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Published in:
Energies

DOI (link to publication from Publisher):
10.3390/en15124366

Publication date:
2022

Document Version
Publisher's PDF, also known as Version of record

energies

MDPI

Systematic Review

Fault Detection and Diagnosis Encyclopedia for Building Systems: A Systematic Review

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Abstract: This review aims to provide an up-to-date, comprehensive, and systematic summary of fault detection and diagnosis (FDD) in building systems. The latter was performed through a defined systematic methodology with the final selection of 221 studies. This review provides insights into four topics: (1) glossary framework of the FDD processes; (2) a classification scheme using energy system terminologies as the starting point; (3) the data, code, and performance evaluation metrics used in the reviewed literature; and (4) future research outlooks. FDD is a known and well-developed field in the aerospace, energy, and automotive sector. Nevertheless, this study found that FDD for building systems is still at an early stage worldwide. This was evident through the ongoing development of algorithms for detecting and diagnosing faults in building systems and the inconsistent use of the terminologies and definitions. In addition, there was an apparent lack of data statements in the reviewed articles, which compromised the reproducibility, and thus the practical development in this field. Furthermore, as data drove the research activity, the found dataset repositories and open code are also presented in this review. Finally, all data and documentation presented in this review are open and available in a GitHub repository.

Keywords: fault detection and diagnosis (FDD); systematic review; building systems; heating, ventilation, and air conditioning (HVAC); model-based methods; data-based methods; data repositories

Citation: Melgaard, S.P.; Andersen, K.H.; Marszal-Pomianowska, A.; Jensen, R.L.; Heiselberg, P.K. Fault Detection and Diagnosis Encyclopedia for Building Systems: A Systematic Review. *Energies* **2022**, *15*, 4366. https://doi.org/10.3390/en15124366

Academic Editor: George Kosmadakis

Received: 15 April 2022
Accepted: 8 June 2022
Published: 15 June 2022

1. Introduction

Buildings are responsible for 36% of the global energy use and 39% of CO_2 emissions in the world [1]. Due to buildings' significant share of energy use and options for onsite energy production, buildings are key in mitigating the European Union (EU) targets for energy efficiency and renewable energy [2]. However, the actual buildings' energy use is usually much higher than their design. This mismatch can arise due to discrepancies in the design inputs [3], operational conditions [4], or faults occurring in building systems.

As heating, ventilation, and air conditioning (HVAC) units are measured to account for up to 50% of the total energy use in the buildings [5], this system is a foremost lead. Poor design, installation mistakes, and faults that arise due to equipment wear can increase energy use significantly and degrade the indoor environment [6], especially when faults go undetected for several years. Actually, in the United States of America, typical faults in buildings are estimated to account for 103 to 500 TWh of additional yearly energy use [7]. To tackle this problem, fault detection and diagnosis (FDD) in building systems can be employed to reduce building operation and maintenance costs by effectively finding, identifying, and providing insight into how to treat these faults [8].

There is an immense existing body of literature on FDD in building systems produced since the late 1980s [9], and several articles have investigated the state of the art through the years [10–14]. Nevertheless, one of the first collected works on FDD in building systems was carried out by international experts under the umbrella of the International Energy

Agency's Energy in Buildings and Communities Programme (IEA-EBC) in 1998, the IEA-EBC Annex 25. Here, real-time simulation of HVAC systems for building optimization, fault detection, and diagnostics was investigated [15,16]. This work was continued in IEA-EBC Annex 34 in 2006 in "Computer-aided Fault detection and Diagnosis" [17,18]. The recent progress in the IEA-EBC Annex on FDD is the Annex 81 subtask C2, "Automated Fault Detection, Diagnostics, and Recommissioning Applications" [19].

1.1. Current Reviews on FDD in Building Systems

Highly acknowledged extensive reviews of FDD in building systems by Katipamula et al. 2005a and 2005b are still highly relevant [10,11]. These were found to be the fundaments for all later reviews. In a recently updated review, Woohyun and Katipamula categorized the FDD methods according to the modeling approach (gray or black box) [14]. The following reviews on FDD had their specific scope and aims. Mirnaghi et al. reviewed data-mining methods [13], while Gourabpasi and Nik-Bakht focused on data-driven methods [20]. Zhao et al. focused on the strengths and weaknesses of the algorithms and discussed future challenges [21]. Ahmad et al. carried out an extensive review of computational intelligence techniques for FDD methods for HVAC, and suggested grouping them into five key modeling approaches: metaheuristic, artificial neural networks (ANNs), pattern-recognition-based methods, multiagent systems, and fuzzy logic [12]. Li et al. categorized the reviewed articles as feature engineering (FEng) and fault-relevant features (FF), with a focus on discussing the features of faults in the reviewed articles [22].

Building system-specific reviews were also performed for air-handling units (AHUs) and heat pumps (HP). Yu et al. investigated typical faults in AHUs and proposed desirable characteristics for FDD algorithms: quick detection and diagnosis, isolatability, robustness, novelty identifiability, classification error, adaptability, explanation facility, modeling requirement, storage and computation, and multiple fault identifiability [23]. Rogers et al. reviewed FDD methods for residential air-conditioning systems [24]. Bellanco et al. studied the fault behavior of HPs and methods for the measurement, detection, and diagnosis of faults, including virtual sensors [25].

Table 1 presents the key features of the above-described reviews for the collection of building systems.

Table 1. Reviews on fault detection and diagnosis in building systems. Times cited are from Google Scholar and were collected in April 2022.

Review Article	Keywords	Scope	Times Cited
Srinivas Katipamula and Michael R. Brambley "Review article: Methods for Fault detection, Diagnosis, and Prognostics for Building Systems—A Review, Part I", 2005 [10]	Not found	One of the first reviews on FDD in building systems. It focuses on generic FDD and prognostics, providing a framework for categorizing methods, describing them, and identifying their primary strengths and weaknesses.	Total: 1061 Annual: 62
Woohyun Kim and Srinivas Katipamula "A review of fault detection and diagnostics methods for building systems", 2018 [14]	Not found	Update on publications since reviews I and II. Categorizes automated fault detection and diagnosis methods into two main groups and discusses applicability for each building system.	Total: 229 Annual: 57
Yang Zhao, Tingting Li, Xuejun Zhang, and Chaobo Zhang "Artificial intelligence-based fault detection and diagnosis methods for building energy systems: Advantages, challenges and the future", 2018 [21]	Fault detection; fault diagnosis; building energy systems; artificial intelligence; big data	Reviews a large quantity of FDD articles and divides them into two classes: data-driven-based and knowledge-driven-based. Discusses the algorithms in detail and suggests research tasks for the future.	Total: 172 Annual: 43

Table 1. *Cont.*

Review Article	Keywords	Scope	Times Cited
Srinivas Katipamula and Michael R. Brambley "*Review article:* Methods for Fault detection, Diagnosis, and Prognostics for Building Systems—A Review, Part II", 2005 [11]	Not found	Continuation of the first review. It focuses on research and applications specific to the fields of HVAC&R, provides a brief discussion on the current state of diagnostics in buildings, and discusses the future of automated diagnostics in buildings.	Total: 567 Annual: 33
Maryam Sadat Mirnaghi and Fariborz Haghighat "Fault detection and diagnosis of large-scale HVAC systems in buildings using data-driven methods: A comprehensive review", 2020 [13]	Large-scale HVAC system; fault detection and diagnosis; data-driven model; supervised data-mining method; unsupervised data-mining method	Reviews the existing literature and identify research gaps in mainly data-driven FDD methods.	Total: 59 Annual: 29
Muhammad Waseem Ahmad, Monjur Mourshed, Baris Yuce, and Yacine Rezgui "Computational intelligence techniques for HVAC systems: A review", 2016 [12]	Heating, ventilation and air conditioning (HVAC); optimization; computational intelligence; energy conservation; energy efficiency; buildings	Presents a comprehensive and critical review of the theory and applications of CI techniques for the prediction, optimization, control, and diagnosis of HVAC systems. Classifies and thoroughly discusses each method's applicability for HVAC systems.	Total: 153 Annual: 25
Zixiao Shi and William O'Brien "Development and implementation of automated fault detection and diagnostics for building systems: A review" [26]	Not found	Reviews different methods for feature generation, fault detection, and fault diagnosis. Proposes ways to improve their current limitations from other research disciplines. Discusses potential research topics for further development and applicability.	Total: 49 Annual: 16
Guannan Li, Yunpeng Hu, Jiangyan Liu, Xi Fang, and Jing Kang "Review on Fault Detection and Diagnosis Feature Engineering in Building Heating, Ventilation, Air Conditioning and Refrigeration Systems", 2021 [22]	Building energy system; data analytics; feature engineering (FE) *; fault detection and diagnosis (FDD); fault-related feature (FF); heating ventilation air conditioning and refrigeration (HVAC&R)	Introduces feature engineering and fault-relevant features in a step toward FDD methods. The main focus is on the feature of faults in a large volume of articles.	Total: 6 Annual: 6
Arash Hosseini Gourabpasi and Mazdak Nik-Bakht "Knowledge Discovery by Analyzing the State of the Art of Data-Driven Fault Detection and Diagnostics of Building HVAC", 2021 [20]	Data mining; AFDD; HVAC; machine learning; association rule mining; FP-Growth	Uses the ASHRAE standard to classify data-driven methods. Focuses on knowledge discovery and discusses investigated faults and the applied algorithms.	Total: 0 Annual: 0

* Feature engineering (FE) is abbreviated in this article as FEng.

1.2. Shortcomings

With the exponential increase in articles and the development of algorithms in recent years, there seems to be an inconsistent use of terminologies and definitions related to FDD for building systems. Nevertheless, it is natural that changes occur along with the developments in research areas. However, if a common understanding of terminologies and definitions is not reached, there is a risk that the field will begin using different glossaries, thereby potentially hindering its growth.

The existing reviews regarding FDD in building systems have mainly focused on describing the specific FDD algorithms and their characteristics in detail [10,12,14,21]. Two reviews described the application and applicability of FDD in building systems [11,26]. Furthermore, two reviews primarily described the data-driven approaches and discussed research gaps [13,20]. In addition, all the previously mentioned review articles in Table 1 discussed the future directions and applicability of FDD. Moreover, dissertations have also contributed to the field of FDD. Behravan [27] provided a framework for demand-controlled ventilation (DCV) and thermal-control strategies. The dissertation focused on an in-depth assessment of the involved components' functionality and effective parameters, especially in the case of component failures. Furthermore, Shi [28] also developed a framework to holistically detect, identify, and evaluate building faults for stakeholders to facilitate decision making. Najafi [29] focused on a framework to optimize the architecture of sensor networks from a diagnostics perspective. Despite the substantial research efforts, there is still a lack of an overview of the different data requirements and necessary inputs to move further toward actual building implementation.

The most advanced FDD algorithms employ machine learning (ML) approaches, such as supervised or unsupervised learning. The flexibility of these algorithms to learn from patterns and trends in the collected building data has great potential for applicability in complex and real-world applications [21]. Despite that, these algorithms are dependent on system-specific data, since building systems are unique. This requires tailored modeling and increases the engineering time and cost, especially for buildings and programming competencies. Supervised learning provides a numeric value or a qualitative variable, such as a class or a tag, consequently needing labeled data with ground truth for the faulty data. Unsupervised learning creates a categorical output, and thus is not dependent on labeled data, but needs a dataset to validate the model. These datasets are expensive to develop, require expert personnel, and have an available controlled environment to be developed. In addition to this, availability of open datasets was found to be limited. With the increase in accessible data and the popularity of data analytics and big data, sharing data has become especially interesting in all research and industry sectors [30–32].

Based on the observations described above, three shortcomings were identified in the field of FDD in building systems at present: (1) a lack of a uniform glossary for FDD, especially for building systems; (2) a need for an up-to-date overview of the FDD algorithms for building systems, along with the different data requirements and necessary inputs to move further toward actual building implementation; and (3) a shortage of open-source FDD repositories for data and code.

This article investigated approximately 220 articles from the very early time of FDD to the present. As mentioned earlier, terminologies and FDD definitions in building systems were inconsistent. Hence, the first step was to collect the current work on FDD and streamline the terminology definitions for the FDD framework.

Further, this article aimed to provide an FDD encyclopedia for building systems consisting of the used algorithms and components, which could help tackle the second shortcoming in the list above. To tackle the third shortcoming, a data-sharing community may mitigate this. Therefore, we identified the data used in each article, and have provided a table in which they can be found.

1.3. Contribution and Structure of the Review

This review provides an up-to-date comprehensive and systematic summary of FDD in building systems. The review was designed to provide insights into the following topics:

- Glossary framework—a systematic and scientifically designed review of the existing terminology and definitions in the field of FD and FDD in building systems to provide a clear explanation of the applied terms, their context, and examples of use.
- Coherent classification framework—using the Energy System Terminology (EST) group developed by Andersen et al. [33]. Further, a novel classification of the existing body of literature on FDD frameworks in building systems is introduced.
- Applied data and FDD codes—a cornerstone in FDD is the availability of the data and the algorithms to treat it. Therefore, a comprehensive analysis aimed to provide awareness of the available data and codes and diversity across data and codes descriptions.
- The future directions are discussed to present potential future research outlooks.

The authors also hope to raise awareness about the large body of knowledge on FDD that has been produced in the last half-century for building systems specifically, with a focus on the data used in the articles. This might help the building community to realize the great potential of FDD to improve the building sector to become more efficient, reliable, and sustainable in the emerging data-driven society.

This systematic review has the following structure:

Section 1 accounts for the introduction and motivation of this review. It also discusses the most cited and extensive reviews of FDD in building systems. Section 2 presents the methodology for this systematic literature review. Section 3 (Results Part I) presents the terminology and definitions of the FDD process and classification of FDD algorithms to mitigate shortcoming 1. Section 4 (Results Part II) addresses shortcoming 2. The identified literature from Section 2 is presented, discussed, and visualized. Section 5 (Results Part III) focuses on the data used in each article and addresses shortcoming number 3. In addition, this section presents the found datasets and open code for FDD in building systems. Section 6 presents a discussion of the key findings. Section 7 makes concluding remarks and presents the future outlook for FDD in building systems. Abbreviations contains the abbreviations used in this review. Appendix A contains an overview of all the articles used for the analysis in Sections 4 and 5.

2. Methodology

This article used a semiautomated literature search and reference-filtering process, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) principle to ensure replication and quality assurance of this review [34]. The semiautomated methodology consisted of six steps; (1) initial keywords search; (2) search block development; (3) selection of reference databases; (4) query string creation; (5) reference filtering and quality check; and (6) final reference selection. A flowchart containing the expanded steps can be seen in Figure 1 below. The RefWorks reference handler was used in this semiautomated methodology [35].

