical application in the industry, the studies included in the literature review in this paper were divided into four categories, as defined in Table 1: simulation, experimental, case and implementation studies. This categorization helps to provide a comprehensive overview of the current state of academic research in the field of FDD in building systems. It is important to note that a single study can belong to multiple categories.

Generally, the categories of simulation and experimental studies have primarily focused on the development of FDD methods, while case and implementation studies focused on evaluating the capabilities and real-world application of the various methods. The experimental and case studies have been characterized by two distinct aims. The first involves method testing, while the second is focused on generating a dataset for independent or collaborative use. This dual focus is reflected in the classification of study types, which is structured into two distinct rows in Table 1.

The following areas were considered in the pros and cons columns:

- Data resolution
- Data quality
- Data access
- Choice and control of fault types
- Control of fault severity
- Measurement accuracy
- Control of measurement location
- Cost
- Validation of the FDD method

As one can observe in Fig. 2, the analysis of the literature review showed that the number of experimental studies has increased over the years. The articles were classified according to Table 1, and the distribution of studies over the years is visualized in the figure. The data shows that a majority of the experimental studies conducted in the period of 2020–2022 (28 out of 61) utilized the datasets for chillers published as part of the ASHRAE RP-1043 [17] project, driving the trend towards an increase in experimental studies.

2.2. Implementation studies

Among the 281 articles analyzed, as shown in Fig. 2, only 12 articles, corresponding to roughly 4 %, were found to have a specific focus on implementation. It is, therefore, crucial to examine the underlying motivations and potential advantages of conducting such studies, as well as the challenges and benefits encountered during their implementation. This subsection is divided into two subsubsections based on the FDD methods tested for implementation and the challenges encountered during the implementation. The primary objective is to answer the following research questions: What is the current state of implementation studies in academic reserach, and which methods have been employed in these studies? Additionally, what are the challenges faced during building system implementation?

2.2.1. FDD methods used for building system implementation

The implementation of Automated Fault Detection (AFD) methods in several studies has been reported using various techniques. In Bang et al. [18] and Alexandersen et al. [19], the Chernoff bound method was employed, first in a linear format and subsequently in a stair-step format, applied to four identical AHUs in a university building. The results showed that both methods performed effectively, with the stair-step version performing better as the linear approach at times produced incorrect start and end dates for abnormal periods. In Pakanen and Sundquist [20] a model, based on individual processes, was used to compare measured outcomes with expected outcomes, and determine if residuals followed a normal distribution. The findings indicated that the ability to detect faults varied significantly based on the control variable. A similar approach was used by Yoshida et al. [21], where a recursive autoregressive exogenous formulation was employed as the model. Salsbury and Diamon [22] also employed a similar approach where the residuals were compared against a static threshold for fault detection.

Focusing on the FDD and AFDD methods. In Norford et al. [23] two identical AHUs were used to evaluate two FDD approaches for their performance. The first approach tested was a first-principle-based method, in which the various subsystems/components were modeled individually and combined with a rule-based method (utilizing either expert knowledge or predefined limits) to facilitate the diagnostic capabilities. The second method tested was an electrical power correlation approach, which utilized gray box models to establish the relationship between the electrical power of components such as fans or pumps and variables such as airflow or motor speed control signals. This approach was combined with an expert system to provide limited FDD capabilities. The methods were trained using four days of normal operation data, and then run for 17 days with different faults being introduced in the AHU during continuous operation. Both methods were found to have limitations in terms of false or missing alarms and incorrect diagnoses. In a separate study by Han et al. [24], an HVAC system was tested with a rule-based FDD methodology, and it was discovered that providing clear and accurate feedback to operational personnel is a crucial aspect of the FDD process. Hosamo et al. [25] used an expert rule-based approach, based on the Air handling unit Performance Assessment Rules (APAR) from Nehasil et al. [26] and Schein et al. [27]. Dey et al. [28] focused on

Table 1
Classification of the four study types for FDD in academic research and their pros and cons.

Study type	Description	Pros	Cons
Simulation studies	• The study is performed entirely in a simulation environment The training, testing, and validation data are generated artificially in a simulation environment	• The data resolution can be adjusted to what is needed or wanted No problems with data quality and missing data All types of faults can be emulated The severity of the fault can be controlled No uncertainty due to measurements Low cost as only a simulation environment is needed Validation of the FDD method is possible	• The quality of the faulty data generated depends highly on the implementation of the simulation Simulated data does not represent reality entirely Highly dependent on the simulation environment, e.g., accuracy and resemblance to reality? Realistic faults may be hard to generate or emulate in a simulation environment
Experimental studies	Aim 1: create a labeled dataset with faulty ground truth The study focuses on emulating faults and creating labeled datasets with faulty ground truth for FDD methods experimentally, in a laboratory	• The data resolution can be adjusted to what is needed or wanted Typically high-quality datasets with few missing data Real measurement dataAll types of faults can be (generated / emulated) (depending on the equipment) The severity of the fault can be controlled Low measurement error as instruments are typically lab-grade Possible to adjust the setup to get optimal sensor placement	• Increasing data resolution can be expensiveTypically high costs due to necessary equipment and experimental facilities (calibrating sensors or laboratory space) Can be time consuming
	Aim 2: test a method using a labeled dataset with faulty ground truth The study uses data from existing labeled datasets with ground truth made experimentally to train, test, and validate new FDD methods	• Typically high-quality datasets with few missing data Real measurement data Low cost as only a simulation environment is needed Validation of the FDD method is possible	• Data resolution is dependent on the dataset used and can only be downsampled Fault types limited by the dataset Fault severity limited by the dataset Fault/non-fault balance and occurrence limited by the dataset
Case studies	Aim 1: create a labeled dataset with faulty ground truth The study focuses on observing faults and creating labeled dataset with faulty ground truth for FDD methods in a real building The data have been gathered either in a measurement campaign or as a data dump from the BMS	• Measured under real operating conditions Many newer buildings are already highly monitored, making it possible to use the data from the BMS Cheap to obtain an unlabeled dataset with measurements	• Data resolution can be difficult to adjust if obtained from the BMS Many BMS are made for monitoring, not easy export of data Data quality varies and can include a high amount of missing data Many existing buildings will have limits on the bandwidth of data flow available due to the communication protocols used in the systems, thereby restricting the data resolution or number of measurement points No control over the faults observed or their severity To get the faulty ground truth of the dataset, an expert must analyze the entire measurement period to identify the faulty and non-faulty periods Unknown measurement error as typically commercial-grade instruments with no guaranteed calibration are used, if not part of a measurement campaign with its own instrumentation Physical constraints limiting the sensor location The cost of labeling the dataset with faulty ground truth can be high
	Aim 2: test a method using a labeled dataset The study uses data from existing labeled datasets with faulty ground truth generated from real buildings to train, test, and validate new FDD methods The data used for the FDD method is not in real-time but rather a selected investigation period	• Real measurement data Low cost Validation of the FDD method is possible if the dataset is labeled with faulty ground truth	• Data resolution is dependent on the dataset used and can only be downsampled Data quality depends on the dataset Fault types limited by the dataset Fault severity limited by the dataset Fault length limited by the dataset
Implementation studies	• The FDD approach focuses on implementing an existing FDD method in a real building in operation The validation of the method can be from a simulation or experimental studies	• Showcases the real-life operation of the FDD method Identifies shortcomings that can occur. E.g., practical challenges associated with the implementation, which do not necessarily appear in the other study types	• Data resolution depends on the possibilities in the BMS and can be difficult to adjust Data quality varies and can include a high amount of missing data Normally no labeled training data with faulty ground truth, which limits the number of viable methods applicable Many existing buildings will have limits on the bandwidth of data flow available due to the communication protocols used in the systems, thereby restricting the data resolution or number of measurement points No control over which faults are observed or their severity

(*continued on next page*)

Table 1 (*continued*)

Study type	Description	Pros	Cons
			The physical constraints limit sensor locationDifficult to quantify the benefit (needs to be performed over a longer time period and is building/system specific) The cost is dependent on the system/building

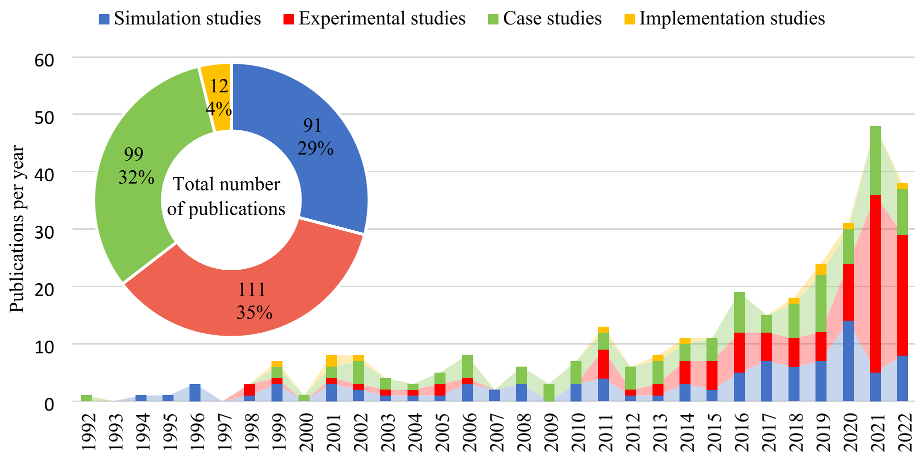

Fig. 2. Number of studies each year sorted according to study type and the summed number of each study type. Be aware that the same study can fall into multiple study types, which is why the sum is larger than the number of studies included.

Terminal Units (TU) and applied X-means clustering along with a Multi-Class Support Vector Machine (MC-SVM) to extract features of the PID controller. O'Neil et al. [29] employed EnergyPlus models, either created from the building design if it was a new construction or calibrated using operational data for existing buildings, along with Principal Component Analysis (PCA), Hotteling T^2 and Q statistics for fault detection, and a contribution score for fault diagnosis. Berguist and O'Brien [30] utilized a finite difference model with thresholds for fault detection and an expert ruleset for fault diagnosis. O'Neil et al. [31] used a combination of probabilistic graphical models and expert rule-based thresholds. The probabilistic graphical model was trained using operational data; it was then manually validated using domain knowledge and a physical understanding of the system. When in operation, the trained model generated anomaly scores which were compared to the expert rule-based thresholds to detect and diagnose the faults.

2.2.2. Building system implementation challenges

For the instrumentation requirements and their impact on the implementation of FDD methods, Norford et al. [23] analyzed the various sensor needs for two distinct FDD methods in AHUs. One method required only the standard sensors utilized in AHUs for thermofluid measurements, while the other necessitated a smaller number of sensors for submetered energy use. The results indicated that the method relying solely on standard thermofluid measurements showed satisfactory performance, though an additional sensor measuring the supply airflow was required to address a lack of sensitivity to certain faults. Despite this, the installation of this sensor is still not standard practice in many AHUs, as they are typically controlled based on the supply and extraction pressure in the ducts, making it unnecessary for control purposes. With regards to the method utilizing submetered measurements, it was found to be effective, though more challenging to implement under less controlled conditions. Currently, submeters are also not standard equipment in AHUs. Salsbury and Diamond [22] also emphasized the importance of air flow measurements for optimal performance. O'Neil et al. [31] concluded that to reduce the cost and scale of upgrading BMS to include technologies such as FDD certain initiatives should completed. These include a design guide for the required sensors in building systems, virtual sensors, low-cost submetering of electrical and thermal systems, better and simpler data acquisition methods.

Once a building has been equipped to the necessary instrumentation level, the next task is to gather and standardize the collected data for effective utilization. In a study by Nehasil et al. [26], the authors addressed the challenge of applying an FDD tool on different AHUs, highlighting the issue of variable naming. The names of variables currently adhere to the ontology prescribed by either Project Haystack [32] or Brick [33], but it is acknowledged that achieving complete unambiguousness is difficult. As a result, there is an ongoing effort to integrate both ontologies into ASHRAE SPC 223P [34,35]. In a separate study by Hosamo et al. [25], a combination of these ontologies was employed to name the variables. Standardization of naming conventions will allow for easier and faster implementation and integration of e.g., sensors or systems. Furthermore, the transferability (such as e.g., replication) of models will increase as less resources will be used on translation and understanding.

The selection of baseline period and threshold values is a crucial step in implementing FDD algorithms. This challenge is not unique to implementation studies, but is present across different types of studies and methodologies, as discussed in Chakraborty and Elzarka [36], and Andriamamonjy et al. [37]. Salsbury and Diamond [22], which focused on AHUs, found that normal operation is often selected as the baseline, but this selection may not necessarily be appropriate and can lead to difficulties and uncertainties in determining the thresholds. Setting the thresholds too loosely can result in failing to detect faults, while setting them too tight can lead to excessive false positives. Various methods exist for setting the threshold values, including expert selection [38–40], fixed statistics based on the data [41,42], and adaptive methods based on the data [36,37,43–46].

Implementation studies often encounter difficulties in evaluating the FDD algorithm's performance, as exemplified in Pakanen and Sundquist [20], Yoshida et al. [21] and Norford et al. [20,20,23]. All of these studies attempted to conduct implementation evaluations but had to resort to artificially inducing faults in the system for testing purposes. This highlights some challenges associated with implementation studies, including the absence of faults in the testing period and the difficulty in obtaining accurate performance metrics. In real-life conditions, faults may not occur during the testing phase, which makes it challenging to evaluate the performance of the methods. Moreover, determining the precise moment when a fault occurred raises uncertainties in evaluating the detection accuracy, hindering the distinction between true and false negatives.

2.2.3. Summary

The literature review can be summarized with the following conclusions:

- Few implementation studies are carried out, and currently, there does not appear to be an increasing trend.
- Most of the methods implemented use expert rules in some form.
- Most studies do not describe why they do implementation instead of a case study.
- In general, few implementation studies are found, with several attempting to perform implementation but becoming a case study as instead of letting the faults occur naturally; they induce faults into the system [20,21].
- There appears to be a clear lack of assessing the benefits gained from the FDD methods.
- For FDD in AHUs, submeters for more component specific energy use and an air flow sensor are not standard, and the lack of them can contribute to poor performance in FDD algorithms [22,23].
- There is a lack of a standardized ontology for tagging and naming everything needed for building systems and their use in FDD tools.

3. Methodology

Semi-structured qualitative interviews were used as the methodology in this article. This methodology was chosen due to the nature of this method, as it allows for more interaction with the interview participant. On the contrary, structured qualitative interviews, surveys, questionnaires, database search or other written communication does not allow for a "deep dive" into the specific products or services. Furthermore, it does not allow for rapid communication and can increase misunderstanding and wrong interpretation in a topic such as this article aims to provide [47].

The interview participants and the company they work for are chosen to be held anonymously. All interview participants signed a consent form.

3.1. Interview guide

The authors developed and designed the interview guide to target the research questions defined in subsection 1.3. The interview guide can be found in Appendix A in [48]. The interview guide consists of 4 main parts and has in total approximately 40 questions.

3.2. Selection of companies and interview participants

The interview participants for the study were selected based on a multi-step approach. Firstly, the authors aimed to gather a diverse range of companies from the HVAC systems industry, including both small and large companies. Secondly, the companies were considered relevant if they were involved in HVAC systems-related activities such as research, engineering, production, or management, primarily in North Europe or Scandinavia. However, given the importance of relevant companies working in the HVAC systems and FDD domain, the search for such companies was expanded beyond Scandinavia's geographical confines. The authors conducted a search for potential companies using keywords such as fault detection, fault detection and diagnosis, energy optimization, optimization of HVAC systems, and data-driven decisions on their respective webpage.

For an interview participant to be relevant to this study, the following criteria were set:

1) Works or have worked within the following HVAC system categories.

- Heating- and/or cooling systems
- Ventilation systems
- Building Management System companies
- Components for HVAC systems
- Third-party software companies
- FDD companies

2) Have the following professional competencies.

- More than five years of experience within the field of HVAC systems projects related to FDD or high HVAC system knowledge were prioritized.
- Background in engineering, physics, technical business
- Extensive knowledge of HVAC systems and the company's products and services.
- Primarily works in the respective company in Scandinavia and speaks English. However, if the contacted interview participant recommends another person based on the criteria, the authors contacted this respective person.

The selection of interview participants was made based on three criteria: 1) the predefined criteria set by the authors above and 2) the authors' professional networks, both nationally and internationally, and 3) a search using various online search engines. Additionally, individuals from the group of sales managers who lacked technical expertise were excluded. The authors reached out to all the selected interview participants via email. Regardless of the interview participants' position within the company, all interview participants were either directly invited or recommended by their colleagues due to their presumed expertise on this subject.

Fig. 3 shows a summary of the interview requests to the final number of interview participants and company categories. As one can observe, a total of 42 interview participants were contacted, and 29 agreed to

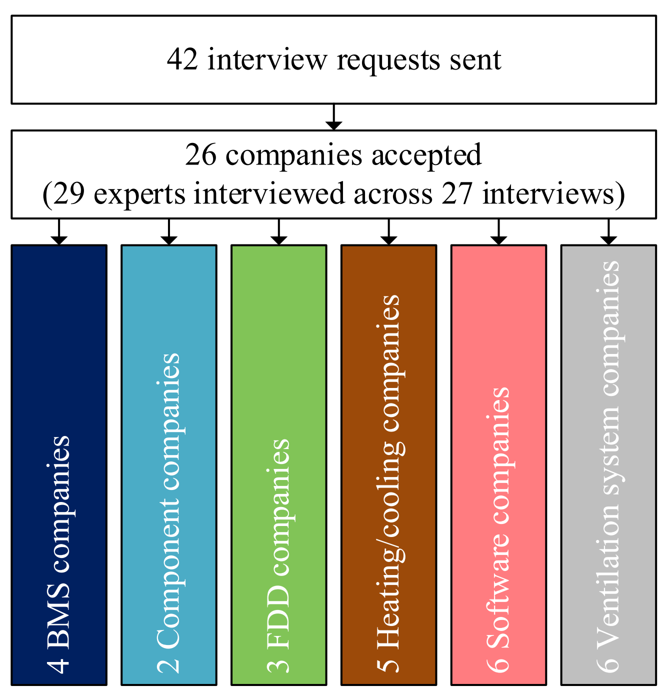

Fig. 3. Overview of the number of interview requests sent and the final number of interview participants and companies.

participate in the interview. Two companies respectfully declined, while the others did not respond after two follow-up emails.