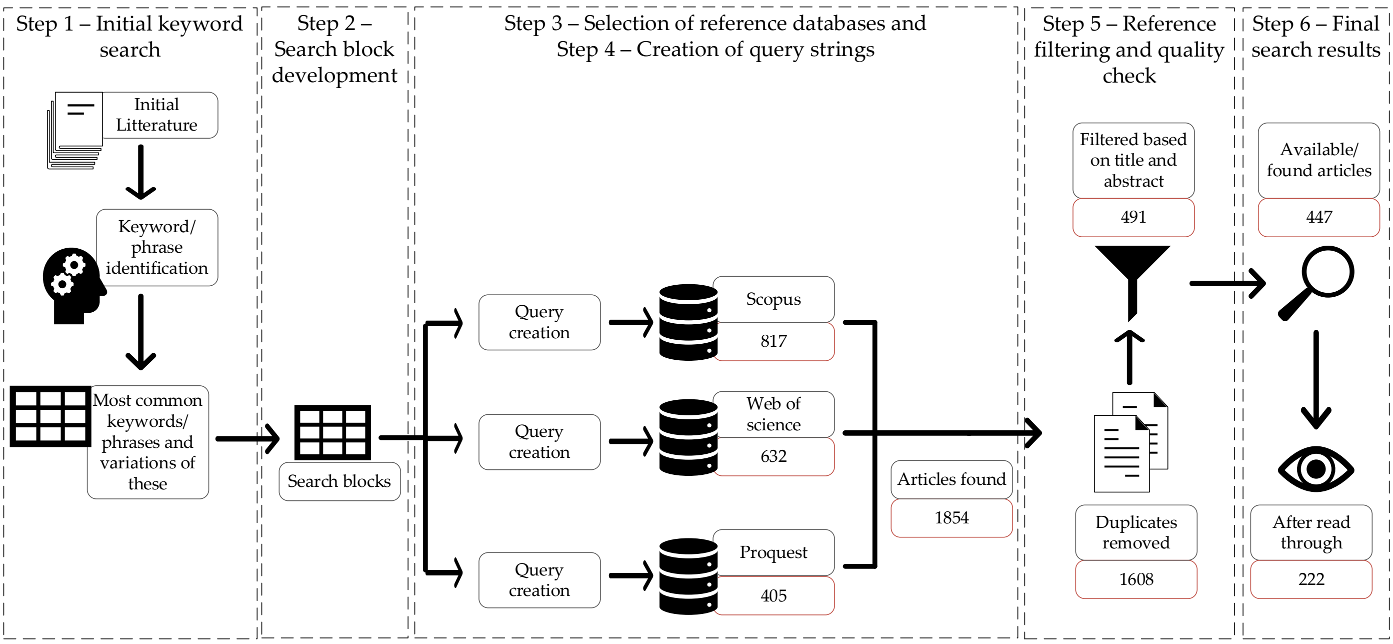

Figure 1. Flowchart of literature search methodology. The black boxes identify the action, and the red boxes quantify the number of relevant articles remaining after the corresponding action was performed.

The references, keywords, and search blocks from steps 1 to 6 in the semiautomated methodology can be found in a GitHub repository [36].

Step 1: Initial keyword search

This step consisted of identifying the keywords relevant to the article by reviewing a handful of existing articles in the field of fault detection and diagnosis in building systems. Here, the keywords and phrases that appeared most commonly and the variations/acronyms were analyzed and chosen for step 2.

Step 2: Search block development

Three individual search blocks were defined from the identified keywords in step 1, which used the OR operator internally and the AND operator between the blocks. The three blocks covered different modeling approaches (search block 1), fault detection (and diagnosis) (search block 2), and building and their systems (search block 3).

Step 3: Selection of reference databases

The three databases selected for this article were Scopus, Web of Science, and ProQuest, as these were deemed the most suitable databases within the article's scope. The collection of literature was completed in April 2021, so works published after April 2021 were therefore not included in this article.

Step 4: Creation of query strings

The query strings were created for each database individually by combining the search blocks with the database-specific options to filter accordingly. These options included language, subject area, and category, among others. The filters were imposed to filter out as many irrelevant articles as possible without filtering out any articles from relevant areas. Therefore, if there was any doubt whether certain filters might exclude relevant material, they were not used, thereby lowering the risk of removing relevant articles but increasing the necessary efforts in the later manual filtering process.

Step 5: Reference filtering and quality check

This step consisted of filtering all the collected articles by removing the duplicates and then filtering the relevant articles based on their titles and abstracts in RefWorks. After the filtering, a quality check was performed to ensure that specific "indicators" were found. For example, articles expected to be found in the search were among the well-cited articles in the field, but were not detected automatically. Delimitations of the articles were determined as follows: articles containing multiple faults, only supervised and unsupervised machine learning algorithms, or only FDD concerning HVAC systems in buildings were not investigated; for example, not photovoltaic systems or FDD in connected building networks such as district heating.

The first and second authors conducted the reference filtering and quality check. The specific indicators and relevancy were agreed upon beforehand to obtain a uniform filtering process.

Step 6: Final reference selection

This step consisted of (1) removing articles that could not be found online and (2) a final quality check for delimitations.

The final number of relevant articles was 221 for Sections 3–5 in this literature review, approximately 12% of the 1854 references found in the selected databases.

3. Results of the Review, Part I: Terminology and Categorization of FDD Methods

3.1. FDD Terminology

3.1.1. The Classical FDD Framework and Related Fields

Isermann defined a fault as the following: "A fault is an unpermitted deviation of at least one characteristic property (feature) of the system from the acceptable, usual standard condition" [37]. The primary objective of an FDD process is to detect faults, diagnose their causes, and possibly enable correction before additional damage to the system or loss of service occurs. The existing FDD procedures differ in the modeling methods employed, the input and output parameters, and the overall purpose. Fault detection (FD) aims to discover faulty operations in a system. However, it can only reveal a fault if something is wrong in the system; it cannot discover the fault source (when detection and diagnosis are not performed in one step). Consequently, the fault diagnosis aims to identify the physical fault factors in the systems (type, location, severity, and time). Typically, FDD has three main processes: fault detection, fault isolation, and fault identification. Together, fault isolation and fault identification are commonly designated as fault diagnoses. Fault evaluation follows fault diagnoses. This process evaluates the impact on the system in terms of, for example, energy use, cost, or effects on other performance indicators. Based on this step, a decision is then made regarding how to respond to the fault (action or no action). Together these four steps (detection, isolation, identification, and evaluation) enable what is commonly referred to as automated fault detection and diagnosis (AFDD) [37].

A related process in FDD is fault-tolerant control (FTC), which accounts for the feedback to the control system; for example, when the FDD system provides the fault information to the control system of the building. In a simple manner, the control system will react by retuning the existing control parameters, rescheduling the current control strategy, or both. The latter is performed with the aim of optimizing the operation of the postfault system. This part is typically called control reconfiguration (ConRec). For example, a typical active fault-tolerant control (AFTC) consists of two parts: FDD and ConRec. However, the ConRec needs to be automatically performed online or in real time by the control system itself [37]. Zhang et al. [38] conducted a bibliographical review of FTC and discussed a general framework consisting of FTC and FDD for active fault-tolerant control systems.

Another process related to FDD is the modeling of fault behavior, typically called fault impact analysis (FIA) or fault evaluation (FE). Here, the aim is to assess the impact of the faults on specific systems. For HVAC, this is typically energy, cost, or indoor environment. Selected articles within HVAC are briefly discussed next. Li et al. critically reviewed the fault modeling of HVAC systems in buildings. Typical faults in HVAC systems were presented, and modeling tools such as HVACSIM+, Modelica, TRNSYS, and EnergyPlus were discussed [39]. Another widely used tool is MATLAB/Simulink. Ginestet et al. modeled the impact of faults in the AHU controller of a three-way valve, mixing box dampers (flow problems), and sensor inversion using MATLAB/Simulink to model the effects on energy use and IEQ of such faults [40]. Roth et al. presented an extensive list of typical faults and investigated the impact of faults in commercial buildings in the USA regarding their energy use [7]. Andersen et al. investigated typical faults occurring in demand-controlled ventilation. Here, they modeled the faults' impact on energy use and indoor environmental quality (IEQ) in a Nordic climate with the building performance simulation tool IDA ICE [6].

3.1.2. A Suggestion for a Common FDD Framework

There is a vast amount of literature on FDD for the different engineering disciplines. Consequently, similar concepts have been defined and named differently across those fields. Table 2 describes the frequent abbreviations, definitions, and typical synonyms of key concepts found in the explored literature on FDD. Table 3 describes the sub-processes for FDD.

Table 2. The main nomenclature of terms frequently used for FDD in building systems.

Abbreviation	Full Name	Synonym	Definition
AFDD	Automated fault detection and diagnosis	Automated fault detection and diagnostics/fault detection, diagnosis, and evaluation (FDD&E)	Consists of fault detection, fault isolation, fault identification, fault evaluation
FDD	Fault detection and diagnosis	Fault detection and diagnostics	Consists of fault detection, fault isolation, and fault identification (with the last two commonly known collectively as fault diagnosis)
FD	Fault detection	-	This step involves monitoring the physical system or device and detecting any abnormal conditions (problems)

Table 3. Nomenclature of subprocesses for FDD in building systems.

Abbreviation	Full Name	Synonym	Definition
FI	Fault isolation	Fault analysis	This process involves isolating the specific fault that occurred, including determining the type of fault, the location of the fault, and the time of detection
FI	Fault identification		This process includes determining the size and time-variant behavior of a fault
FDI	Fault detection and isolation	-	Fault detection and fault isolation
FDI	Fault detection and identification	-	Fault detection and fault identification
FE	Fault evaluation	Fault impact analysis (FIA)	Fault evaluation assesses the size and significance of the impact on system performance (in terms of energy use, cost, availability, or effects on other performance indicators)

Figure 2 above presents a generic fault detection and diagnosis process for all engineering systems expanded from Katipamula et al. [10]. As shown in Tables 2 and 3, the authors used the abbreviation AFDD in their article without clarifying the definition. As automatic indicates an automatic process, it was unclear whether the FDD process was automatic or manual. Therefore, it is suggested to use FDD&E instead of AFDD if this process is not occurring automatically (not working by itself with little or no direct human control). To clearly distinguish whether this process is automatic or not, it is suggested to use AFD, AFDD, and AFDD&E for methods requiring minimal human input or interaction while running, and FD, FDD, and FDD&E if the methods require human input or interaction while running. In the case of the implementation of AFDD, other essential factors, such as IT structure and data handling, need to be addressed.

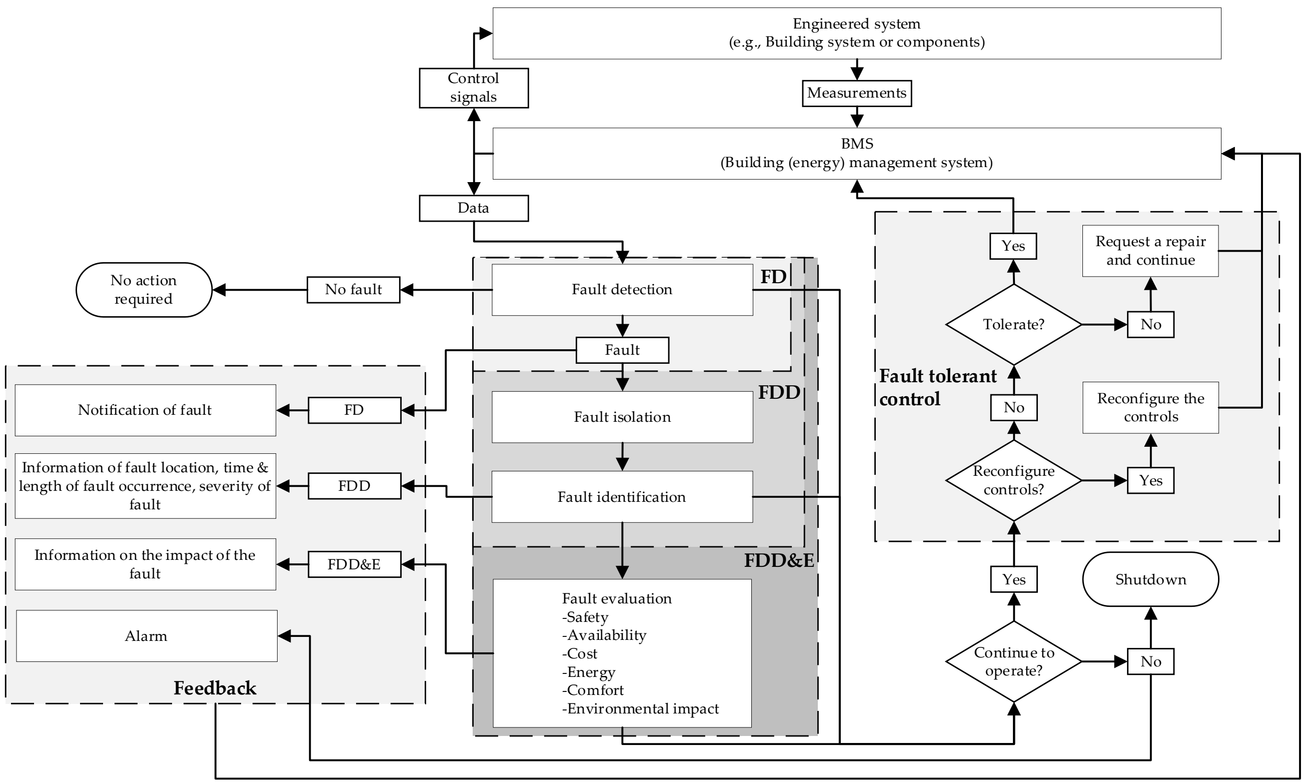

Figure 2. A generic FDD framework expanded from Katipamula et al. [10]. Permission to modify the figure was obtained from the main author of the original reference.

3.2. Method Categorizations for FDD

Several classifications regarding FDD methods have previously been created (see Table 4).

Table 4. Categorization of methods in selected articles used to streamline the categorizations found in the explored literature. The mentioned references below created categorizations in their review.

Ref.	Categorizations of FDD Methodologies
Katipamula et al. [10]	- Qualitative-model-based - Quantitative-model-based - Process-history-based
Zhao et al. [21]	- Data-driven-based - Knowledge-driven-based
Mirnaghi et al. [13]	- Data-mining methods - Statistical methods
Zhang et al. [38]	- Model-based methods - Data-based methods
Li et al. [22]	- Manual feature engineering - Automated feature engineering
Ahmad et al. [12]	- Prediction - Optimization - Control and diagnosis

An attempt to streamline the categorizations found in the explored literature in Table 4 above is presented in Figure 3. This file is available in a GitHub repository [36] and is open for additional contributions. Zhao et al. [21], Katipamula et al. [11], Woohyun and Katipamula [14], Gourabpasi and Nik-Bakht [20], Li et al. [22], Shi et al. [26], and Ahmad et al. [12] were not included due to similar definitions and not the focus of these reviews. Zhang et al.'s [38] data-based methods and model-based methods were chosen as the base for further division of the articles, since (1) this article mainly concerned a bibliographic review of FTC, but also discussed the FDD process; and (2) these definitions were simplistic.

In Figure 3, the suggested categorization consists of model-based methods and data-based methods to distinguish if historical measurements of the building are needed to initialize the method or not. In the case of model-based methods, experts can set up this model while only knowing the metadata of the building or system. However, data-based methods require initial data and calibrated measurement training data. Even though these divisions seem intricate, the transition from one to the other can be relatively un-demanding for some methods. For example, if a simplified physical model (white-box model) is used, it can become a gray-box model by having coefficients that require building or system-specific training data to be approximated. This is why gray-box models were classified as data-based methods in this review, but they are always on the border between model-based and data-based, as they are created using physical knowledge but trained using historical data of the system. An examples of this was found in [41], in which a gray-box model (in this case, a resistor–capacitor (RC) model) was compared to a detailed physical model (EnergyPlus model). The deviation between the selected key performance indicator (KPI) was then used for FD. The gray-box model was trained using two weeks of data from the physical model, and it predicted an indoor air temperatures close to the physical model under fault-free conditions. Gray-box models also have been used as a basis in FD or FDD schemes for providing the reference model needed for residual comparison [42–46].

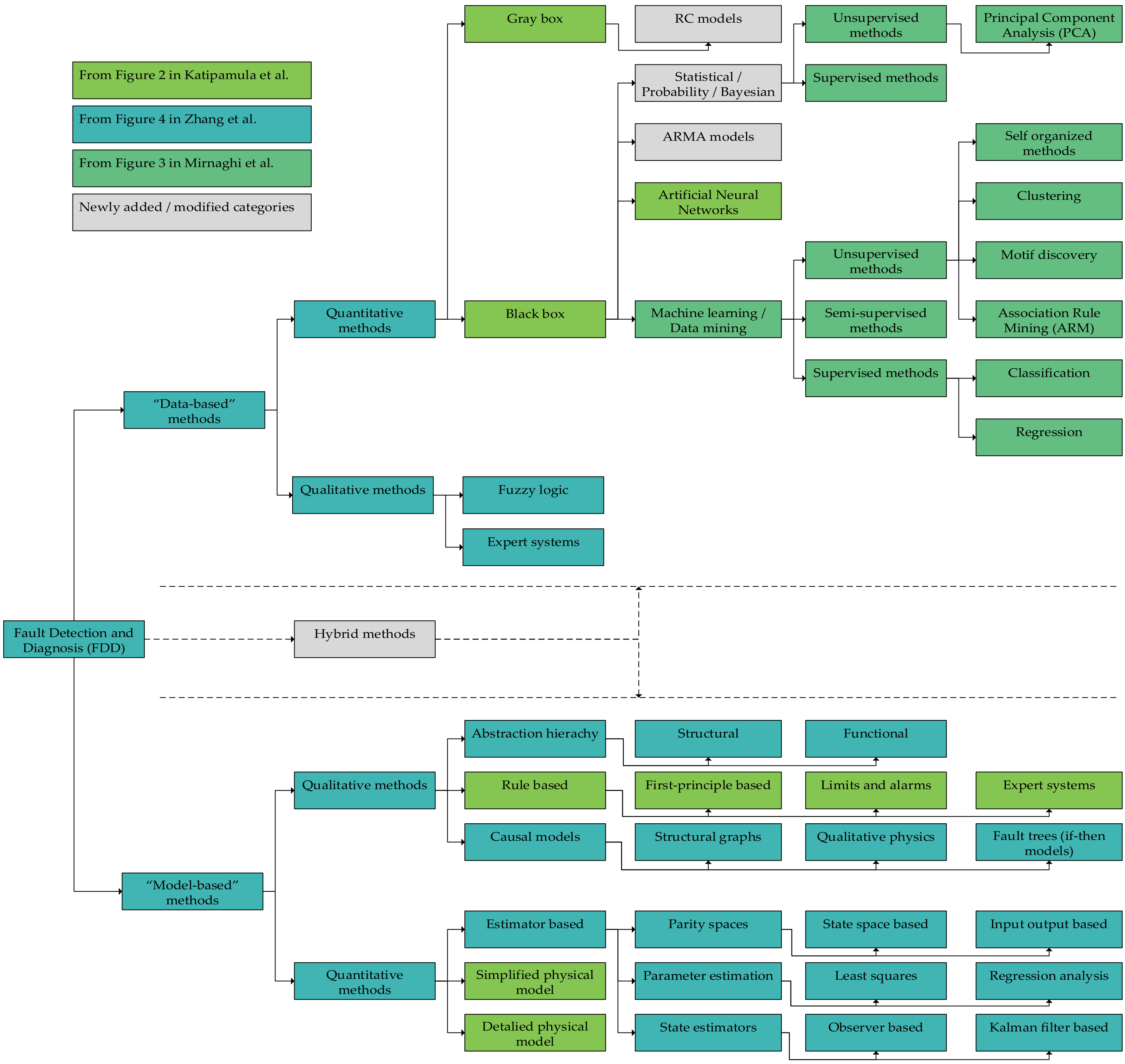

Figure 3. Attempt to streamline the existing FDD methods based on "data-based" and "model-based" methods. Katipamula et al. [10], Zhang et al. [38], Mirnaghi et al. [13].

This review's main dividers (model-based and data-based) were further split into qualitative and quantitative methods. Both model-based and data-based qualitative methods focus on rules [47–49] and relations between parameters [8,50,51]. Contrarily, the model-based quantitative methods focus more on using a reference model to compare the measured data from the system [42,43,52]. Data-based quantitative methods use statistics for, among others, data clustering [53–55], pattern recognition [56–58] and classification [59–61] to extract the knowledge from the data.

3.2.1. Data-Based Methods

As mentioned above, data-based methods rely on initial measured data to train the model serving as a system reference. This is one of the strengths of these methods, as they do not necessarily rely on knowing the system's physics and characteristics beforehand.

On the contrary, they are calibrated with real measurement data to fit the system's actual behavior [62–64]. Furthermore, this is also a weakness of data-based methods, as using the data from the specific systems means that the model is well fitted for the system, but cannot be directly applied to another similar system. Even though it is the same type, the specific behavior might differ significantly. This problem was demonstrated in [65], in which several different FD models for a reversible heat pump were trained using an experimental dataset [66] and then applied in FD using a real building dataset [67]. The results can be seen in Figure 4. For all the methods, just applying the trained model to a different system meant that the Matthews correlation coefficient (MCC) [68] dropped from 0.40–0.75 to 0–0.05, except for the naïve Bayes classifier (NB), which had a poor performance from the beginning. When modifying the labels of the actual building dataset to also include timesteps right before failure, the classification and regression tree (CART) and random forest classifier (RFC) models could predict the faults before they occurred, but not well enough to serve as the sole FD method of a system.

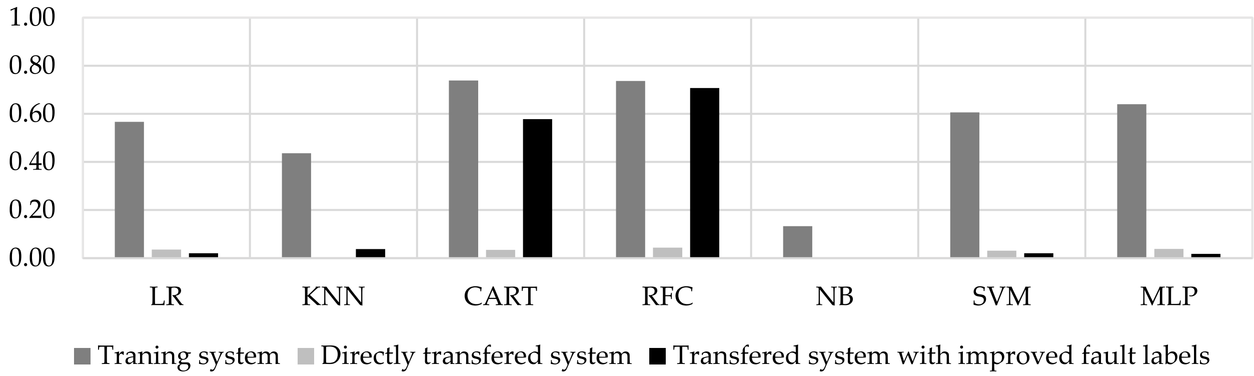

Figure 4. MCC for the FD model. The training system is the system on which the model is trained. The directly transferred system is the new system in which nothing is changed about the model or system. The transferred system with improved fault labels uses the original models, but has better fault labels. This figure is adapted from [65], Figures 7–9, which was published in the Energy journal, 198, G. Bode, S. Thul, M. Baranski, D. Müller, "Real-world application of machine-learning-based fault detection trained with experimental data", 5–6, Copyright Elsevier 2020.

In addition the data-based method's ability to be fitted to a system, it is also common for these methods to continuously be updated over time to adapt to a system's changes [69,70]. Of course, the update frequency and relevance depend on the method used. Some methods are based on this continuous fit of parameters, with the change in fitted parameters being the fault indicator. This was performed with both autoregressive with exogenous input (ARX) and autoregressive moving average with exogenous input (ARMAX) models [71]. The data-based methods can be fast and easy to set up in this case, and were recommended in [13,14] to be used in future FDD implementations.

3.2.2. Model-Based Methods

On the one hand, model-based methods have the advantage of typically being based on a system's physics, thereby enabling easier understanding and interpretation of the behavior and results of the methods [49,72,73]. On the other hand, they have the disadvantage of needing experts to set them up for each system individually, meaning that it the process to create them can be labor-intensive initially. However, transferring them to similar systems requires less labor. This category of methods is broad, spanning from detailed physical models to simple alarms. Quantitative methods are generally based on physics, while qualitative methods are based on rules or relations between variables.

3.2.3. Hybrid Methods

Several of the FDD methods found in the literature consisted of a combination of algorithms from both data-based and model-based methods. Examples of combined data-based quantitative and model-based qualitative methods [72,74] and combined data-based quantitative and model-based quantitative methods [75,76] were found. These were defined as hybrid methods. However, for identifiability, we chose to classify them according to their individual methods; otherwise, every combination would need to be included.

4. Results of the Review, Part II: FDD in Building Systems

4.1. Overview of the Articles

The keywords, journals, and countries (of the publishing research teams) found in the reviewed articles are presented in this section. As shown in Figure 5, the prominent actors working in the field of FDD in building systems are China and the USA. The latter were involved in approximately 60% of the publications. An interactive figure is available on a GitHub repository [36].

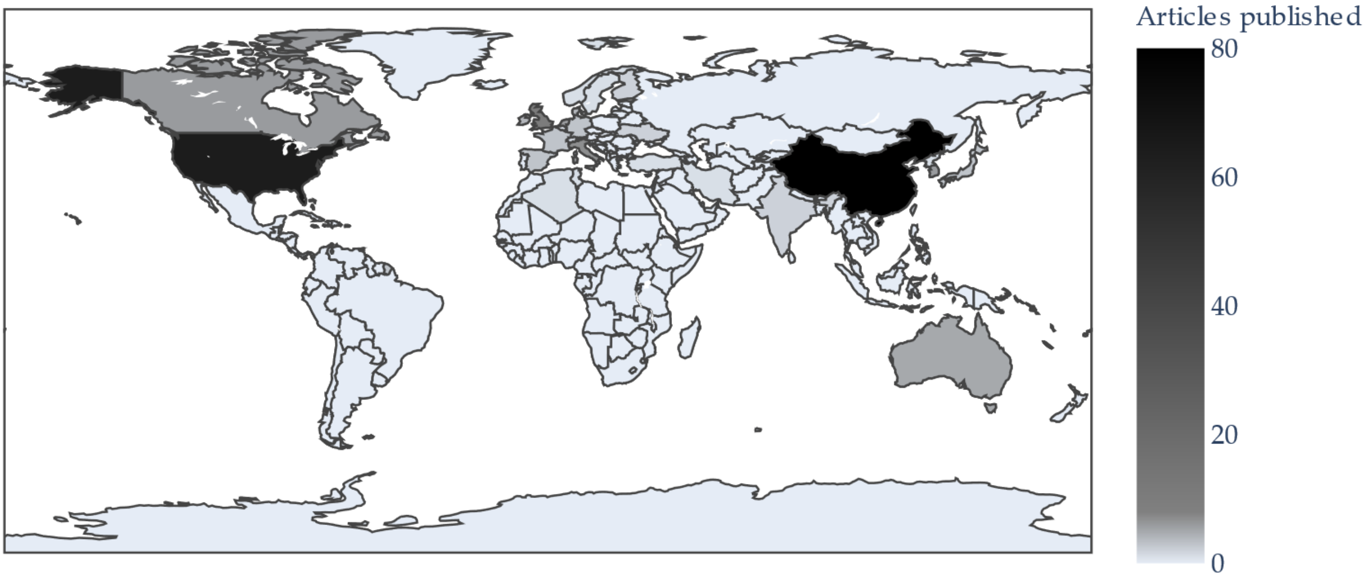

Figure 5. Authorship countries represented in the reviewed articles.

In the left part of Figure 6, one can observe that the journal *Energy and Buildings* accounts for almost 25% of the literature on the topic, followed by six other journals (between 10 and 20 articles each). The journals with less than 10 articles made up 19% of the literature. In the word cloud of keywords in the right part of Figure 6, one can observe that the articles investigating FDD in building systems usually used fault detection, fault diagnosis, fault detection and diagnosis, and FDD. Diagnose, diagnostic, and diagnostics were also common variants used instead of diagnosis.

4.2. Categorization of the Articles

The explored literature was sorted based on EST groups (see Figure 7) according to [77], which provided a clearer perspective from the building and systems point of view. Table 5 describes the explored literature within the EST groups, the corresponding building system, and its components. The delimitations of the investigated articles resulted in the following EST groups being excluded: building envelope, energy storage (EV battery), energy storage (other), energy grid, environmental energy, and appliances.

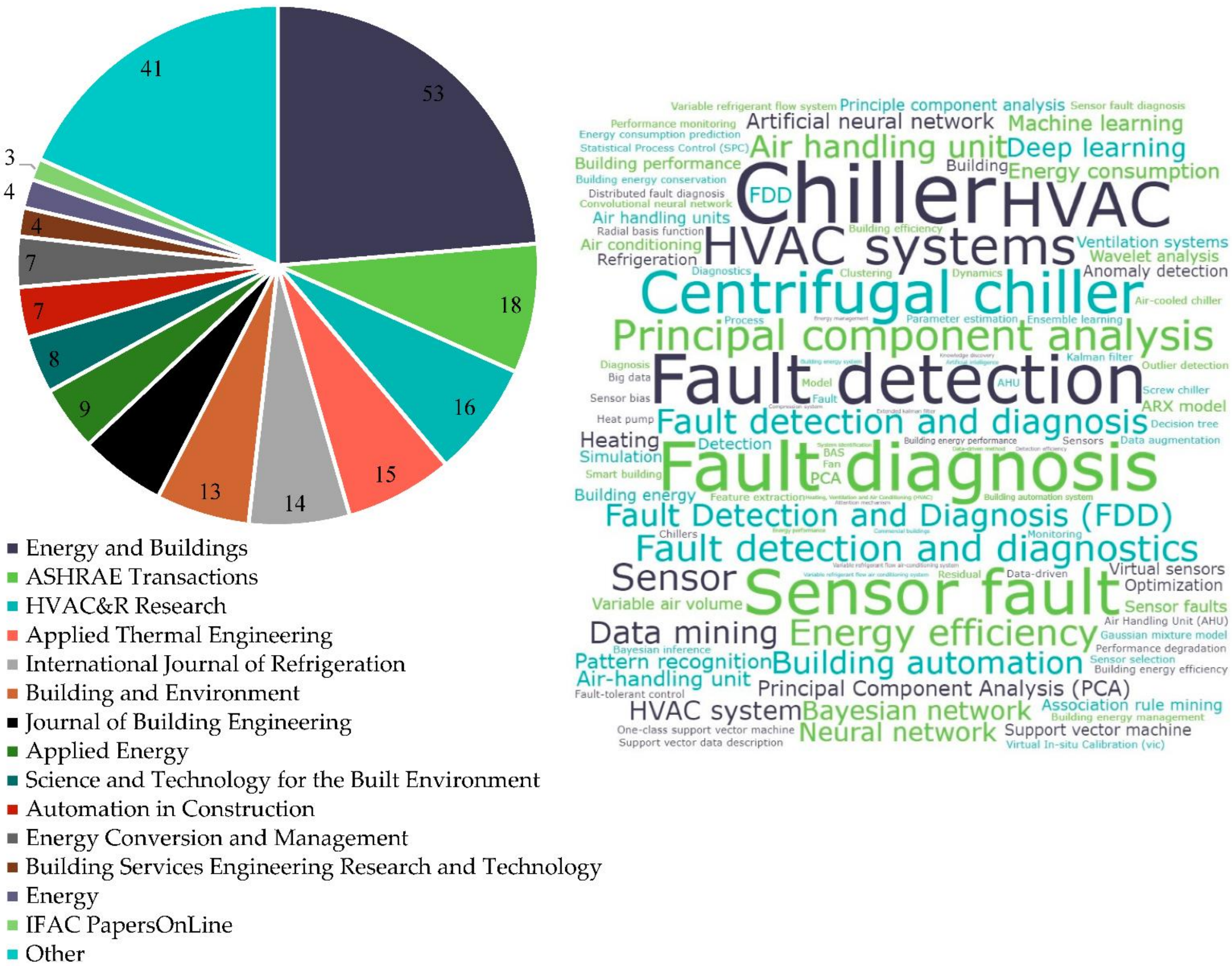

Figure 6. (**Left**) Top 35 journals that published the reviewed articles. The journals containing two or fewer published articles were not listed in this figure. (**Right**) Most commonly used keywords in the reviewed articles; an increased font size indicates that it was used more times. The 405 keywords used only once were excluded from this figure.