The authors aimed to obtain a minimum of four companies within each predefined category. However, due to a lack of response from potential interview participants, only two companies within the Component company category were included. Despite this limitation, it is noted that the two selected Component companies hold a substantial market share and are, therefore, well-represented.

Table 2 provides detailed information on each interview participant and their respective companies. Each interview participant in the HVAC system category is assigned a unique Identifier (ID) which remains consistent throughout the study. The company location is classified into three categories: National (located in only one country), Continental (located in only one continent), and International (located in multiple continents). The size of the company is determined based on the EU's definition of Small and Medium-sized Enterprises [49]. Furthermore, the term "FDD practitioner" refers to participants who engage with FDD on a near-daily basis. "Frequent contact with FDD practitioner" describes participants who, while not directly executing FDD tasks themselves, maintain near-daily interactions with those identified as FDD practitioners.

To maintain anonymity, the interview participant's work experience is rounded to the nearest five years. For example, 23 and 27 are both rounded to 25. The interview participant's education is simplified into main categories, such as engineering, management, or plumbing. The primary working location of the interview participant may be a company office or a home office and is divided based on the United Nations Geoscheme [50]. Northern Europe is shortened as NE, Western Europe as WE, Southern Europe as SE and North America as NA.

3.3. Interview implementation

The interview process and handling of personal information were reported to the Danish data protection agency before contacting the interview participants to comply with the European General Data Protection Regulation (GDPR) legislation.

In total, 27 interviews were conducted between June and December 2022. 25 of the interviews were held online and 2 were held in person. 13 interviews were held in English, 8 were held in Danish, and 6 were held in Norwegian. The online interviews were recorded. Two of the interviews were conducted with two interview participants present, and for one company, two interview participants were interviewed separately.

3.4. Interview participant answers interpretation

In order to properly and as correctly as possible interpret the answers from the interview participant's into different classifications, the

Table 2
Characteristics of the interview participants.

ID	Company			Interview participants				
	Company type	Office locations	Size	FDD practitioner	Frequent contact with FDD practitioner	Years of working experience	Education	Main working location
B1	BMS company	International	Large	Yes	–	35	Engineer	NE
B2	BMS company	Continental	Large	No	Yes	15	Plumber	NE
B3	BMS company	International	Large	Yes	–	25	Engineer	NE
B4	BMS company	International	Large	Yes	–	25	Technician	NE
C1	Component company	International	Large	No	Yes	25	Engineer + PhD	NE
C2	Component company	International	Large	No	No	35	Engineer	NE
F1	FDD company	International	Small	Yes	–	20	Technician + IT	SE
F2	FDD company	National	Micro	Yes	–	< 3 years	Entrepreneurship	NE
F3	FDD company	International	Medium	No/ Yes	Yes/ -	20/ 35	Computer science/ Engineer + Marketing	NA/ WE
H1	Heating/cooling company	National	Small	No	Yes	< 3 years	Engineer	NE
H2	Heating/cooling company	International	Large	No	Yes	15	Plumber	NE
H3	Heating/cooling company	National	Medium	Yes	–	5	Engineer	NE
H4	Heating/cooling company	Continental	Small	Yes	–	5	Engineer	NE
H5	Heating/cooling company	International	Large	No	No	10	Engineer	NE
S1	Software company	National	Small	Yes	–	10	Engineer + PhD	NE
S2	Software company	National	Small	Yes	–	10	Physicist	NE
S3	Software company	National	Small	Yes	–	25	Engineer + Management	NE
S4	Software company	National	Small	No	Yes	25	Business	NE
S5	Software company	International	Large	Yes	–	5	Engineer	NE
S6	Software company	International	Large	Yes	–	10	Innovation and management	NE
V1	Ventilation system company	International	Large	No	Yes	30	Technician	NE
V2	Ventilation system company	National	Medium	No	Yes	25	Engineer + PhD	NE
V3	Ventilation system company	Continental	Large	No/ Yes	No/ -	20/ 25	Engineer/ Engineer + marketing	NE/ NE
V4	Ventilation system company	International	Large	No	Yes	20	Business management	WE
V5	Ventilation system company	Continental	Medium	No/ Yes	Yes/ -	35/ 20	Engineer/ Electrician	NE/ NE
V6	Ventilation system company	International	Large	No	Yes	25	Technician	NE

authors decided to use quotes from the interview participants where it is suitable or where assumptions were made. The quotes are in *italics* with quotation marks; « ». The parentheses following the quotes correspond to the company ID in Table 2, while the numbers indicate the quote number. Brackets within quotes are written by the authors to cleairfy the meaning of a spesific statement by the interview participants. Futhermore, the responses provided by the interview participants were used in the development of the AFDD implementation/definition matrix (subsection 4.2) categorizing the various HVAC companies.

4. An industry perspective on the implementation of fault detection and diagnosis in building systems

This section describes the results of the semi-structured qualitative interviews. Firstly, an outlook on the general knowledge of FDD in the companies and FDD services provided by the companies are presented in the following subsection. Secondly, an FDD building implementation matrix is presented and further used to categorize the companies' FDD services. Lastly, the drivers, barriers, and future outlooks of the interview participants are presented.

4.1. Correlation between company knowledge of FDD and focus on FDD services in their business model

The recruitment process for the interview participants was initially based on awareness of FDD, and it was assumed that all company categories would have some prior knowledge of the topic. However, during the interview, the participants were asked about their general understanding of FDD within their company, and an assessment of their company's level of familiarity with FDD services was made based on their answers. It should also be noted that the level of knowledge about FDD in the company does not necessarily reflect the level of implementation or the quality of the FDD services provided by the company. The level of knowledge is just a way to categorize the general understanding of FDD in the company and is used to assess the level of familiarity with the topic.

An FDD service has been defined as follows: A service provided by a company, often in the form of a system, which is designed to perform (at least the first two functions): 1) detect faults (such as anomalies, deviations, or outliers), 2) diagnose the faults, and 3) manage the fault handling process, including how the fault is fixed, who is responsible for fixing it, and what happens after the fault is diagnosed.

The level of knowledge on FDD in companies offering FDD services was categorized into low, medium, and high. The definitions for each level are as presented in Table 3.

An example of an interview participant's answer with low knowledge of FDD:

«No, ehm, not really. I understand the concept [FDD] and the idea, but not the main features of this if I may say that.»

(C1.1).

An example of an interview participant's answer with medium knowledge of FDD:

Table 3
Description of the defined FDD knowledge levels (low, medium, and high) used in Fig. 4.

Level	Description
Low	The employees in the company recognize the FDD definition, but it is not commonly understood.
Medium	The employees in the company are familiar with the FDD definition though with limited knowledge, but can refer to the FDD process in the company or product and discuss how it works with FDD.
High	The FDD definition is part of the everyday vocabulary of the employees. Possess high technical knowledge and can discuss the processes with high accuracy.

«The concept [FDD] is very familiar, but the technicalities or all the possibilities of how it can be done - very little … We used a Kalman filter for fault detection in a University course once, I remember… ()»

(H1.1).

An example of an interview participant's answer with high knowledge of FDD:

«This [FDD] is very familiar and the core of our business…()»

(F1.1).

The FDD service levels was also categorized into low, medium, and high. The categorization of the companies offering FDD services has been defined as presented in Table 4.

An example of a company offering a low level of FDD services:

«We mainly focus on providing a product for satisfying the customers and try to adapt to the different climate zones in the world to either heat or cool closed spaces.»

(H2.1).

An example of a company offering a medium level of FDD services:

«We want(!) and need to provide some sort of FDD services, both for our customers and ourselves. We need to know if the systems are working as they should because we do not sell a model for what you define as the fault handling process. Our customers are mainly private companies, and the services we are providing aim to satisfy the customers by saving costs.»

(S1.1).

An example of a company offering a high level of FDD services:

«We have a variety of services, direct or partner. The tool is intuitive, but no software by itself solves a problem. You need to have a workflow, you need to understand who is going to engage and how they will engage with the tool. In addition, we offer extra services for this model … () The partner service is sold as is, and they use it with their own service or maintenance model.»