Table 5. The defined EST groups, the corresponding building systems, and components.

Energy System Terminology Groups	Building System
Energy conversion	Centralized heating system (CHS)
	Centralized cooling system (CCS)
	Terminal unit/air conditioning system (TU/AC)
Energy distribution	Air-handling unit (AHU)
	Terminal unit/air-conditioning system
Energy use	Whole building (WB)

Figure 7 presents the distribution of the articles in each EST group sorted by the building systems above. As one can observe, the energy conversion and the building system CCS had the highest share of publications (approximately 55%). Energy distribution and AHU were present in close to 40% of the articles.

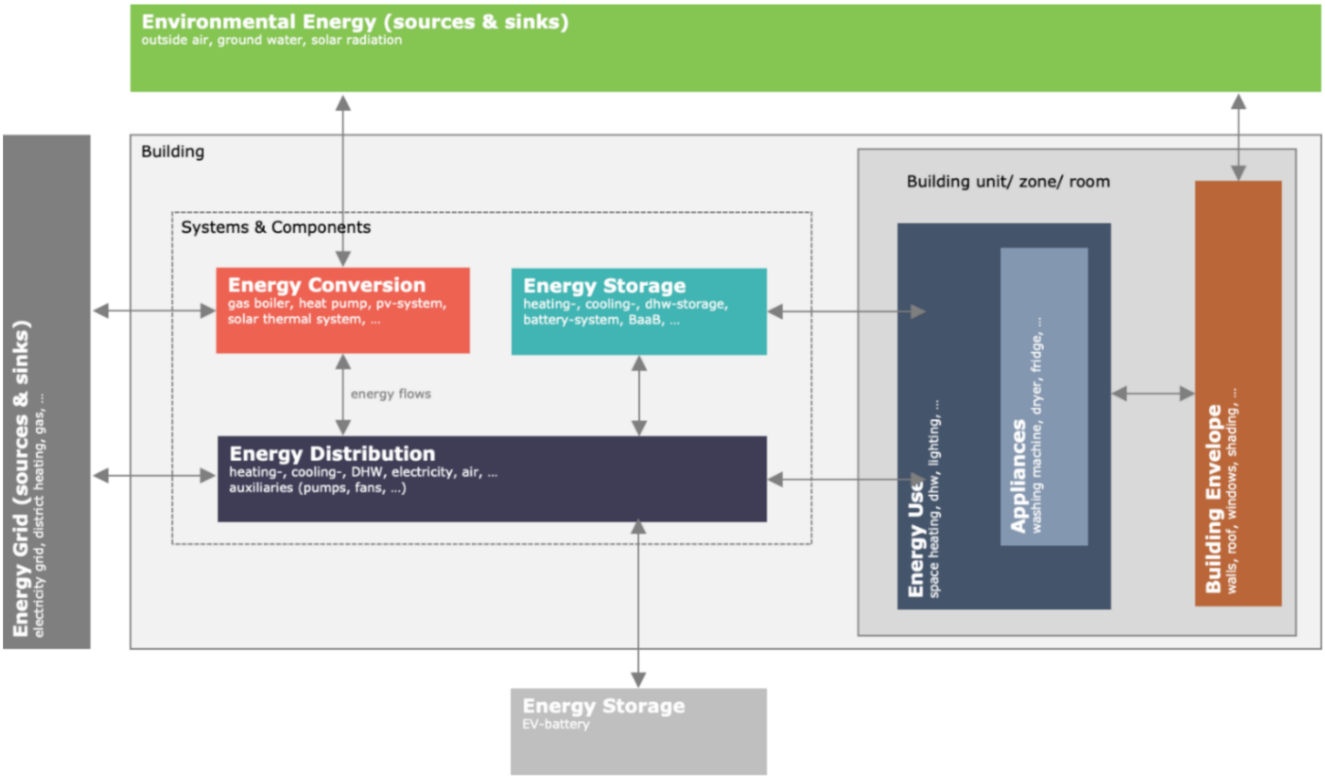

Figure 7. The EST groups as defined in [77].

Figure 8 describes the articles sorted by building system and year of publication. The year 2021 only included articles investigated until April 2021. On the one hand, the AHU was the most-investigated building system in the last decades. On the other hand, the CCS building system also was widely studied, but has seen an increased interest since 2008. Figure 8 contains a treemap of the EST groups and the number of articles.

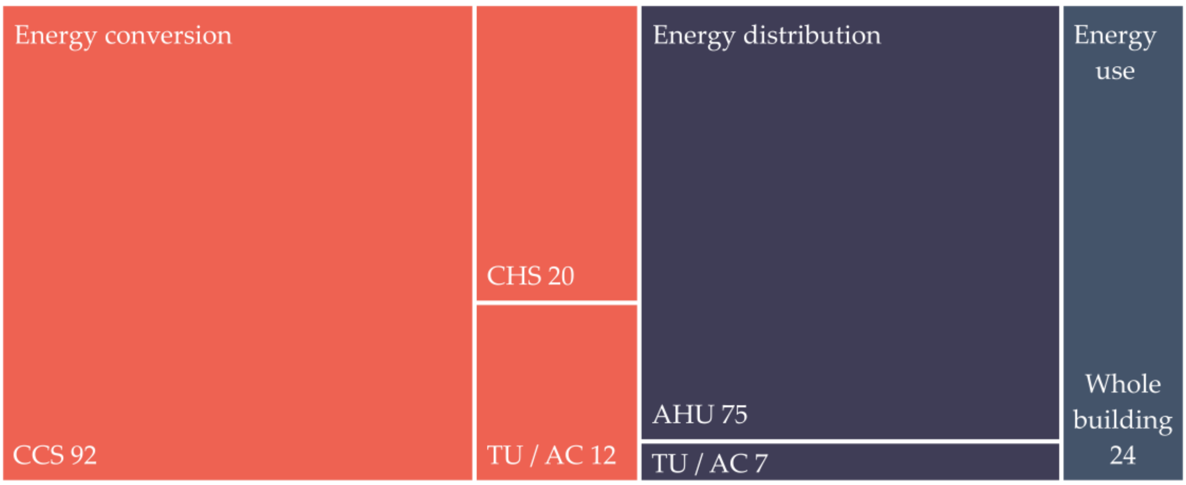

Figure 8. Number of articles within each EST group.

Figure 9 describes a two-layered structure of the number of articles (layer two) within each EST group (layer one). The color code from layer two is represented in Figure 10, in which the number of articles is sorted by building system and year of publication. The year 2021 only covers publications until April 2021.

Figure 9. Number of articles within each EST group and building system.

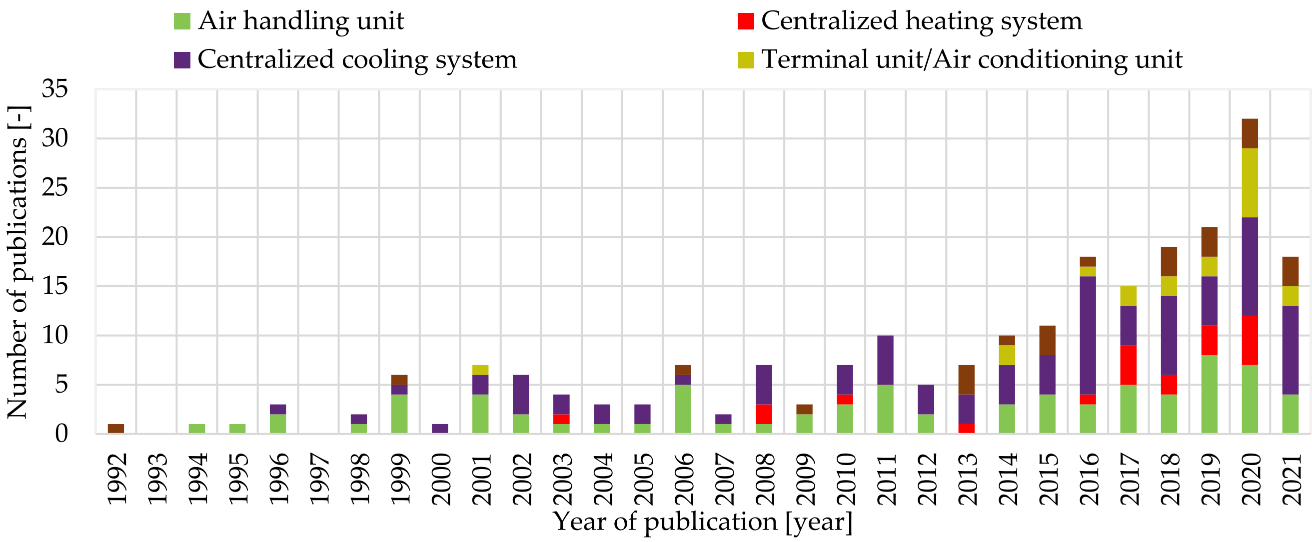

Figure 10. Articles sorted by building system and year of publication. The year 2021 only covers publications until April 2021.

4.3. Modeling Approach

Based on the EST groups in Figure 7, the reviewed articles were further sorted into the categories defined in Figure 3 and presented in Figure 11. This figure presents four layers. Layer one is the EST groups and is further divided into layer two, data-based or model-based methods. Layer two is then further divided into quantitative and qualitative methods (layer three), separately for the data- and model-based methods. Layer three is then further divided into algorithms in layer four. The algorithms were adopted from Figure 3 and were divided into the following categories: machine learning, statistical, artificial neural network, gray box, fuzzy logic, physical model, estimator-based, casual model, and ARMA. These categories are further described in the respective literature presented in Table 4.

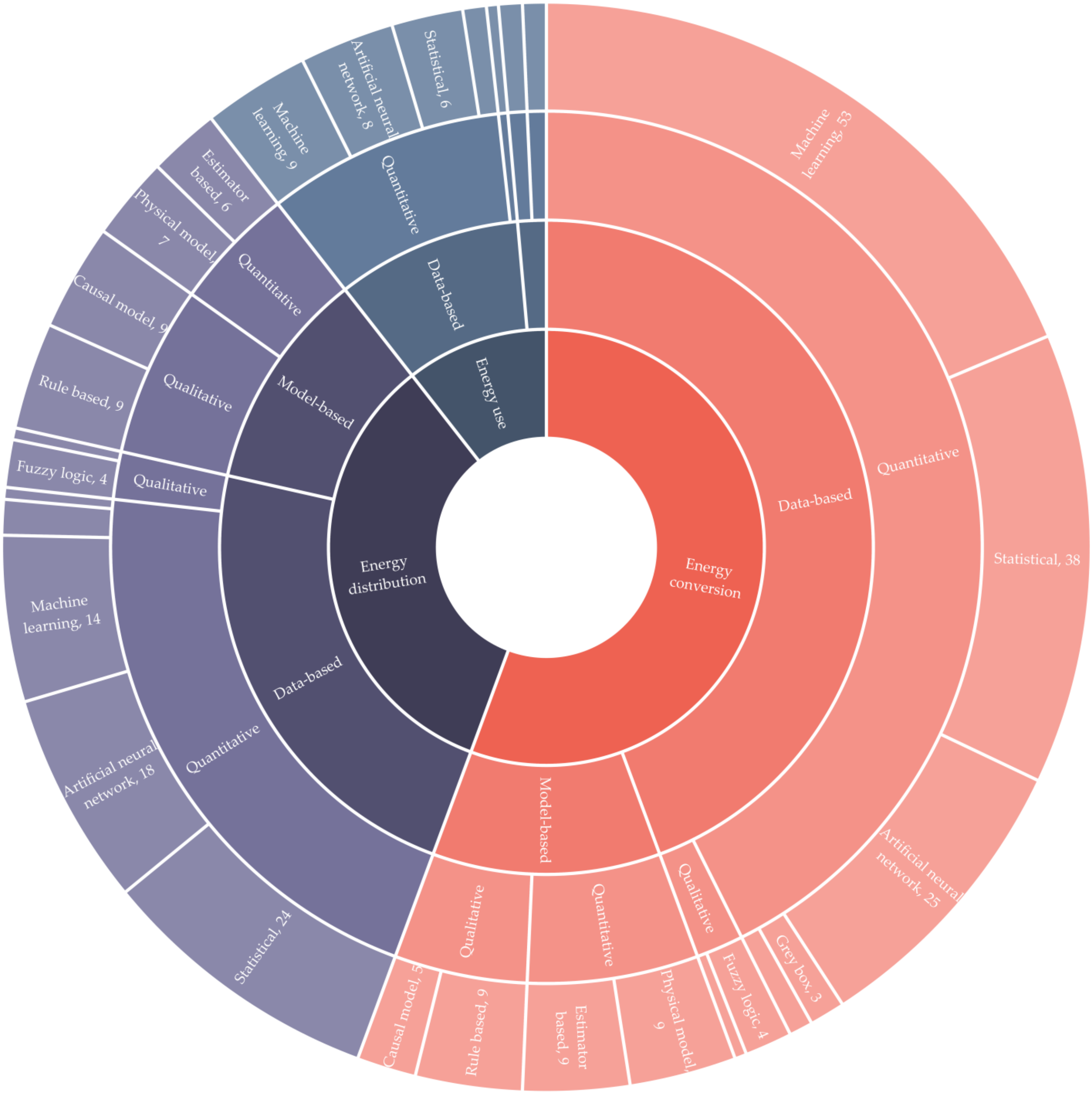

Figure 11. Articles categorized according to EST group and modeling approach.