(F1.2).

The categorization of the companies is presented in a matrix form (Fig. 4), where each company has been assigned a category based on their level of knowledge of FDD and the FDD services they provide. Each circle has a color, a letter and a number corresponding to the interview participant in Table 2 with the given ID. The colors assigned to each category follow throughout this article.

In the matrix of categorized companies (Table 5) those that specialize in FDD tend to fall under the "High/High" category, meaning they have a high level of knowledge about FDD and offer a wide range of FDD services. Additionally, one ventilation company and one BMS company also fall under this category because they provide extensive FDD services and possess a high level of knowledge.

Four of the six software companies are categorized in the "Medium" category of FDD service, with «high» knowledge. This is due to the fact that their focus was not on selling FDD services but instead offering an optimization service, whereas FDD might be incorporated.

Table 4
Description of the defined FDD service levels (low, medium, and high) used in Fig. 4.

Level	Description
Low	These companies offer simple FDD services as a part of their overall product offerings, primarily focusing on customer relations and repairing broken equipment.
Medium	These companies offer basic FDD services as an additional product or service, but their focus is on selling the value that it creates, such as reducing energy use, optimizing energy use, and lowering operational costs, rather than solely selling an "FDD service".
High	These companies explicitly offer FDD services, focusing on all aspects of fault detection, diagnosis, and handling processes.

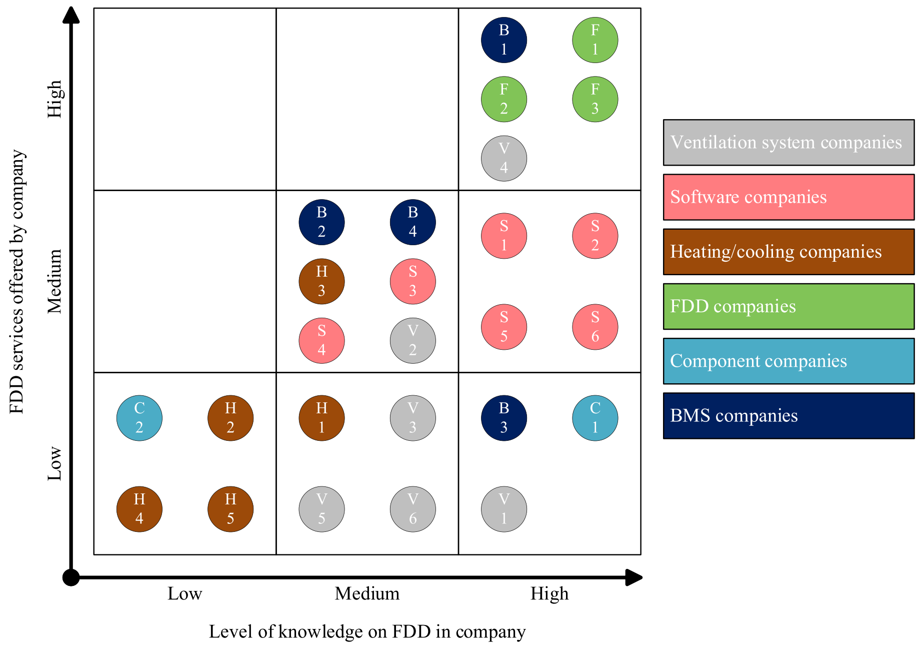

Fig. 4. Correlation between company knowledge of FDD and FDD service focus in the business model. The company categories are as follows: B: Building Management System companies, C: Component companies, F: Fault detection and diagnosis companies, H: Heating and cooling companies, S: Software companies, and V: Ventilation system companies. Each circle with a color, letter, and the number corresponds to the interview participant in Table 2 with the given ID.

Generally, the ventilation companies' knowledge and offerings of FDD services were diverse. However, in general these companies reported a focus on ensuring well-functioning systems. E.g., investing in competencies within the area of air pollution and exposure or dedicating resources to Internet of Things (IoT) components.

The heating and cooling companies were primarily in the lower categories of knowledge and offerings of FDD services. This could be due to the high demand for heat pumps in the past year, which led to a shift in focus toward simply providing enough heat pumps for the current demand. Furthermore, some heating and cooling companies interview participants reported receiving customer requests for information about parameters such as status and operating efficiency, which was not a typical request five years ago. This could be due to the rising energy prices in the world. However, one heat pump company was placed in the "Medium/Medium" category due to their efforts to use data to improve their efficiency in diagnosing the faults occurring. This company stated that their diagnosis process was time-consuming and inefficient, but they lacked the resources and competencies within the company to focus on FDD using data-driven methods.

The BMS companies were found to have a medium to high level of knowledge about FDD. This aligns with the nature of BMS companies that typically work with supervision processes. However, there is a range of FDD services offered by the BMS companies, ranging from low to high. This variability results from the diverse range of services and focus of each BMS company. Nevertheless, one BMS company has developed an FDD system specifically and was classified as "High/High" in the categorization matrix. However, this interview participant reported a low demand for the system and stated that they are working on promoting it.

The two component companies who participated in the interviews were classified in the "Low" category for their FDD services. However, one of them had a "High" level of knowledge about FDD, while the other had a "Low" level. The interview participants stated that their customers were generally not interested in the data from their components, making it difficult to sell a product that is not in demand.

4.2. Automated fault detection and diagnosis implementation matrix

The AFDD implementation and definition matrix has been developed based on the following:

- Authors knowledge
- Existing literature
- Interview participants answers

Table 5 describes the developed categorizations of FDD implementation in buildings and HVAC systems.

The matrix is built up based on three levels (1, 2 and 3). A sublevel of a, b, or c is developed at each level. Furthermore, each sublevel has a description and is based on key elements from «Fault detection», «Fault diagnosis», and «FDD as a service» criteria. Another important factor in developing the matrix was the company's investments/motivations for actively engaging in an FDD system or providing FDD services.

Additionally, the matrix is structured such that transitioning within a level (e.g., from sublevel a to sublevel b) is technically straightforward. Conversely, transitioning from one level to another (e.g., from Level 1 to Level 2) necessitates additional considerations.

In general, these are overall considerations:

- Data collection and storage. Additional equipment. E.g., computers and sensors.
- Business model, investment of an FDD system and the fault handling process.
- Type of feedback/communication to end-user.
- Ease of implementation (required level of competencies to implement the FDD system).
- Ease of use (required level of competencies to operate the FDD system), daily operations, maintenance/updates, or interface.
- Cost investment or cost savings for each FDD system.
- Type of FDD system. E.g., data understanding, preparation and analysis, and modeling. Attributes of the data and identification of key features for informed decisions for FDD.

Specifically, transitioning from level 1 to level 2 requires the

Table 5
Categorizations of FDD/AFDD implementation in buildings and HVAC systems.

Level Category	1 a	1 b	2 a	2 b	3 a	3 b	3 c
Description	**No FDD**	**Manual FDD**	**Passive data-assisted FDD**	**Active data-assisted FDD**	**Unsupervised AFDD**	**Supervised AFDD**	**Model-based AFDD**
Fault detection	Based on occasional complaints from occupants/users and manual verification of components by expert personnel. No monitoring system. Only scheduled maintenance. E.g., changing the filters based on a calendar date.	Based on occasional complaints from occupants/users and manual verification of components by expert personnel. Limited amount of pre-set alarms based on expert knowledge in the monitoring system.	Specific faults are/can be detected automatically, but are based on expert knowledge, pre-set alarms, and rule-based decisions.		Faults are detected using dynamic thresholds and updated by recommendations from unsupervised learning models.	The fault detection model(s) is adapted for each component/system by learning its behavior with historical data (black box).	The fault detection is based on a digital twin (white box/gray box), e.g., residuals from a simulation environment.
Fault diagnosis	Diagnosis is performed if there are many complaints that something is not working. Based on expert knowledge. E.g., a technician inspecting a system based on non-working components in the HVAC system.	Diagnosis is performed with only current operational data and if there are any complaints or complete shutdown of component/system. Based on expert knowledge. E.g., a technician inspecting a system based on non-working components in the HVAC system.	Specific faults are/can be diagnosed automatically, but are based on expert knowledge, pre-set alarms, and rule-based decisions.		Diagnosis is adapted to each component/system, and chosen faults are diagnosed automatically but still require expert knowledge for final diagnosis.	Diagnosis is chosen for each component/system, and faults are diagnosed automatically.	Diagnosis is chosen for each component/system, and faults are diagnosed automatically but can require expert knowledge for final diagnosis.
FDD as a service	No focus on FDD as a service.	No focus on FDD as a service.	The perception of FDD is viewed as a supplementary benefit rather than a primary focus.	Has actively invested in an FDD system and has designated personnel for handling this service.	Has actively invested in an FDD system and has designated personnel for handling this service.	Has actively invested in an FDD system and has designated personnel for handling this service.	Has actively invested in an FDD system and has designated personnel for handling this service.

following.