As one can observe in Figure 11, the data-based methods were the major modeling approaches in all the EST groups. Within the data-based methods, the quantitative modeling method (machine learning, statistical, and artificial neural network algorithms) was predominantly used; while in the model-based methods, estimator-based, rule-based, and causal models were found to be used. Nevertheless, several of the articles within energy conversion under the machine learning algorithm category used principal component analysis (PCA) in correlation with other algorithms; PCA is not, by definition, a machine learning algorithm.

4.4. Algorithm Distribution

This subsection presents the FD, two-step FDD, and one-step FDD algorithm distribution. The two-step FDD typically requires two different algorithms: one to detect the fault and one to diagnose the fault. In comparison, one-step FDD uses a single algorithm to simultaneously perform fault detection and diagnosis. A complete list of all the articles with the year of publication, building system, component, and EST group can be found in Appendix A. As this review was focused on creating a common glossary and understanding of FDD, the specific workings of the different algorithms are not explained. To read more about the details of each algorithm, it is suggested to read either the individual articles associated with each algorithm, or see the previously mentioned literature reviews, especially for building systems [12,14,22,78–80] for a three-part review on fault detection and diagnosis explicitly targeting the characteristics of each algorithm.

Table 6 presents the general overview of the algorithms used for FD and one- and two-step FDD in all the articles in the selected EST groups. Please note that Table 6 consists of the sum across the EST groups. Table 7 presents the FD and one- and two-step FDD grouped by the EST groups. The four most used algorithms are discussed in further detail hereafter.

Table 6. Fault detection (FD) and one- and two-step FDD methods used in all the articles.

Category	**Fault Detection**	**Two-Step Fault Detection and Diagnosis (Fault Detection/Diagnosis)**	**One-Step Fault Detection and Diagnosis**
	(70 Articles)	**(55 Articles)**	**(97 Articles)**
The four most applied algorithms for all articles. Building system was not taken into account in this category.	PCA (8) [81–88]	PCA + Q-statistics/Q-contribution plot (3) [89–91]	SVM (18) [56,57,70,92–106]
	ANN (4) [107–110]	Gray-box model/expert ruleset (2) [111,112]	Ruleset (4) [48,49,113,114]
	ARX (3) [71,115,116]	-	Residuals (3) [42,43,117]
	-	-	DBN (3) [118–120]

A complete list of all the articles with the year of publication, building system, component, and EST group can be found in Appendix A. See [7,13,20] for a broader overview of typical faults, building systems investigated, and trends in this research area.

In Table 6, one can observe that PCA, ANN, and ARX were the most used methods for only fault detection. PCA was the most common, as it was used in 13% of the articles performing only FD. When used in combination with other methods, it was used in 22 articles (31%). PCA was also the most common algorithm for two-step FDD, combined with Q-statistics for detection and a Q-contribution plot for diagnosis. Further, a gray-box/expert ruleset also was used. As the variability in the algorithm combinations was high in the two-step FDD, it was not possible to conclude the historically preferred algorithm. A support vector machine (SVM) was mainly used in the one-step FDD methods, appearing in 17% of the articles. Finally, ruleset, residuals, and diagnostic Bayesian network (DBN) were typical methods for one-step FDD.

Figures 12–14 describes the distribution of articles within each EST group and FD, two-step FDD, and one-step FDD. Articles with algorithms only used once do not have a label in the figures, but can be found in Appendix A.

Figure 12 shows that a vast amount of algorithms were applied in the different reviewed articles. However, a few of them stood out. For energy-conversion systems, these were PCA and variations of PCA. Further, residuals, multilayer perceptron (MLP), and ANN + residual algorithms were applied twice. Moreover, for energy distribution, the Chernoff bound, and for energy use, ANN were both found to be applied two times.

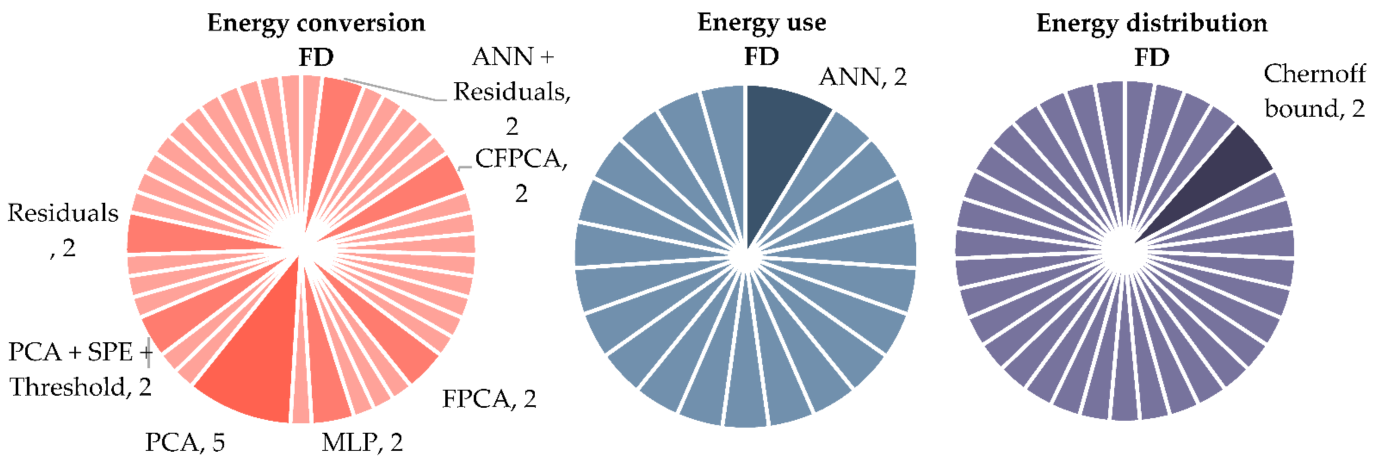

Figure 12. Energy-conversion, energy-distribution, and energy-use EST groups for FD.

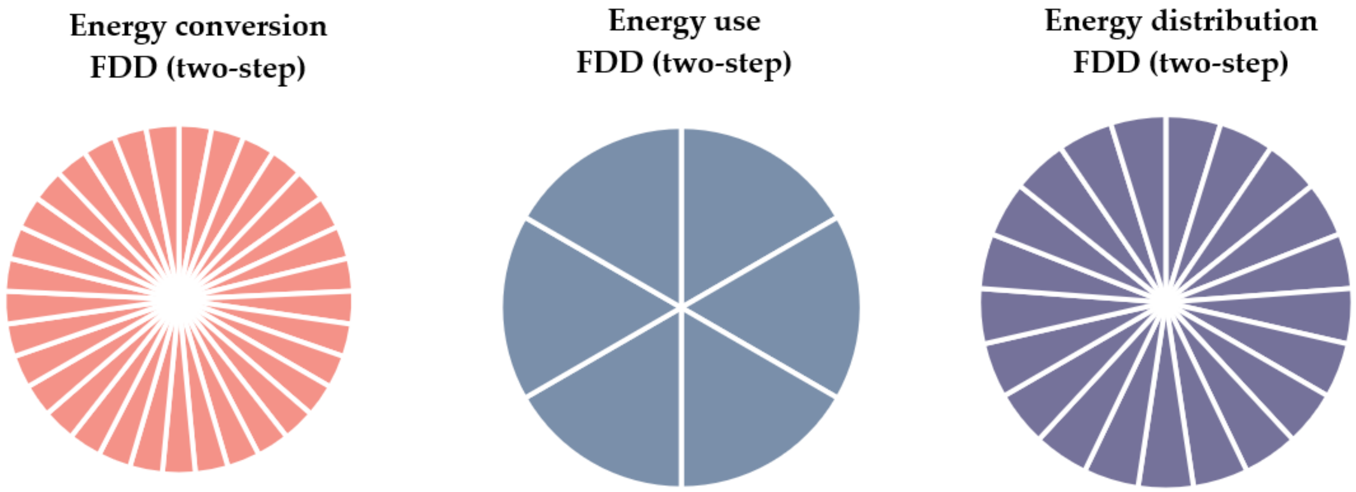

Figure 13. Energy-conversion, energy-distribution, and energy-use EST groups for two-step FDD.

For two-step FDD, which can be seen in Figure 13, all algorithms were found to be only used once. As two-step FDD requires two various algorithms, one for fault detection and one for diagnosis, this was considered a natural finding. It could, however, also imply that the field is still in the process of maturing through testing different combinations of algorithms.

The distribution of the one-step FDD can be seen in Figure 14. SVM was applied five times in the energy-conversion group. Further, the Bayesian network (BN), back-propagation neural network (BPNN), DBN, decision tree (DT), multiclass SVM, radial basis function exponentially weighted moving average (RBF-EWMA), and residual + fault pattern analysis were all found to be applied two times. In the energy-distribution group, the ruleset was applied three times, while a wavelet neural network (WNN), DBN, fuzzy model + degree of belief, and residuals were all found to be applied two times. Moreover, all algorithms in the energy-use group were found to only be applied once.

In Table 7, it can be seen that a variety of algorithms have been used for different building systems. PCA was generally used for CHS and CCS in energy conversion for fault detection. The PCA algorithm's main feature is based on the possibility of reducing a higher-dimensional space into a lower-dimensional space. This algorithm is appropriate for fault detection as a fault deviates from a reference behavior, and is therefore a relatively simple and easily applicable method for FD. It is more challenging for fault diagnosis, as it typically requires labeled data. For AHU in the energy-distribution group, Chernoff bound (CB) was found to be applied two times. The method is generic, with the potential to be applied to many different systems, as stated in [121]. In addition to the generic properties of this method, it is also relatively simple to implement and scale to different systems, as it is based on outlier detection. The method itself was developed in [122]. For TU/AC, the combination of a model for predictions and residuals (the difference between model and actual measurements) was applied in two cases. This method is simple to implement, but requires significant expert knowledge. In [41], the method was deployed as an RC model to be compared with an EnergyPlus model instead of an actual building. The method detected faults correctly in 70 to 82% of the cases. CART was used in four articles on FD for the EST energy-use group. This method is used because it provides a decision tree with if–then rules, meaning that the outcome is interpretable by both humans and computers [55,61,123]. Regarding classification accuracy (CA) [61], it was between 80 and 90%, while the rest did not provide a detection-accuracy measure.

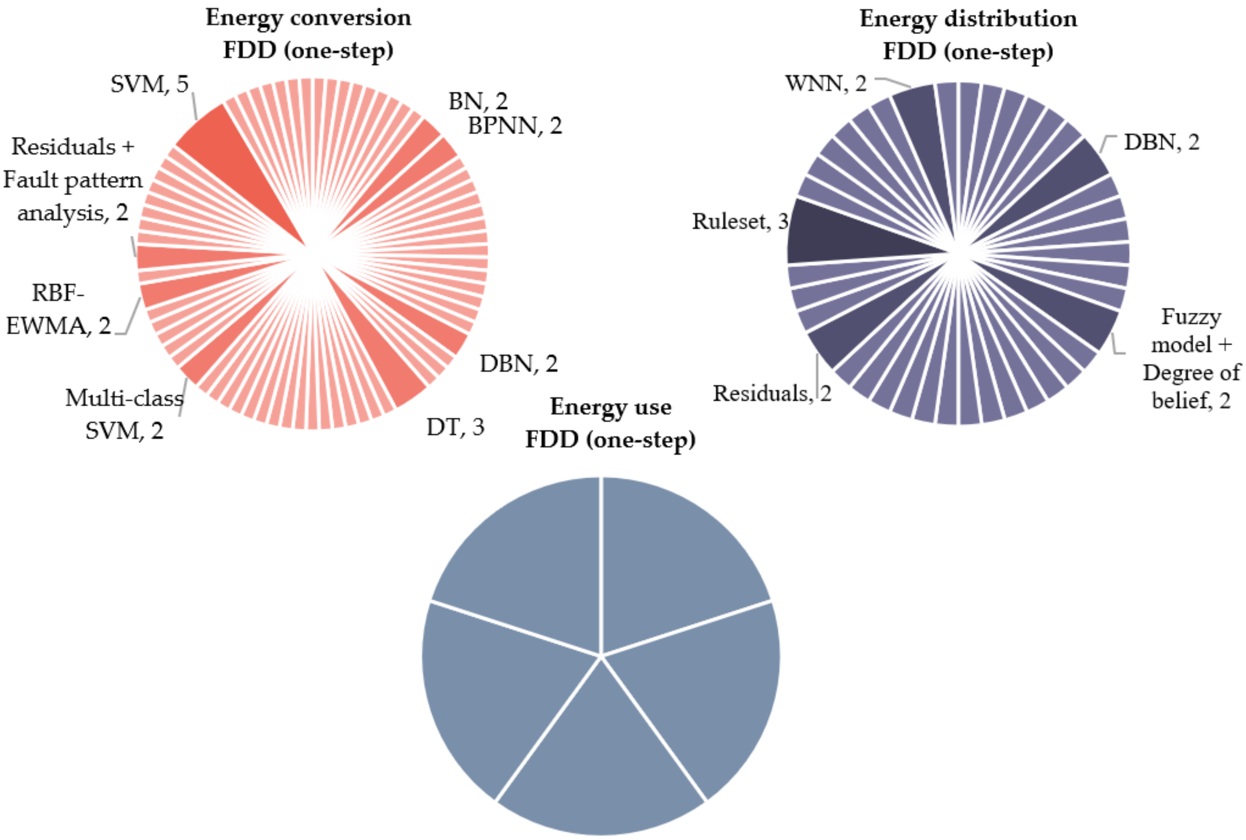

Figure 14. Energy-conversion, energy-distribution, and energy-use EST groups for one-step FDD.

For two-step FDD, the general trend was challenging to observe, as there was a great variety in the algorithms. However, gray box and expert ruleset, as well as PCA with Q-statistics and Q-contribution plot, were tested twice each. In the case of the gray-box model and expert ruleset, the gray box is a reference model that is meant to be compared to the available measurements, while the expert ruleset determines the fault threshold [111,112]. In [111], the expert ruleset was determined based on the physical behavior of the parameters, and implemented as dividers based on the ratio between the measurement and reference model and the normalized heat-transfer coefficient. The method does suffer from the choice of the confidence interval, as increasing the sensitivity to faults also increases the number of false positives (detecting faults when there are no faults). The vital point is that no dataset with ground truth is needed for the method. The PCA with Q-statistics and Q-contribution plots were based on calculating the Q-statistics for each component, with a threshold for the fault-detection part, followed by a Q-contribution plot for the fault diagnosis, to identify the most probable cause of the fault [89–91]. One point noted in [90] was that the PCA model needed to be updated when the measurement conditions excessively changed. Otherwise, there was a risk of an increase in the false-positive results.

Table 7. FD and one- and two-step FDD algorithms divided by the EST groups. Fields indicated with (-) mean that no trend was found.