- Domain knowledge of building systems.
- Investment in a standard monitoring system. E.g., a BMS.

Specifically, transitioning from level 2 to level 3 requires the following.

- Domain-knowledge of data science and building systems. E.g., method implementation and online training.
- Investment in a customized system suitable for FDD.

Fig. 5 presents the classification of the companies and their AFDD implementation service. If a company is placed twice, it is because they offer several FDD services.

Overall, it can be observed that none of the companies fall under the categories 3b (supervised FDD) or 3c (model-based FDD). This suggests that research in these areas is likely ongoing and may be of interest for future development. Moreover, out of the 26 companies studied, 10 (40 %) actively offer FDD services, while the remaining 16 (60 %) do not.

As previously mentioned, there is currently no emphasis or demand from customers for data or monitoring from the component companies. The interview participants from these companies noted that they are still encountering difficulties in transmitting data. In terms of FDD services, they offer an expert system that employs alarms triggered by thresholds that indicate a fault. However, this was a rare case.

An example of an answer from an interview participant placed in level 1 was as follows:

> «Heh, how do we implement products and then get data back to us such that we can use them? We have not found the solution to this because no customer, so far, requests this. We only have a few frontrunner customers, but its very few out of thousands.»

(C2.1).

Among the ventilation system companies, only one out of five companies place significant emphasis on offering FDD services. These companies tend to prioritize sales-oriented customer service and commissioning facilitation over FDD. Typically, the FDD service provided by these companies relies on expert systems that utilize alarm thresholds to detect and diagnose faults, often supplemented by manual diagnosis using historical data if available.

In contrast to the ventilation system companies, software companies possess a high degree of knowledge regarding HVAC system control. While only two out of six software companies offer explicit FDD services, most companies view and market FDD as an optimization service that can create value for clients, rather than a stand-alone service.

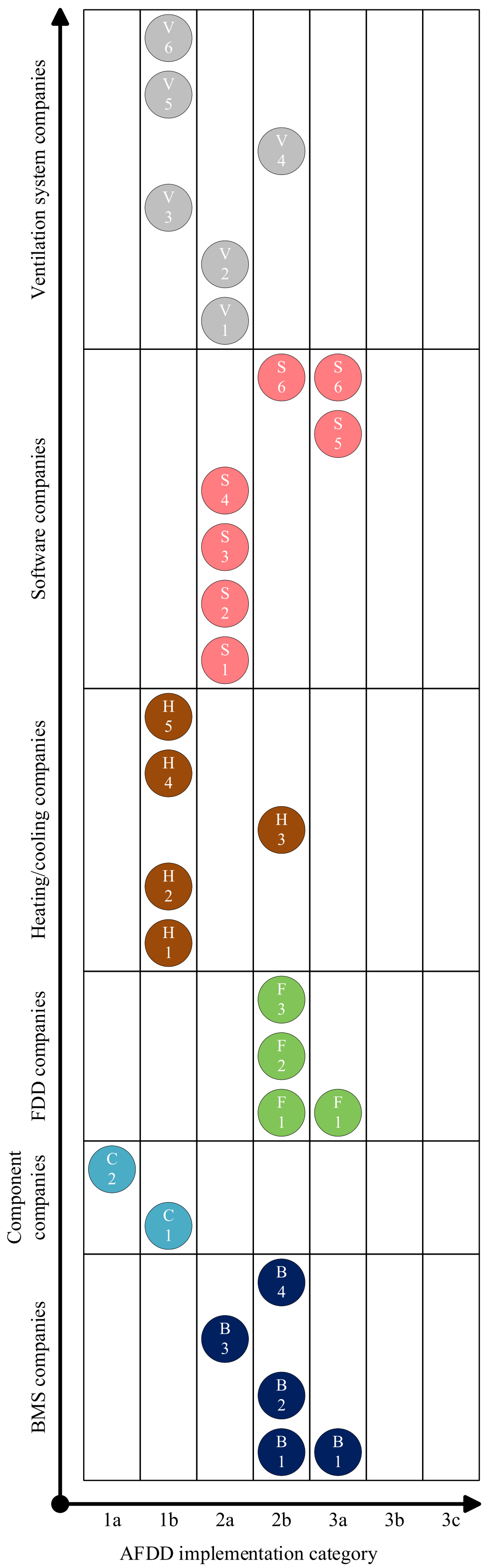

Fig. 5. Classification of the companies and their AFDD implementation according to the levels defined in Table 5.

An example of an answer from an interview participant placed in level 2a can be seen in quote V1.1.

«We do have a basic FDD solution integrated in the control. There is a fault and there is a reccomendation connected to that fault. Furthermore, we have also integrated more data analysis, such as investigating e.g., higher energy use than normal for fault indication. However, our take on this is not the fault perspective, it is more on the optimization part of indoor climate, and from this you will get the fault trace and fault detection included in that. The angle is not to detect faults, but more angled towards how the customer can minimize the energy usage and etc.

(V1.1).

Furthermore, it was found that heating and cooling system companies generally have a limited focus on FDD services. The typical FDD approach involves expert systems that rely on alarm thresholds for fault detection and manual diagnosis by inspecting data when the fault is not immediately apparent. Due to the HP companies typical business model (sold via wholesalers to installers to private consumers in residential buildings), they often have direct contact with the customer. This facilitates for a optimal customer-relation, but also can contribute to hinders for growth in a small company with limited resources. The HP interview participants reported that many faults in HVAC systems are caused by installation or customer errors, which can be difficult to detect and diagnose directly due to the subjective parameters present in residential buildings that are often unknown. An example of an answer from an interview participant can be seen in quote H4.1.

«Our main problem is when people are replacing their old heat generation system with a heat pump. When the heat pump reports a fault, the heat pump is [considered] bad, even if the fault is caused by something else, such as the installation. Therefore, we are trying to make good recommendations for our customers to avoid most of these stupid mistakes and ensuring that the heat pump has good operation conditions. This way, we ensure that the road to faults is as far as possible and that the end-user needs as little knowledge as possible for operating the heat pump in their heating system»

(H4.1).

«In our experience, about 90 % of the faults are externally caused, meaning poor handling, installation, or settings cause the problems for a heat pump. The rest of the faults are probably caused by product faults, meaning non-functioning components or similar, but this is a rough estimation.»

(H4.2).

«It [COP] can vary as the COP is very dependent on the installation, is it installed correctly?, is it adjusted correctly?, etc. It could be a nice tool for the end-user. I think it would also give us a large task, if you on the front [of the heat pump] could see that the COP is currently 3,8, then I think that many consumers would call us, when they can see that there is an sCOP value tested in accordance with a norm of 5,0, but the COP is currently only 3,8. Then they will call us, because it does not live up to the expectations of the customer. In that regard it would be risky if it is just displayed without any additional information regarding what it is dependent on and why it will vary throughout the year. It would potentially give us a huge task.»

(H3.1).

It seems that end-users are affecting the parameters of what HP companies offer. This can potentially hinder the growth of data-driven operations as certain parameters or metadata neccecary for data-driven operations are neglected. For example, a lack of comprehension regarding the value and functioning of building systems, such as the Coefficient of Performance (COP) example mentioned in qoute H3.1, can also act as an obstacle.

Contrary to HVAC companies, all FDD companies naturally offer FDD services and demonstrates an active commitment to including FDD as part of their overall service offering. Furthermore, quote F3.1 (ove) was mentioned by an interview participant in the FDD company category emphasizing focus on FDD commitment in their business model.

> «It should also be highlighted that companies with a high focus on detecting and diagnosing faults were able to fix them more quickly, thereby reducing energy usage, enhancing occupant comfort, and improving customer relations.»
>
> (F3.1).

Interestingly, these companies did not express a strong desire to use machine learning as an FDD service. This is largely due to the high cost of introducing machine learning systems. In general, these companies aim to identify faulty behavior through model-based approaches such as expert systems, digital twin models with some favoring black box models such as different variations of neural networks.

The majority of the BMS companies fall within the 2b and 3a categories. An example of an answer from an interview participant placed in level 2b or 3a can be seen in quote B2.1.

> «We actually have two customers where we now are running a pilot project implementing our new optimization platform with FDD features with the aim of optimizing the building operation by saving costs»
>
> (B2.1).

Several of the interview participants highlighted some unique challenges encountered in 2022, including the Ukrainian/Russian war and the increased energy prices. Especially mentioned by the heating and cooling companies, these challenges have resulted in an immense demand for heat pumps, causing these companies to hire more personnel and expanding their production lines to manage the orders for heat pumps.

A reason for this is mentioned by one of the interview participants in quote H2.2.

> «We cannot deliver [heat pumps]; we as a company currently have orders which equate to, before the crisis, seven years of orders. This is not special for us; it is the same for all the well-known German and Swedish producers … () We are all struggling, and everyone is building new factories and supply lines as we have to transition. We had expected and hoped for a slow transition from the world of fossil fuels to the world of green energy. However, it happened in one swoop and over one night. From the 24th of February [2022], the world changed, and we were not ready for that.»
>
> (H2.2).

4.3. *Identified drivers and barriers for the implementation of FDD and AFDD in buildings*

This section provides a synthetic overview of the different drivers and barriers the interview participants have identified. Each driver and barrier have been thoroughly reviewed to ensure consistency, thus allowing for multiple companies to identify and mention the same driver and/or barrier. A driver has been defined to include objectives, motivations, and incentives as they tend to overlap. The drivers and barriers have been categorized into 5 groups:

- technological and technical (technical knowledge, interoperability, infrastructure, data),
- economic and business (costs and benefits for end-users, business limitations),
- users (user experience, interface, misunderstanding),
- social and societal (cultural, community and stakeholders, benefits for society, environmental sustainability),
- regulatory (policies, GDPR, cybersecurity).

No Social and societal barriers were found; hence this category has been removed.

Tables 6, 7, 8 and 9 describes the identidied barriers. Each barrier has been assigned an abbreviation ID, such as "TD1″ for Technological and Technical driver number 1 and "UB1″ for User barrier number 1. Furthermore, the column «Related drivers» are associated drivers identified to mitigate the corresponding barrier.

Table 10 describes the identified drivers. The driver categories have not been divided based on company category, whereas the barrier categories have been divided into company categories. Colors are used to indicate whether the respective company category has mentioned the barrier.

In general, the economic and business drivers are strongly connected to the economic and business barriers, particularly within the EB1 and EB2 categories. This could be because these economic and business drivers often lead to the emergence of corresponding barriers. For example, a strong economic driver for a certain product or service may result in increased competition, which could create economic barriers for businesses/companies trying to enter the market. Additionally, economic and business barriers in these categories may be more closely related to each other, creating a feedback loop where the presence of one barrier leads to the emergence of others.

A mentioned cornerstone within the barrier category "Users" was that FDD tools implicitly provide negative information, thus not being socially desirable to disclose the use of such systems publicly. See the example in quote S1.2.

> «From a business perspective FDD is a tricky thing in the building sector, because you are essentially looking at provision of negative information in a context. If FDD is giving you results, you are going to tell people, you know what something is not working. There is a person who has delivered that system, there is a person who is maintaining it and then depending on the sort of dynamics in the team you are interacting with, that is not necessarily very welcome. So specifically in complex buildings with BMS, you can have a lot of difficulties interfacing to that BMS, because people for many reasons, but one of them might be that they know how badly the BMS is working. It functions, but it is never fully optimal and quite often it will be adjusted in a few ways here and there, and having something that looks into partially well working systems is going to provide negative feedback that some people, understandably enough, would like to do without, so you can experience significant friction or difficulties to get in buildings, when you start introducing that kind of things.»
>
> (S1.2).

Furthermore, an interview participant shared that providers of FDD services regularly need to engage with customers to keep them from wanting to discontinue the FDD service once the system appears to run smoothly and the savings have stabilized.

> «There are examples I have seen where we have saved companies into the hundreds and hundreds of thousands of dollars in energy costs in year 1, and in year 2 it continues and in year 3 it continues, but they start saying, why are you not saving me the same amount every single year or more and they say, can we remove this service after a certain peiod of time?, it gets crazy, not from a buisness perspective, but things does not just continue working, the reason the building was in that state when we got there, was because no one was monitoring it and now you want to remove the thing monitoring it after 1 or 2 years. It [customers cancelling the FDD service] never really happens, we have a very low turn rate, we do not lose customers but it is a question that gets asked every single time I go to a customer.»
>
> (F1.3).

It is also worth noting that the barriers indicated "Not identified" under the "Related drivers" (regulatory barriers (RB1, RB2, and RB3),

Table 6
Identified economic and business barriers for implementation of AFDD. B: BMS companies, C: Component companies, F: FDD companies, H: Heating and cooling companies, S: Software companies, V: Ventilation companies.

Abbreviation ID	Economic and business barriers	Related drivers	B	C	F	H	S	V
EB1	Additionally to the low awareness of FDD in general, most companies and stakeholders in the building sector are very conservative and have difficulties moving towards new ideas or paradigms	TD1-3+7, ED1-3+7-9, UD1-3, RD2-3			■		■	■
EB2	Standardization of AFDD components and interoperability is necessary to decrease prices and enable large-scale deployment, especially in residential buildings. The AFDD solutions are still too expensive at the moment, and the customers or potential customers do not necessarily see their benefit or return on investment in it	TD5+7, ED1-9, UD1-3	■		■			■
EB3	Siloed activities with limited cooperation between BMS providers, building systems manufacturers and AFDD solution companies. Component producers might not want to share the details of their controllers to the BMS providers	ED4-6, RD1-3					■	■
EB4	Generally companies have a lot of data which they do not know what to do with; it is therefore difficult for them to create a viable business plan	ED9, RD2-3	■		■			
EB5	High costs for retrofitting/upgrading and implementation of BMS and AFDD solutions in existing or new buildings are usually prohibitive. AFDD solutions are very low on the priority list of building project and, therefore, are the first ones to be cancelled	TD1-2+5+7, ED1+4-9, RD2-3		■	■		■	
EB6	Many AFDD software solutions are developed by start-up companies. This increases the risks of service discontinuation, which deters system manufacturers from integrating these AFDD solutions into their products	ED4+7+9, RD3				■		
EB7	Customers are reluctant to pay regular service fees for AFDD and cloud-based solutions, they prefer a one-time fee	TD7, ED8-9, RD2-3	■		■		■	
EB8	Customers do not necessarily understand the economic benefits of FDD induced by the increased productivity of employees with improved indoor climate and building services	ED3+7-9, UD1+3, SD1+4	■		■		■	
EB9	The costs/benefits and return on investments for BMS data access, visualization and FDD is hard to estimate and value for customers, especially for private residential buildings	ED1-2+5-8, UD3, RD2-3		■	■	■	■	
EB10	Modern building data access solutions (e.g., API) sometimes have prohibitive costs compared to perceived benefits from the customers point of view	TD7, ED1-2+4-6+8-9, RD1-2	■					
EB11	Misalignment between interests of the tenants and the building owners regarding the investments and benefits of AFDD. The building owners pay for the AFDD solutions but the savings go to the tenants	RD2-3, SD2				■		

two technological and technical barriers (TB9 and TB10) and one user barrier (UB9)) do not have any identified drivers to mitigate them. For the regulatory barriers, it is possible that the regulations are highly specific or restrictive, making it difficult to identify alternative approaches that would achieve the same regulatory objectives. Additionally, regulatory barriers may reflect broader societal values or political priorities, which can make them difficult to change without significant political will or public support. For technological and technical barriers, it could be that the necessary technology or technical expertise is not yet available to overcome these barriers. Alternatively, the costs associated with developing or implementing new technology or technical solutions may be prohibitively high. As for the user barrier, it is possible that the users themselves may be resistant to change or may not fully understand the benefits of alternative approaches, making it difficult to identify effective strategies to overcome this barrier.

Notably, technological and technical barriers (TB1, TB4, and TB9) were identified by all interview participants, indicating that they are widely recognized barriers in the industry.

Many of the identified barriers were found to have cross-disciplinary implications, often stemming from economic and business factors, but also incorporating user perspectives and technological and technical considerations. This interdisciplinary nature of the barriers makes them challenging to categorize and quantify, further highlighting the complexity of addressing them.

A large share of the user barriers consisted of answers centered around the value FDD can create.

"I have not really seen that many wishes from the customers regarding this [FDD] and I think it becomes… It is probably due to the fact that they have been in the building industry for such a long time, many of them, so they have not seen it, they have not been exposed to it, but then when you exemplify it, when you actually exemplify it with your car for instance, then then they can understand the value. So, you need to have some sort of trigger in to the discussion for it, they think it is logical when you explain it to them and you say it and so forth, but it is very seldom that they come up with the question themselves so to say."

(V6.1).

«I think one of the largest barriers is the business model, what will they [the customers] pay for, they do not understand the value, they do not have the experience, and that means they do not want to pay very much, they do not understand the value of the data and that means they do not understand how valuable it is what we are delivering. Because they have not tried other people so we are in a very immature market where you have a lot of players and a lot of players say they can do everything, but then when it comes down to it, how are you going to compare it [the performance of different FDD services]. If you look at the website, you do not even understand what they deliver, I can look at my competitors, and many of them I do not understand what they deliver. And also pricing, it is impossible to find the pricing, how is their business model, it is not always clear on the websites. So, it is a very very complex and fragmented

Table 7
Identified technological and technical barriers for implementation of AFDD. B: BMS companies, C: Component companies, F: FDD companies, H: Heating and cooling companies, S: Software companies, V: Ventilation companies.