Energy System Terminology Category	Fault Detection	Two-Step Fault Detection and Diagnosis (Fault Detection/Diagnosis)	One-Step Fault Detection and Diagnosis
Energy conversion			
CHS	(11 Articles)	(1 Article)	(8 articles)
	PCA (3) [81–83]	-	BN (2) [124,125]
CCS	(24 articles)	(26 articles)	(41 articles)
	PCA (6) [82,84–88]	Gray-box model/Expert ruleset (2) [111,112]	SVM (9) [56,57,94–96,100,101,104,105]
	-	-	Residuals + fault-pattern analysis (2) [126,127]
TU/AC	(1 article)	(2 articles)	(9 articles)
	-	-	DT (2) [64,92]
Energy distribution			
AHU	(23 articles)	(18 articles)	(34 articles)
	CB (2) [121,128]	PCA + Q-statistics/Q-contribution plot (2) [89,90]	Ruleset (4) [49,113,114]
	-	-	Fuzzy model + degree of belief (2) [129,130]
	-	-	Hidden Markov model (HMM) (2) [131,132]
	-	-	WNN (2) [133,134]
CCS	(1 article)	(0 articles)	(1 article)
	-	-	-
TU/AC	(2 articles)	(1 article)	(4 articles)
	Model + Residuals (2) [41,135]	-	Residuals (2) [42,43]
Energy use			
WB	(13 articles)	(7 articles)	(4 articles)
	Cart + (various) (4) [55,61,123,136]	-	-

For one-step FDD, SVM was used 18 times [56,57,70,92–106], with 9 of these regarding CCS, while rulesets were used 4 times for AHU [48,49,113,114]. Typically, labeled datasets are needed for one-step FDD, as supervised-learning algorithms are used. This eases the FDD process by skipping the FD step, but might be more computationally heavier. SVM is a supervised-learning algorithm based on finding the hyperplane that results in the most considerable minimum distance to the training examples. The reasons for its widespread use are the high accuracy obtained from the algorithm compared to other algorithms [57,101] and its ability to be combined with other algorithms [57]. In addition, FDD algorithms using rulesets and thresholds can be fast and easy to program. Rulesets require expert knowledge to derive a set of rules (if–then–else). However, the flexibility of these models can be lost if additional rules or changes are needed.

5. Results of the Review, Part III: The Importance of Driving Research Innovation

5.1. Datasets and Code

This subsection discusses reproducibility in the FDD articles and presents the available code and datasets found in the explored literature.

Reproducibility is one of the keys to reliable research, and can contribute to development, innovation, and collaboration between the industry and the scientific community [137]. Generally, there was no uniform guideline regarding what to include in the published articles regarding reproducibility, as this was up to each publisher. Consequently, there was a wide variety of appendices, data, and supporting materials in the published articles. As presented before, there exist numerous approaches applicable to FDD. However, FDD frameworks that mainly use machine-learning algorithms may benefit from the reproducibility potential of machine-learning pipeline practices, which systematically include the code, data, and computing environment [138]. Nevertheless, this is a very valuable praxis that is common in, for example, data science, computer science, electrical engineering, or mathematics, but it has yet to be adopted within civil engineering, as this field increasingly relies on big data.

In Table 8 below, an article from this review is presented if it met one or more of the following criteria: included pseudo-code, dataset (applied to test or validate algorithm), or reference to a dataset, source code, or similar, that could relate and support reproducible research. Several articles included equations or algorithms; however, most of them only described general concepts, and did not provide the details of applied algorithms. Reproducible research was thus cumbersome.

Table 8. Datasets and code used in the explored literature.

Ref.	Dataset	Description	Can be Found Here
[139]	Dataset for building fault detection and diagnostics algorithm creation and performance testing	Open datasets (both numerical simulations and fault emulation in laboratory).	[140]
[93,97,141–147]	ASHRAE RP-1312	States which dataset they used.	[148]
[58]	ASHRAE RP-1020 and ASHRAE RP-1312	States which dataset they used.	[148,149]
[56,57,59,70,84,94–96,101,105,111,132,150–171]	ASHRAE RP-1043	States which dataset they used.	[172]
[173]	ASHRAE RP-1139	States which dataset they used.	[174]
[86,175–179]	Electric factory dataset	States which dataset they used.	[180]
[45,99,142,143,181–184]	-	Provided pseudo code in article.	-
[185,186]	-	Explicit equations in Appendix.	-
[166]	-	Source code in MATLAB and Python under "supplementary material" online.	-
[94]	-	Source code and user manual for method in the data repository.	[187]
[188]	-	Python source code is in the appendix of the article.	-

5.2. Do Available Datasets Drive the Research?

Among the numerous publications that were reviewed in this article, several datasets were identified. However, some of them had a higher applicability and openness than others. In this subsection, these identified datasets are presented and discussed in brief. Of the different datasets, two were predominantly used: "ASHRAE RP-1043" [172] and an "electric factory" [180]. These datasets focused on a CCS. The ASHRAE RP-1043 dataset was part of the ASHRAE Research Project 1043, in which the objective was to develop tools for the evaluation of FDD algorithms suitable for chillers. The electric factory dataset contains measurements from a screw chiller system in a real electric factory located in Wuhan, China.

5.2.1. Dataset Analysis

Figure 15 shows the number of articles investigating CCS and how many used the ASHRAE RP-1043 or the electric factory datasets. Green and red arrows indicate when the ASHRAE RP-1043 and the electric factory datasets became available. One can observe in the figure below that the publications on CCS were highly investigated using the datasets presented above—the ASHRAE RP-1043 (green column) and the electric factory dataset (red column), respectively. Especially in 2016 and 2018, 8 out of 12 and 7 out of 8 articles on CCS used these datasets. The use of the electric factory dataset decreased after 2018. However, the ASHRAE dataset is still frequently applied.

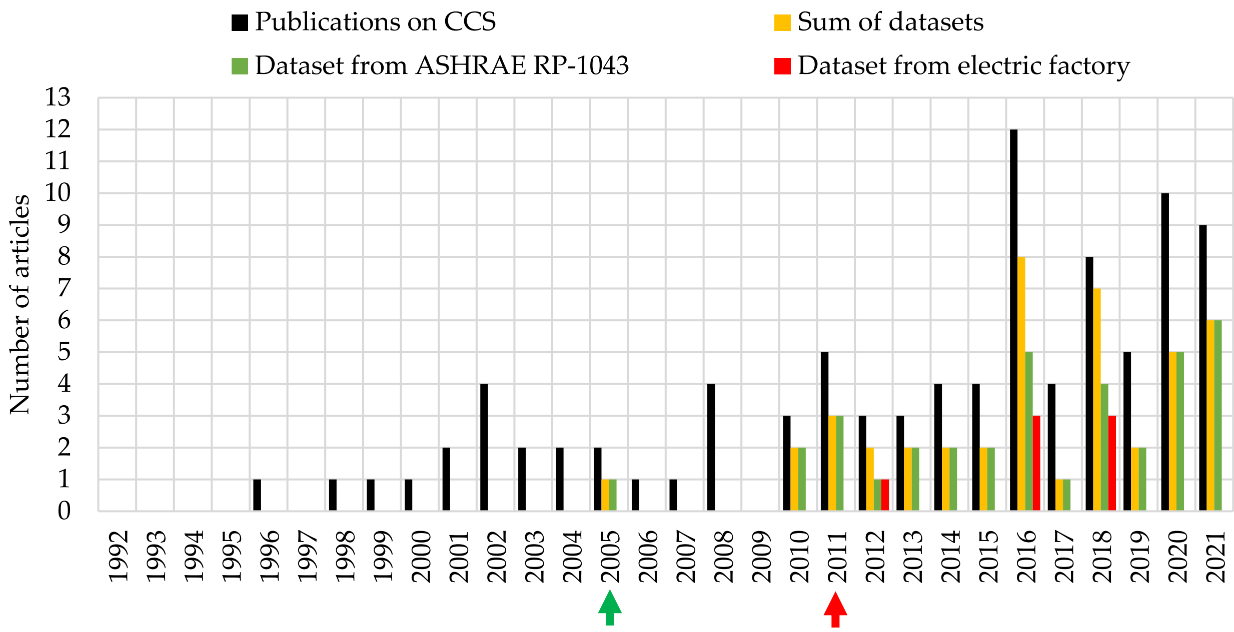

Figure 15. Number of publications on CCS and datasets used. Black: total number of publications on CCS per year. Yellow: the sum of the presented datasets. Green: number of articles on CCS using the ASHRAE RP-1043 dataset. Red: number of articles on CCS using the electric factory dataset. The green and red arrows indicate when the ASHRAE RP-1043 dataset and the electric factory dataset, respectively, became publicly available.

A cumulative sum chart (CUSUM) analysis performed on the data in Figure 15 indicated a sharp and significant increase in the number of publications after the release of these two datasets, as can be seen in Figure 16. A changepoint analysis was performed using the bootstrap method to determine the confidence level [189]. The boxplot shows that the bootstraps returned a lower Sdiff value, indicating a significant changepoint, with a confidence level of >99%. The negative values of the CUSUM plot indicated that, as expected, there was an upward shift, meaning that the number of articles had increased. The results of the CUSUM estimator confirmed that a change occurred in 2010.

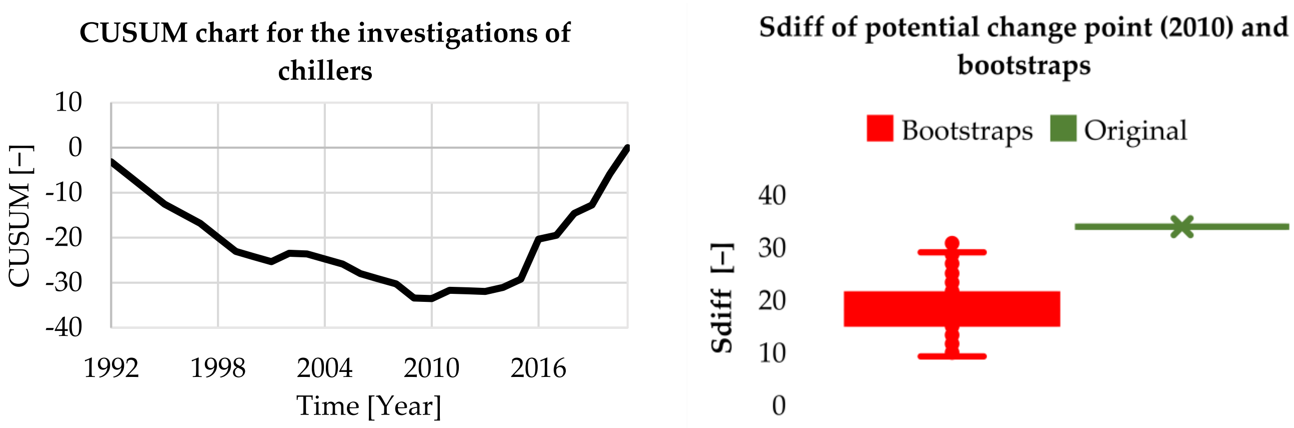

Figure 16. CUSUM chart for investigations of chillers (on the **left**) and the Sdiff boxplot for the changepoint and the bootstraps (on the **right**) for CCS articles.

5.2.2. Performance Evaluation Metrics

The performance evaluation metrics for the articles applying the ASHRAE RP-1043 dataset are further presented and discussed in this subsection. Furthermore, four challenges arose from these findings. Firstly, it was apparent that there were several definitions for the same metric. For example, in the case of FD, it was found that one of the metrics had seven different definitions: fault detection rate, correct rate, detection accuracy, classification accuracy, hit rate, recall, and true positive rate. This can be seen in Table 11. Secondly, there were cases in which a similar definition was used when specifying different metrics. This was especially the case for "False Alarm Rate" (FAR), which was shown to be calculated using two different algorithms for both FD and FDD, with the algorithms not providing the same result. Thirdly, many articles stated what metric was used without making it clear how it was calculated. This might not be a problem if a consensus about the naming of the different metrics existed, but as shown, it did not appear to be settled. The last challenge was that the reviewed articles used different metrics, meaning that comparisons between the articles became either complicated or impossible, depending on the information available in the different metrics.

To alleviate some of these challenges, several proposals were discussed. For the first and second challenges, a standardized definition convention for the confusion matrix is proposed in Table 9 (confusion matrix of FD, one faulty and one nonfaulty class) and Table 10 (confusion matrix of FDD, multiple faulty and one nonfaulty class). These two tables were inspired by the work in [104]. Examples of how the confusion matrix previously was used can be found in [96,104,105,111,150,155,156,158,160,161,163,168,170]. The variations in the performance evaluation metrics definitions are described in Table 11. The performance evaluation metric with an underscore is the name suggested for future application to avoid confusion. The references in bold specified precisely how the metric was calculated and the name of the metric. The references without bold text only stated the name of the metric, and not the numerical calculation. The third challenge can be solved by encouraging authors of future articles to clarify precisely how the metric is calculated. Lastly, the fourth challenge requires a joint initiative, as standard metrics should be defined or developed. However, it can only be alleviated by authors providing the confusion matrix, as performed in [96,104,105,111,150,155,156,158,160,161,163,168,170]. This will allow other authors to calculate the metrics they need from the different articles, thus enabling better comparison.

Table 9. Proposed generalized definition template for confusion matrix of FD (one faulty and one nonfaulty class).

		Predicted Class N_P	
		Negative (Nonfaulty) $N_{P,N}$	**Positive (Faulty) $N_{P,P}$**
True class N_T	**Negative (Nonfaulty) $N_{T,N}$**	T_N (No alarm)	F_P (False alarm)
	Positive (Faulty) $N_{T,P}$	F_N (Missed alarm)	T_P (Alarm)

Table 10. Proposed generalized definition template for confusion matrix of FDD (multiple faulty and one nonfaulty class).

		Predicted Class N_P				
		Negative (Non-Faulty) $N_{P,N}$	**Positive (Fault 1) $N_{P,P,cp}$**	...	**Positive (Fault n − 1) $N_{P,P,cp}$**	**Positive (Fault n) $N_{P,P,cp}$**
True class N_T	**Negative (Nonfaulty)** $N_{T,N}$	T_N (No alarm)	$F_{P,cp}$ (False alarm)			
	Positive (Fault 1) $N_{T,P,ct}$	$F_{N,ct}$ (Missed alarm)	$T_{P,ct} = T_{P,1}$ (Alarm)		$F_{P,ct,cp}$ (Misdiagnosed alarm)	
	⋮			$T_{P,ct}$ (Alarm)		
	Positive (Fault n − 1) $N_{T,P,ct}$		$F_{P,ct,cp}$ (Misdiagnosed alarm)		$T_{P,ct} = T_{P,n-1}$ (Alarm)	
	Positive (Fault n) $N_{T,P,ct}$					$T_{P,ct} = T_{P,n}$ (Alarm)

T_P is the true-positive result (fault is detected and is present), T_N is the true-negative result (fault is not detected/diagnosed and is not present), F_P is the false-positive result (fault is detected and is not present), F_N is the false-negative result (fault is not detected/diagnosed and is present), N is the total number of samples (both faulty and nonfaulty), $N_{T,P}$ is the total number of true positive (faulty) samples, $N_{T,N}$ is the total number of true negative (nonfaulty) samples, $N_{P,P}$ is the total number of predicted positive (faulty) samples, $N_{P,N}$ is the total number of predicted negative (nonfaulty) samples, and N_c is the number of classes (both faulty and nonfaulty).

$T_{P,ct}$ is the true-positive result for each fault class (fault is diagnosed and is present), T_N is the true-negative result (fault is not detected/diagnosed and is not present), $F_{P,cp}$ is the false-alarm result (fault is diagnosed and is not present), $F_{P,ct,cp}$ is the misdiagnosed-alarm result (fault is diagnosed and is not the correct class), $F_{N,ct}$ is the false-negative result (fault is not detected/diagnosed and is present), N is the total number of samples (both faulty and nonfaulty), $N_{T,P,ct}$ is the number of true positive (faulty) samples for each fault class, $N_{T,N}$ is the total number of true negative (nonfaulty) samples, $N_{P,P,cp}$ is the number of predicted positive (faulty) samples for each fault class, $N_{P,N}$ is the total number of predicted negative (nonfaulty) samples, and N_c is the number of classes (both faulty and nonfaulty).