Abbreviation ID	Technological and technical barriers	Related drivers	B	C	F	H	S	V
TB1	Lack of common knowledge, standardized methods and tools for FDD. FDD is still a very complex and labour-intensive process that requires expertise in multiple fields	TD5-7, ED4, RD1-3	■	■	■	■	■	■
TB2	Lack of awareness, knowledge and skills in the building industry in general regarding FDD and AFDD solutions, potentials and impacts	TD2-3+7, ED7-8, RD1-3			■	■	■	■
TB3	Building engineers typically do not have the required skills to work with complex AFDD tools. Conversely, control and computer engineers typically do not have the required building physics knowledge and interpret and tackle the issues and faults occurring in buildings	TD7, ED4, RD1-3			■	■	■	■
TB4	Lack of interoperability between the different components and building systems. Low data exchange/stream compatibility between the different building systems. Too many proprietary communication protocols in the different building systems make interoperability cumbersome and costly. A greater effort is needed to standardize data exchange and BIM and generalize “plug-and-play” components that are operational with BMS and AFDD tools	TD5+7, ED4-6	■	■	■	■	■	■
TB5	AFDD algorithms are tailored for specific brands of components but lack scalability and usefulness when changing the brand or type component's model. Different actors make their own app or software focusing on their segment only. Multiplication of brand-specific apps with low capabilities and no interoperability	ED4-6+9, RD1-3	■		■			■
TB6	The rapid deployment of AFDD in the built environment is restricted by the limited share of buildings equipped with a BMS (very rare in residential buildings; only 20-30% of commercial buildings are equipped with BMS)	TD5+7, ED1-3+7-8, RD1-3					■	
TB7	The deployment of AFDD solutions cannot be implemented in current controllers, it should be cloud-based but this increases structure complexity and costs	TD5-7, ED4-6+8-9, RD1-3	■					
TB8	Reliable measurement logging and transmission to secured servers are still major problems in many BMS. The verification of the reliability and placement of sensors and their calibration is rarely performed correctly. The communication and storage infrastructures are not at the necessary quality levels to enable reliable operation	TD5+7, ED1+6+8-9, UD1+3, SD1+4						■
TB9	Clear lack of good training labeled datasets with ground truth to develop, test and benchmark AI-based AFDD algorithms on a wide range of components and systems. Many companies and actors of the building sectors have a lot of data, but it is of poor quality with insufficient features and too little meta-data to be useful. No actors seem to put in the effort to change that and generate useful datasets	None identified	■	■	■	■	■	■
TB10	Lack of standardized and efficient methods to assess the baseline building performance of buildings with or without a specific system’s fault	None identified					■	
TB11	The amount of required data and monitoring points to perform AFDD correctly is significantly larger that what is needed for simple control of the building, which is not well understood by customers	TD5-7, ED1+4-6+8-9, RD2-3		■				

market with a lot of pitfalls where people have no clue. They think that they just offer a google service, how difficult can it be to collect data. We are just used to clicking on the app and we get it, they think it should be very cheap. Once you are able to deliver the data and give them the insides, then it is different. So if you look at the basic service, which is the data collection, the do not want to pay for it.»

(S4.1).

5. Discussions on key findings

The study aims to gain insight into the barriers and drivers for implementing or enhancing the implementation of FDD or AFDD capabilities in their respective products. The five key findings are discussed below.

5.1. FDD does not sell

Many interview participants mentioned that their company does not look at FDD as a service. They instead market it as the benefits it brings, such as energy optimization, cost reduction, and improved customer relations and satisfaction. It was also mentioned that some customers of FDD services preferred to keep their use of the system confidential, as they perceived that admitting to potentially having faulty systems was not socially desirable.

Another important factor identified was the lack of a viable business model. Many customers were found to be hesitant to pay a subscription fee for FDD services, and once their building was performing well, they perceived the cost of sustaining the system to be higher than the current savings. As a result, they wanted to unsubscribe from the service, which could lead to a decline in performance. This highlights the dual nature of the problem, where customers are willing to pay for FDD services when the performance is poor, but then unsubscribe when the performance is good, leading to a decline in performance once again.

Table 8
Identified user (customer, building owner, manager and occupant) barriers for implementation of AFDD. B: BMS companies, C: Component companies, F: FDD companies, H: Heating and cooling companies, S: Software companies, V: Ventilation companies.

Abbreviation ID	User (costumer, building owner, manager and occupant) barriers	Related drivers	B	C	F	H	S	V
UB1	General lack of understanding of what AFDD is, what it can achieve and what customers can benefit from	ED6-9		X	X		X	X
UB2	Current BMS software solutions for FDD are overwhelming: too many alarms with no prioritization. The accumulation of alarms lead to building managers ignoring them	TD2, ED4+9,	X				X	X
UB3	Potential friction between the AFDD providers and the building maintenance team: the AFDD tool only delivers bad news and more work to be done by the maintenance team	TD1-3, ED1-2, UD2-3					X	
UB4	Customers get disappointed by the poor performance of their buildings that is emphasized by FDD and continuous building performance monitoring solutions	ED1-2+8-9				X		
UB5	The significant performance gap between what is promised by smart solution technology companies and the real operational effectiveness. This undermines customers' trust in what is on the market	TD1-3, ED1-2+6	X		X			
UB6	Complex AFDD schemes might scare the building owners away because of a lack of transparency in the whole process and lack of understanding of the AFDD solutions in general	TD2, ED5-6+9			X			X
UB7	Possible misunderstanding of FDD long-term benefit by building managers: a well-functioning FDD tool can lead to fixing many faults in building systems in the first years. After an initial sharp increase of the building performance, the number of new faults stays low and further performance improvements are not noticeable (optimum operation has been reached). The customers might thus loose interest in FDD services, stop paying for it, which increases the number of unnoticed faults and the degradation of the building performance	TD7, ED1-2+5-6+8-9, RD2-3	X		X		X	
UB8	Mismatch between the ambitious sustainability goals of certain customers and either the FDD strategy set in place by the them, or the current technical feasibility of FDD solutions	TD5-7, ED9	X	X				X
UB9	Some building managers might not trust the AFDD solutions and overrule automated fault handling processes	None identified			X			
UB10	Convincing customers to allow the recording and exploitation of some of their building data to enable AFDD is sometimes complicated	ED1-3+8-9, RD2-3				X		
UB11	Expectations, requirements, configurations, situations and data types are very different from one customer to another	ED4-6		X				

Table 9
Identified regulatory barriers for implementation of AFDD. B: BMS companies, C: Component companies, F: FDD companies, H: Heating and cooling companies, S: Software companies, V: Ventilation companies.

Abbreviation ID	Regulatory barriers	Related drivers	B	C	F	H	S	V
RB1	The General Data Protection Regulation (GDPR) can be a tough limitation to access and use important data for AFDD, especially if the costumers do not see the benefits of sharing their data	None identified	X	X				X
RB2	Data regulations and other AFDD-related regulations vary significantly between different countries and markets	None identified						X
RB3	Companies and building owners are reluctant to transfer large amount of building data onto a cloud-based AFDD solution because of the responsibilities regarding data governance, cybersecurity risks, data leaks and anonymization of the data	None identified	X	X			X	

5.2. There are many types of FDD services on the market, but most of the industry companies does not actively engage in selling and promoting FDD

The AFDD building implementation matrix, which was used to categorize the FDD services provided by the companies, showed that while some companies are already providing FDD services, there is still a need for further development and implementation of AFDD solutions in the building industry. A question remains whether this is an attractive service for the building industry. Furthermore, this is reflected in the developed AFDD matrix, where one of the key criteria was based on actively engaging in an FDD service.

5.3. FDD seems to be an academic definition

It was noted that some interview participants were not initially familiar with the definition of “FDD,” but after engaging/discussing the topic, they understood it. This suggests that the term “FDD” may be more commonly known in academic areas. In contrast, in industry, it is more frequently understood in terms of its impact on energy optimization and sustainability, leading to a knowledge gap between academia and the industry.

Table 10
Identified drivers for implementation of AFDD.

Abbreviation ID	Technological and technical drivers
TD1	Building performance optimization
TD2	Ease of reactive and preventive building maintenance
TD3	Increase building service reliability
TD4	Improve building resilience to natural hazards, climate change and energy grid outages
TD5	Boosting the digitization and digitalization of the built environment
TD6	New applications for machine learning methods and smart control algorithms
TD7	Synergy with other smart building technologies and services: demand response, demand-side management, building-to-grid services, user-in-the-loop control, predictive control, digital interfacing with building occupants, data-driven technologies, building monitoring, building safety and security
	Economic and business drivers
ED1	Lower long-term operational costs of buildings
ED2	Reduction of short-term operational costs of buildings linked to higher energy efficiency and thus lower building energy costs (crucial in the current and future periods of high energy prices)
ED3	Rapid return on investments due to increased productivity in commercial and office buildings
ED4	Scalable AFDD approaches require standardization and interoperability of systems. This is typically driven by a few large companies with sufficient resources to engage in such a process while smaller companies follow the emergent dominant solutions
ED5	Development of new renting and service agreements for continuous AFDD and optimum maintenance by HVAC systems' manufacturers, installers, BMS providers and third-party companies specialized in AFDD on multiple systems from different brands
ED6	Selling or renting indoor comfort as a service with a specified level of reliability instead of investing and maintaining an asset providing the service
ED7	Implementation of AFDD services on legacy building systems with a limited density of sensors
ED8	Clear improvement of the building service reliability in pilot cases incentivizes the real estate developers and building owners to integrate AFDD in their new projects
ED9	Specifiers on large projects are gaining experience with FDD and are increasingly requiring it in future projects, indicating a growing demand for FDD services
	User (costumer, building owner, manager and occupant) drivers
UD1	Improving occupants' comfort, health and well-being
UD2	Contribute to the amelioration of the relationship between tenants and residential building owners
UD3	Improving customers' service and satisfaction
UD4	Account for users/occupants' feedback and provide information to the latter
	Regulatory drivers
RD1	The commitment of national governments to the UN sustainability goals and to the Paris agreement for the reduction of CO2 emissions entails a drastic improvement of building energy efficiency
RD2	Incentive or legislation from the EU, national and local policy-makers to improve the energy efficiency in the building stocks
RD3	Building systems' commissioning, effective maintenance and reliability is rewarded in popular sustainability programs such as BREEAM
	Social and societal drivers
SD1	Contributing to establishing healthier homes, sustainable cities and buildings, in line with the UN sustainability goals
SD2	Sustainable resource management by increasing of the building systems' lifespan and usage
SD3	Improved indoor comfort, occupants' well-being and health leading to reduced pressure on the healthcare system
SD4	Improvement of the working and studying environment enhancing cognitive performances

5.4. The bottlenecks: The fault handling process and user's mindset towards FDD

It was found that a clear bottleneck in the FDD proces is the company's business model. This significantly impacted the fault-handling process, with some company categories leaving the responsibility of fixing faults to the customers. Reasons for customers not addressing faults in their systems included a lack of penalties, perceived benefits, and limited financial impact. Clearer initiatives on the fault handling process of the customer side are thus necessary to establish. Furthermore, To address this issue, a clear and well-defined guideline regarding the responsibilities of different parties could be established.

Furthermore, it was found from the interviews that the FDD service was usually neccecary to be brought up by the seller, as customers rarely knew that this is an existing beneficial feature. Furthermore, the work load and the value of FDD was often underestimated by the customer. This can imply that here is potential for increased adoption of FDD in the building industry, but that customers may need more information and exposure to the benefits of FDD in order to express interest in it. Moreover, there also seem to be a need for more education and transparency around FDD, as well as clearer pricing and service offerings, in order to increase adoption of FDD in the building industry.

5.5. Governmental regulations and legislatives drive the implementation focus

During the interviews, a significant number of participants reported that the current market do not incentivize building owners to incorporate monitoring systems or data analytics tools, such as FDD systems, into their buildings, primarily due to the high costs associated with their implementation. This reluctance is further compounded by the absence of any national legislation mandating such systems, as noted by the interview participants. Additionally, the interviews revealed that a lack of experience with FDD systems among building owners contributes to their skepticism, as they are unaware of the long-term benefits of these systems.

As an instance of legislative progress in this direction, the Danish building regulation introduced a requirement at the beginning of 2020. According to paragraph 295 of the current Danish building regulations (BR18), new buildings and existing buildings with a designed heating or cooling need above 290 kW (provided it is technically feasible and economically viable, as per paragraph 275) must install a building automation system for the control of the building's technical systems [51].

The system must have the following capabilities:

- continuously monitor and analyze the energy use,
- communicate with the technical systems and control these systems in a energy-efficient manor according to the needs of the building,
- express the energy efficiency of the building and its technical systems, and
- detect faults in the systems and notify the operating personnel of these faults.

In Denmark, the deadline for installing the various initiatives in existing buildings is set at the end of 2025. However, numerous buildings in Denmark currently have HVAC systems that do not meet the specified level of monitoring requirements. This initiative is expected to raise awareness about fault detection and diagnosis tools in buildings. As a result, this regulation has the potential to serve as a powerful catalyst for energy-efficient practices in the building industry.

6. Conclusions and outlook

This study aimed to assess the current state of FDD implementation in building systems from both an academic and industry perspective. A literature review was conducted to evaluate the academic perspective, while a series of interviews with 29 experts from various companies and branches in the building industry, including ventilation system and heat pump companies, software companies, BMS companies and FDD companies, were conducted to gather insights on the industry perspective.

What is the status of AFDD implementation in buildings or systems, and what AFDD approach is used?

FDD has been available for building systems for some time, but it has not gained widespread adoption in the industry. One of the key factors identified is the gap between actively investing in and developing AFDD services versus passively integrating a threshold into the system. This gap affects the effectiveness of fault detection, diagnosis, and the fault handling process. Additionally, expert systems based on predefined thresholds continue to dominate the industry. Although some interview participants believe that data-driven FDD will eventually replace traditional FDD services, several barriers remain to be overcome.

Companies providing FDD services should use a common language and adopt a uniform framework, such as an ontology or taxonomy, to enhance integration and interoperability. Companies who log data for their customers often have access to large datasets with numerous units. However, due to a lack of knowledge, they may not know how to make optimal use of this data. In particular, the datasets are not usually transformed into training labelled datasets that can be used for FDD purposes. Therefore, it would be relevant to develop guidelines that illustrate the process of transforming logged data into a useful dataset for FDD applications. This guideline should offer companies a step-by-step approach that they can follow to effectively utilize their data, develop and train FDD models that can detect faults in their systems. This would enable companies to capitalize on their data and ensure that their customers benefit from more energy-efficient systems.

What are the barriers and drivers to increasing AFDD implementation in buildings today?

The most commonly cited drivers were within the Economic and business category, along with the regulatory category. The barriers on the other hand were spread evenly between the Technological and technical, Economic and business and Users categories.

There was common ground among the interview participants regarding three barriers. These were, in short, 1) lack of common knowledge, standardized methods and tools for FDD (TB1), 2) too many proprietary communication protocols in the different building systems make interoperability cumbersome and costly (TB4), and 3) clear lack of good training labeled datasets with ground truth to develop, test and benchmark AI-based AFDD methods on a wide range of components and systems. Many companies and actors in the building industry have a lot of data, but it is of poor quality with insufficient features and too little *meta*-data to be useful. No actors seem to put in the effort to change that and generate useful datasets (TB9).

To overcome many of the identified barriers, there is a need for more awareness and education about the benefits of FDD. Additionally, AFDD can take FDD to the next level, by enabling real-time monitoring and automated response to faults. To successfully adopt AFDD, effective communication with and education of building owners and operators is crucial. Furthermore, FDD implementation demonstrators were identified as a significant driver of FDD interest, and closer collaboration between industry and academia, bridging strong knowledge and theory of building systems, can increase interest in developing FDD services.

Currently, most academic articles concentrate on developing and testing specific FDD methods, typically of either simulation or a limited number of experimental datasets. However, these methods need to be tested and validated on real-life systems to demonstrate their efficacy and establish their benefits. Building owners and operators are unlikely to see the value of implementing FDD methods in their buildings until such evidence is provided. Consequently, further research is required to demonstrate the practical benefits of these FDD methods to ensure their widespread adoption in the building industry.

Closing quote on the expected future perspectives of FDD in buildings and HVAC systems from Ventilation company, V6.

> "I think it [FDD] will be a natural part of the building in the future, that you actually have this kind of fault detection. I think that buildings will catch up at some point and will be similar to what we see in cars today for instance. That it is actually indicating that something is wrong, that it gives you a hint or advise that you need to go to service. [skipped an anecdote]. It needs to be a natural part of all the products and all the things that is happening inside the building. And I also think that will help us do more sustainable choices in the future, because then you do not need to replace things that are not broken for instance. You can predict when it is broken, you can predict how to make use of it, and you can actually repair the things that are needed. I think that will be the driver at the end of the day, why it will happen." (V6.2)

CRediT authorship contribution statement

Kamilla Heimar Andersen: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Simon Pommerencke Melgaard:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Hicham Johra:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Supervision, Writing – original draft, Writing – review & editing. **Anna Marszal-Pomianowska:** Conceptualization, Methodology, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Rasmus Lund Jensen:** Conceptualization, Methodology, Supervision, Validation, Visualization, Writing – review & editing. **Per Kvols Heiselberg:** Conceptualization, Funding acquisition, Methodology, Project administration, Supervision, Validation, Writing – review & editing.

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.

Data availability

The interview guide, the contact email template, and the consent form can be downloaded from the dedicated open-access GitHub repository of the First and Second author: https://github.com/aauphd2024/FDD_implementation_HVACsystems The raw data from the interview participant's answers are not openly available due to anonymization.

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