Table 11. The performance evaluation metric with an underscore is the name suggested for future application to avoid confusion. The references in bold specifies precisely how the metric was calculated and the name of the metric. The references without bold text only stated the name of the metric, and not the numerical calculation.

	Reference	Performance Evaluation Metric	Equation
	[96,104,105,111,150,155,156,158, 160,161,163,168,170]	Confusion matrix	-
	Used in FD (1 nonfault class and 1 fault class)		
Global	[104,105]	Correct rate (CR)	$\frac{T_P+T_N}{N}$
	[104]	Misclassification rate (MisCR)	$1-\frac{T_P+T_N}{N}=\frac{F_P+F_N}{N}$
Local	[57,153,164,168,171] [154] [70,84] [101] [104,105] [104] [104]	Fault-detection rate (FDR) Correct rate Detection accuracy Classification accuracy Hit rate Recall True-positive rate	$\frac{T_P}{T_P+F_N}=\frac{T_P}{N_{T,P}}$
	[153]	False-alarm rate	$\frac{F_P}{F_P+T_P}=\frac{F_P}{N_{P,P}}$
	[57,84,104,105,111,154,168,171]	False-alarm rate (FAR)	$\frac{F_P}{F_P+T_N}=\frac{F_P}{N_{T,N}}$
	Used in FDD (1 nonfault class and multiple fault classes)		
Global	[56,57,94,95,151,152,155,156,158, 161,163,166] [96,104,105,150] [159,160,165,169,190] [101] [162]	Accuracy Correct rate (CR) Correct diagnosis rate Classification accuracy Diagnosis rate	$\frac{T_N+\sum T_{P,ct}}{N}$
	[159,165,169,190]	False-diagnosis rate (FaDR)	$1-\frac{T_N+\sum T_{P,ct}}{N}$
	[94]	Macro-F1 (MF1) [191]	$\frac{\sum_{c=1}^{N_c-1} F1}{N_c}$
	[95]	Matthews correlation coefficient (MCC)	$\frac{T_N*\prod T_{P,ct}}{\sqrt{N_{T,N}*\prod N_{T,P,ct}*N_{P,N}*\prod N_{P,P,cp}}}$
	[95]	G-mean	$\sqrt{\prod PREC}$
Local	[155,161]	False-alarm rate	$\frac{\sum F_{P,cp}+\sum F_{P,ct,cp}}{\sum F_{P,cp}+\sum F_{P,ct,cp}+\sum T_{P,ct}}=\frac{\sum F_{P,cp}+\sum F_{P,ct,cp}}{\sum N_{P,P,cp}}$
	[56,104,105,167]	False-alarm rate (FAR)	$\frac{\sum F_{P,cp}}{\sum F_{P,cp}+T_N}=\frac{\sum F_{P,cp}}{\sum N_{T,N}}$
	[155]	Fake-alarm rate (FaAR)	$\frac{\sum F_{P,cp}}{\sum F_{P,cp}+\sum F_{P,ct,cp}+\sum T_{P,ct}}=\frac{\sum F_{P,cp}}{\sum N_{P,P,cp}}$
	[155,156]	Misdiagnosed-alarm rate (MisR)	$\frac{\sum F_{P,ct,cp}}{\sum F_{P,cp}+\sum F_{P,ct,cp}+\sum T_{P,ct}}=\frac{\sum F_{P,ct,cp}}{\sum N_{P,P,cp}}$
	[155]	Missed-detection rate (MDR)	$\frac{\sum F_{N,ct}}{\sum F_{P,cp}+\sum F_{P,ct,cp}+\sum T_{P,ct}}=\frac{\sum F_{N,ct}}{\sum N_{P,P,cp}}$
	[156]	Misdiagnosed normal rate (MisNR)	$1-\frac{T_N}{T_N+\sum F_{P,cp}}=1-\frac{T_N}{\sum N_{T,N}}$
Local (calculated per class)	[95,156] [157,167,170]	Precision (PREC) Diagnosis ratio	$\frac{T_{P,ct}}{N_{P,P,cp}}\ or\ \frac{T_N}{N_{P,N}}$
	[104,156] [59] [95] [111] [104,105] [157,167,170]	Recall (REC) Sensitivity index Sensitivity Successful diagnosed ratio Hit rate Detection ratio	$\frac{T_{P,ct}}{N_{T,P,ct}}\ or\ \frac{T_N}{N_{T,N}}$
	[156] [95]	F1-score (F1) F-measure	$\frac{2*PREC*REC}{PREC+REC}$
	[56]	False-negative rate (FNR)	$\frac{F_{N,ct}}{F_{N,ct}+\sum_{cp=1}^{N_c-1} F_{P,ct,cp}+T_{P,ct}}=\frac{F_{N,ct}}{N_{T,P,ct}}$
	[56]	False-positive rate (FPR)	$\frac{\sum_{cp=1}^{N_c-1} F_{P,ct,cp}}{F_{N,ct}+\sum_{cp=1}^{N_c-1} F_{P,ct,cp}+T_{P,ct}}=\frac{\sum_{cp=1}^{N_c-1} F_{P,ct,cp}}{N_{T,P,ct}}$

5.3. Current Dataset and Code Repositories

This subchapter aims to increase the awareness of public repositories containing code and datasets for FDD in the selected building systems listed in Table 12. One should note that not all datasets are available for free.

Table 12. The current dataset repositories sorted based on the building system, type of data/code, and whether the dataset was open source. "Experimental data" and "Simulation data" were defined as the following: experimental data comprised a fault dataset created and emulated in a laboratory; simulation data comprised a fault dataset created and emulated in a simulation environment.

Building System	Description	Reference	Type of Data/Code	Open Source?
Dataset repositories				
Chiller	Tools and data for FDD methods applied to chillers: ASHRAE RP-1043	[172]	Experimental data	No
Air-handling units	Tools for evaluating fault detection and diagnostic methods for air-handling units: ASHRAE RP-1312	[148]	Simulation data	No
Real building	Demonstration of fault detection and diagnostic methods in a real building: ASHRAE RP-1020	[149]	Implementation	No
Vapor compression equipment	Development and comparison of one-lone model training techniques for model-based FDD methods applied to vapor-compression equipment: ASHRAE RP-1139	[174]	Simulation/numerical data	No
Chiller	Electric factory dataset	[180]	Experimental data	No
Heat pump	Validation of the self-diagnosis efficiency system	[192]	Experimental data, hardware-in-the-loop	No
Air-handling unit and rooftop unit	Labeled data for FDD	[140]	Experimental and simulation data	Yes
Air-handling unit	Air-handling fault test data	[193]	Experimental data	No
Chiller and boiler plant	Automated diagnostic algorithms for chillers, boilers, cooling towers, and chilled-water distribution	[194]	Simulation data	No
Open code and data repositories				
Air-handling unit	Development of fault models for hybrid fault detection and diagnostics algorithm	[195,196]	Code and data	Yes
Air-handling unit	Fault detection and diagnosis in air-handling unit using Dymola data	[197]	Code and data	Yes
Building energy-use data	Methods to analyze the available data set of historic building energy fault data	[198]	Code and data	Yes
Heat pump and air conditioner	LabView codes and associated codes for using a rule-based-chart method of fault detection and diagnosis	[199]	Code and data	Yes

6. Discussion of Key Findings

6.1. A Uniform FDD Framework—A Utopia or within Reach?

Three observations were addressed for the first shortcoming: (1) the number of definitions of FD and FDD that existed—these were found both in the definition and terminology for FDD in building systems and in the use of different variations in keywords, especially for FDD; (2) the number of different definitions for the same performance evaluation metrics found in the reviewed articles increased the gap for a uniform framework; and (3) the number of different algorithms, including their variations and combinations for FDD, was immense. On the one hand, this allowed for modeling flexibility, but on the other hand, this diversity could be perceived as an overwhelming and confusing task. It is thus challenging for stakeholders to identify what method is adequate for their specific case without expert knowledge and competencies in FDD, programming, and HVAC implementation. This indicated that this field is still under rapid development in the research area, but lacks practical guidelines; pilot projects; and standardization of vocabulary, methods, and technologies before being market-ready.

6.2. What Are the Common Algorithms Used for FDD in Building Systems?

FDD algorithms are system-specific, and certain adaptations of code and data are necessary for each specific building system. However, to investigate trends, an initiative to divide the building systems into (1) energy system terminologies (energy conversion, energy distribution, and energy use); and (2) fault detection, two-step fault detection and diagnosis, and one-step fault detection and diagnosis was undertaken. Of the 221 articles investigated in this article, PCA was found to be a popular fault-detection method for all building systems. Moreover, in combination with Q-statistics or Q-contribution, PCA was the most used algorithm for two-step fault detection and diagnosis, even though it was only used in 3 out of 55 articles. SVM was the main algorithm used for one-step FDD. However, in general, it was found that the algorithms varied immensely, and it was challenging to determine a specific trend in the used algorithms. This was because most of the algorithms had the potential to perform well or poorly due to the circumstances (system type, measured variables, preprocessing, or combination with other methods).

6.3. How to Drive the Research Innovation and Increase the Reproducibility of FDD in Building Systems

As open-source practices are becoming increasingly common in the sciences, it is crucial to increase the reproducibility of FDD articles. All articles for peer-reviewed publications need to follow a selected principle, for example, the findable, accessible, interoperable, and reusable (FAIR) principle [200] or PRISMA [34]. Contrary to some other fields, such as applied mathematics and statistical science, there was an apparent lack of reproducible material from the reviewed FDD articles. Therefore, more substantial initiatives may be necessary to adapt this culture to the built environment.

Published work on the topic originated mainly from China and the USA. It seemed that Europe and the rest of the world are lagging behind. This can create a skewed focus, as the challenges in these countries might differ. Consequently, the created labeled datasets and scientific work on FDD from China and the USA mainly focused on CCS in warmer weather conditions. In general, there were only a few open-access datasets for FDD in building systems. These consisted of mainly emulated faults in different AHUs. Another observation was mainly the local use of these datasets. For example, the electric factory dataset was observed only to be used in China, and the ASHRAE RP-1043 was mainly used in cooperation with ASHRAE publications. However, increasing the openness of the existing dataset may also contribute to research innovation in other countries.

7. Conclusions and Suggestions for Future Work

The contribution of this paper was to provide a review of articles focusing on the three identified shortcomings for FDD in building systems. The identified shortcomings were: (1) a lack of a uniform glossary in FDD, especially for building systems; (2) a need for an up-to-date overview of the FDD algorithms for building systems, along with the different data requirements and necessary inputs to move further toward actual building implementation; and (3) a shortage of open-source FDD repositories for data and code.

In short, three conclusions were derived from this review. (1) Research on fault detection and diagnosis in building systems is still at the developing stage. This was evident through this review, as the identified definitions varied across different built environment disciplines. In addition, the numerous combinations of the applicable algorithms were evident through the variety in published work. Therefore, this article aimed to contribute to a uniform FDD framework. Firstly, this consisted of providing a table with frequently used definitions, synonyms, and meanings of FDD in building systems, as presented in Section 2.

Secondly, an FDD method map of the explored existing reviews was provided. This file is available in a GitHub repository [36] and is open for additional contributions. Thirdly, as several articles did not concretize whether the FDD process was performed automatically or manually, it was suggested to use the abbreviations FD, FDD, or FDD&E if the process is manual or semimanual; and AFD, AFDD, or AFDD&E if the process is fully automatic. Lastly, a generalized terminology for performance evaluation metrics and templates for a confusion matrix was proposed (Section 5.2.2). (2) Data drives the research activity. (3) Reproducibility is a key to enhancing research innovation. Datasets have been shown to increase research activity. Nevertheless, there is an apparent lack of available open datasets for FDD. It appeared that a handful of research groups with access to purchasable datasets are using these extensively. However, the lack of dataset diversity and availability has restricted FDD research to theoretical articles, and thus has slowed the implementation of these methods in real buildings. The repetitive use of the same datasets, combined with a focus on theoretical research, can impose a challenge in the actual implementation of FDD. This review provided a list and a table of datasets and code to increase the awareness of available repositories.

More substantial initiatives are needed from publishers to increase the reproducibility of the publications in the future. Out of 221 articles, only 65 articles added information that supported reproducible research. This showed that this sector has great potential in open-source practices. Reproducible research is especially essential for innovation, as learning from experience and even negative results can constitute new knowledge for actual building implementation.

Based on the knowledge derived from this review, suggestions for future work are to identify gaps and barriers to the actual implementation of FDD in existing buildings. In addition, investigations on how far they have progressed in the industry and how they approach fault detection and diagnosis in today's building systems are crucial to further practical development and implementation.

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

Funding: The authors gratefully acknowledge the support from the European Union's Horizon 2020 research and innovation program and several partners through the research project "Self-Assessment Towards Optimization of Building Energy" (SATO, https://www.sato-project.eu/, accessed on 7 June 2022), grant agreement No. 957128.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The authors of this review have provided all data, code, figures, and appendices in a GitHub repository [36]. The Ref ID describes the reference number in a RefWorks repository, and is also associated with the additional material found in the GitHub repository.

Acknowledgments: The authors would like to give special thanks to postdoctoral researcher Hicham Johra of the Department of the Built Environment, Aalborg University for fruitful discussions and additional guidance in writing this review, and Zhenyu Yang of the Department of Energy Technology at Aalborg University. The first and second authors would also like to express their gratitude to their colleagues in the corner office at the Department of the Built Environment, Aalborg University, for valuable discussion and support.

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

Abbreviations

General Abbreviations

Name	Abbreviation	Name	Abbreviation
Air conditioning system	AC	Feature engineering	FEng
Automatic fault detection	AFD	Fault-relevant features	FF
Automatic fault detection and diagnosis	AFDD	Fault identification	FId
Automatic fault detection, diagnosis and evaluation	AFDD&E	Fault impact analysis	FIA
Active fault-tolerant control	AFTC	Fault isolation	FIs
Air-handling unit	AHU	Fault-tolerant control	FTC
Centralized cooling system	CCS	Heat pump	HP
Centralized heating system	CHS	Heating, ventilation, and air conditioning	HVAC
Control reconfiguration	ConRec	International Energy Agency	IEA
Cumulative sum	CUSUM	International Energy Agency's Energy in Buildings and Communities Programme	IEA-EBC
Energy system terminology	EST	Indoor environmental quality	IEQ
European Union	EU	Key performance indicator	KPI
Fault detection	FD	Machine learning	ML
Fault detection and diagnosis	FDD	Preferred Reporting Items for Systematic Reviews and Meta-Analyses	PRISMA
Fault detection, diagnosis and evaluation	FDD&E	Terminal unit	TU
Fault evaluation	FE	Whole building	WB

FDD evaluation metric abbreviations

Name	Abbreviation	Name	Abbreviation
Correct rate	CR	Matthews correlation coefficient	MCC
F1-score	F1	Missed detection rate	MDR
Fake-alarm rate	FaAR	Macro-F1	MF1
False-diagnosis rate	FaDR	Misclassification rate	MisCR
False-alarm rate	FAR	Misdiagnosed normal rate	MisNR
Fault-detection rate	FDR	Misdiagnosed alarm rate	MisR
False-negative rate	FNR	Precision	PREC
False-positive rate	FPR	Recall	REC

FDD algorithm abbreviations

Name	Abbreviation	Name	Abbreviation
Auto-associative neural network	AANN	Gordon-Ng model	GN
Adaptive synthetic sampling approach	ADASYN	Gaussian process	GP
Auto encoder	AE	Gradient penalty	GPEN
Adaptive forgetting through multiple models	AFMM	Hidden Markov model	HMM
Adaptive genetic algorithm	AGA	Hidden semi-Markov model	HSMM
Adaptive Gaussian mixture model	AGMM	Isolated forest	IF
Adaptive neuro-fuzzy inference system	ANFIS	Joint angle analysis	JAA
Artificial neural network	ANN	Kernelized discriminant analysis	KDA
Self-adapting principal component analysis	APCA	Kernel entropy component analysis	KECA
Auto-regressive integrated moving average	ARIMA	Kalman filter	KF
Association rule mining	ARM	K-means	K-means
Autoregressive moving average with exogenous input	ARMAX	K-nearest neighbor	KNN
Analytical redundancy relations	ARR	Kriging	KRG
Autoregressive with exogenous input	ARX	Linear discriminant analysis	LDA
Adaptive symbolic aggregate approximation	aSAX	Linear regression	LIR

Unscented Kalman filter	AUK	Logistic regression	LR
Basic ensemble method	BEM	Least squares	LS
Bayesian interference	BI	Long short-term memory	LSTM
Bayesian network	BN	Multiconvolutional neural network	MCNN
Back-propagation neural network	BPNN	Multilayer perceptron	MLP
Borderline synthetic minority oversampling technology	BSM	Multiple linear regression	MLR
Class association rules	CAR	Multiclass neural network	MNN
Classification and regression tree	CART	Mixture of probabilistic principal component analysis	MPPCA
Classification based on association	CBA	Multiregion XGBoost	MR-XGBoost
Complete ensemble empirical mode decomposition	CEEMD	Multiscale interval-valued principal component analysis	MSIPCA
Cascade forest	CF	Multiscale interval principal component analysis	MSIPCA
Complex fuzzy principal component analysis	CFPCA	Nonlinear autoregressive with exogenous input	NARX
Convolutional neural network	CNN	Naïve Bayes	NB
Change point detection	CPD	Naïve Bayes classifier	NBC
Cuckoo search	CS	Neural network	NN
Conditional Wasserstein	CW	Partitioning around medoids	PAM
Conditional Wasserstein generative adversarial network	CWGAN	Principal component analysis	PCA
Data-temporal attention network	DAN	Partial least squares	PLS
Decoupling-based	DB	Probabilistic neural network	PNN
Diagnostic Bayesian network	DBN	Pattern-recognition-enhanced sensor fault detection and diagnosis	Pre-SFDD
Deep belief network	DBNN	Quantitative association rule mining	QARM
Density-based spatial clustering of applications with noise	DBSCAN	Residual subspace (from PCA)	R
Distributed clustering	DC	Recursive autoregressive with exogenous input	RARX
Differential evolution	DE	Radial basis function	RBF
Discrete events system	DES	Resistor–capacitor	RC
Deep neural network	DNN	Reconstruction based	RCB
D-S evidence theory	DSET	Recurrent cerebellar model articulation controller	RCMAC
Decision tree	DT	Recursive deterministic perceptron	RDP
Dynamic Bayesian network	DYBN	Random forest	RF
Evolutionary double attention	EDA	Random forest classifier	RFC
Encoder–decoder network	EDN	Recursive feature elimination and cross-validation	RFECV
Ensemble empirical mode decomposition	EEMD	Recursive one-class support vector machine	ROSVM
Extended Kalman filter	EKF	Rough sets	RS
Expert knowledge-based unseen fault identification	EK-UFI	Simulated annealing	SA
Extreme learning machine	ELM	Supervised auto encoder	SAE
Ensemble diagnostic model	EMD	Stochastic gradient descent with momentum	SGDM
Elman neural network	ENN	Simple linear regression	SLR
Extra trees	ET	Synthetic minority oversampling technology	SMOTE
Entropy weighting k-means	EWKM	Shallow neural network	SNN
Exponentially weighted moving average	EWMA	Self-production	SP
Fractal correlation dimension	FCD	Statistical process control	SPC
Fault detection	FD	Principal component analysis with statistical data cleaning	SPCA
Fisher discriminant analysis	FDA	Square prediction error	SPE
Fault detection and diagnosis	FDD	Semisupervised kernelized discriminant analysis	SSKDA
Failure mode and effect analysis	FEMA	Semisupervised linear discriminant analysis	SSLDA
Feed-forward neural network	FFNN	Steady-state qualitative zones	SSQZ

Feature importance	FI	Support vector data description	SVDD
Fuzzy inference system	FIS	Sensor validity index	SVI
Fisher linear discriminant analysis	FLDA	Support vector machine	SVM
Fuzzy principal component analysis	FPCA	Support vector regression	SVR
Fuzzy reasoning	FR	Threshold denoising	TD
Genetic algorithm	GA	Tree-structured fault-dependence kernel	TFDK
Generative adversarial network	GAN	Univariate feature selection	UFS
General diagnostics engine	GDE	Variational autoencoder	VAE
Generalized extreme studentized deviate	GESD	Wavelet analysis	WA
Generalized likelihood ratio test	GLRT	Wavelet neural network	WNN
Gaussian mixture model	GMM	Extreme gradient boost	XGBoost
Gaussian mixture regression	GMR		

Appendix A. FDD Algorithm and Building System Encyclopedia

Table A1. Energy conversion: centralized heating system.

Ref ID/Ref.	Year Published	Component	Fault Detection	Fault Diagnosis
General CHS articles			FD	
536 [115]	2020	Electrical heating	ARX + residuals; RF + residuals	
702 [81]	2018	Heating reactor; industrial component	PCA + Fisher score + Threshold	
713 [109]	2018		ANN + residuals	
437 [201]	2013	Solar collector	Feature generation + change detection + residuals	
1426 [202]	2008		Residuals	
General CHS articles			One-step FDD	
93 [106]	2020		MSIPCA+KNN; MSIPCA+SVM	
967 [103]	2019	Solar heater	SVM + DSET	
General CHS articles			Two-step FDD	
1654 [203]	2003	Open window; radiator valve	Characteristic parameter + residuals + threshold	Adaptive model + residuals
Heat pump articles			FD	
71 [65]	2020	Heat pump	LR; KNN; CART; RFC; NBC; SVM; MLP	
111 [60]	2019	Air-source heat pump	CNN	
724 [82]	2017	Reversible heat pump; sensor	PCA; FPCA; CFPCA	
785 [204]	2016	Heat pump; geothermal heat exchanger	MLP; DT; FLDA	
1218 [74]	2010	Heating energy use; heat pump; underfloor heating	Statistical analysis + threshold; ruleset; residuals	
1397 [83]	2008	Air-source reversible heat pump	PCA + SPE + threshold	
Heat pump articles			One-step FDD	
265 [205]	2017	Sensor; actuator; heat pump	"Agents" + residuals + threshold	
Both boiler and heat pump articles			One-step FDD	
49 [118]	2020	Gas boiler; heat pump; aquifer thermal energy storage	DBN	
114 [124]	2019		BN	
Boiler articles			One-step FDD	
525 [98]	2020	Boiler	KNN; DT; RF; SVM	
278 [125]	2017	Boiler; pump; radiator	BN	
286 [45]	2017	Condensing boiler	Residuals	

Table A2. Energy conversion: centralized cooling system.

Ref. ID/Ref.	Year Published	Component	Fault Detection	Fault Diagnosis
		CCS articles	FD	
553 [206]	2020	Energy; ground source chiller	CEEMD-LSTM	
157 [176]	2019	Sensor; chiller	EEMD + PCA	
174 [177]	2018	Sensor; chiller	EMD + TD + PCA	
193 [84]	2018	Chillers	PCA + BN	
713 [109]	2018		ANN + residuals	
724 [82]	2017	Reversible heat pump; sensor	PCA; FPCA; CFPCA	
344 [52]	2016	Heat-exchanger system	Residuals + threshold (t-statistics)	
315 [85]	2016	Sensor; chiller	PCA	
337 [164]	2016	Chillers	PCA + R + SVDD	
339 [86]	2016	Sensor; chiller; sensitivity analysis	PCA	
349 [178]	2016	Sensor; chiller	SPCA	
402 [76]	2014	Chiller; cooling tower	SPC limits	
449 [171]	2013	Chillers	SVDD	
1029 [207]	2013	Cooling tower system; chillers; heat-exchanger system	Performance index + SVR + EWMA control charts	
463 [180]	2012	Sensor; chiller	APCA + Q-residuals + threshold	
1366 [208]	2010	Condenser cooling water systems	Performance index + residuals + threshold	
1382 [88]	2008	Cooling tower systems; chillers; sensor; heat exchangers; pumps	PCA	
1397 [83]	2008	Air-source reversible heat pump	PCA + SPE + threshold	
1432 [209]	2008	Sensor; chiller	Wavelet analysis	
1468 [210]	2006	Chillers	Kalman filter + residuals + threshold	
1485 [211]	2005	Chillers	ANFIS	
1663 [212]	2002	Chillers	ARIMA + threshold	
1886 [213]	1996	Sensor; heat exchanger; pump control	DES	
		CCS articles	One-step FDD	
15 [166]	2021	Chillers	Semi-GAN	
18 [161]	2021	Chillers	SP-CNN	
20 [152]	2021	Chillers	SVR+BN	
21 [153]	2021	Chillers	KECA	

Table A2. *Cont.*

Ref. ID/Ref.	Year Published	Component	Fault Detection	Fault Diagnosis
27 [154]	2021	Chillers	Bayesian network	
28 [155]	2021	Chillers	SA-DNN	
495 [214]	2021	Chillers	XGBoost + CART + mean shift clustering + Euclidean distance	
37 [184]	2020	Chillers	Pre-SFDD	
41 [185]	2020	Sensor; chiller plant	Bayesian	
42 [156]	2020	Chillers	EMD	
49 [118]	2020	Heat pump; aquifer thermal energy storage	DBN	
63 [59]	2020	Chillers	CBA	
92 [56]	2020	Chillers	SVM	
101 [94]	2020	Chillers	RF; SVM; DT; NBC; MLP; KNN; LR	
556 [100]	2020	Chillers; unbalanced dataset	ADASYN-SVM; BSM-SVM; SMOTE-SVM	
572 [101]	2020	Chillers	CWGAN-SVM	
122 [215]	2019	Sensor; chiller	DAN + threshold	
126 [95]	2019	Chillers	SVM	
139 [96]	2019	Chillers	LS-SVM	
149 [188]	2019	Chiller	XGBoost + threshold	
176 [181]	2018	Sensor	Penalty function + residuals	
205 [160]	2018	Chillers	ARM + CAR	
207 [75]	2018	Chillers	GMR-AUK	
711 [150]	2018	Chiller	BPNN; PNN	
279 [216]	2017	Chillers	MPPCA	
755 [70]	2017	Chillers	ROSVM-EKF	
304 [165]	2016	Chillers	MLR-EWMA; KRG-EWMA; RBF-EWMA	
306 [169]	2016	Chillers	DE-LSSVR-EWMA	
319 [158]	2016	Chillers	LDA	
321 [163]	2016	Chillers	TFDK	
353 [190]	2015	Chillers	RBF-EWMA	
837 [217]	2015	Vapor compression refrigerant system	FIS; ANN	

Table A2. *Cont.*

Ref. ID/Ref.	Year Published	Component	Fault Detection	Fault Diagnosis
396 [218]	2014	Chillers	UKF	
399 [57]	2014	Chillers	SVM-ARX; SVM; SVM-MLR; MLP-ARX	
1407 [162]	2011	Centrifugal chillers	Performance index + FR + ANN	
1517 [173]	2011	Chillers	Lumped physical GN + parameter tracking	
1361 [104]	2010	Chillers	Multiclass SVM	
1362 [105]	2010	Chillers	Multiclass SVM	
1436 [48]	2008	Chiller	Ruleset + performance index + residuals + threshold	
1318 [219]	2002	Chillers	NN classifier	
1679 [126]	2001	Chillers	Residuals + fault-pattern analysis	
1683 [127]	2000	Chillers	Residuals + fault-pattern analysis	
1970 [186]	1999	Sensor; chiller plant	Bias estimator + confidence interval	
CCS articles			Two-step FDD	
6 [53]	2021	Chilled water pump system; condenser water pump system; cooling tower system; chiller system	Association rules	Expert knowledge
7 [220]	2021	Chillers	MNN	LR (logistic regression)
189 [175]	2018	Sensor; chiller	DBSCAN + PCA + threshold	Contribution analysis
994 [221]	2017	Chillers	Standard deviation of virtual sensor	Virtual sensor + residuals
305 [179]	2016	Sensor; chiller	SVDD-D statistic	SVDD-DV contribution
350 [222]	2016	Chiller; dehumidifier	NARX+LS-SVM+AGA	Expert knowledge + contribution analysis
789 [87]	2016	Chillers	PCA	RCB
364 [151]	2015	Chillers	MLR residuals; SLR residuals; DB residuals	MLR residual relation; SLR residual relation; DB residual relation
1123 [112]	2015	Chillers	Gray-box model + eigenvalues	Expert ruleset
407 [168]	2014	Chillers	One class SVDD	Multiclass SVDD
448 [159]	2013	Chillers	SVR-EWMA	Fault rule table
932 [223]	2012	Chiller; cooling tower	Residuals + threshold; performance index + residuals + threshold	FD on sublevel + ruleset
1030 [111]	2012	Chillers	Gray-box model + performance index + threshold	Expert ruleset
1353 [224]	2011	Chillers	Gray-box model parameters + threshold (mean and standard deviation averaged over 24 h)	The physical meaning of each parameter

Table A2. *Cont.*

Ref. ID/Ref.	Year Published	Component	Fault Detection	Fault Diagnosis
1560 [170]	2011	Chillers	Performance index + residuals + threshold	Ruleset
1605 [157]	2011	Chillers	Performance index + PCA + Q-statistics + threshold + residuals	Contribution analysis
1448 [225]	2007	Sensor; chiller	GLRT	SVM + PCA + PLS
1621 [167]	2005	Chillers	Performance index + residuals + threshold	Fault pattern
1490 [110]	2004	Chillers	ANN + residuals	Expert ruleset
1495 [91]	2004	Chillers	PCA + Q-statistics + threshold	Q-contribution plot
1504 [226]	2003	Chillers	PCA + SPE + threshold	SPE + SVI
1656 [227]	2003	Chillers	Residuals + threshold	Expert ruleset; recursive parameter estimation
1336 [228]	2002	Chillers	GA estimator	Residuals
1664 [229]	2002	Chillers	Residuals + KNN + prototypes and membership functions	Residuals + ruleset
1341 [230]	2001	Chillers	Residuals + threshold	Characteristic quality + threshold
1867 [231]	1998	Chiller; rooftop air conditioner	Probability distribution of residuals + threshold	Fault pattern

Table A3. Energy conversion: terminal unit/Air-conditioning system.

Ref	Year Published	Component	Fault Detection	Fault Diagnosis
TU/AC articles			FD	
884 [232]	2014	Sensor	FCD + residuals + SVR	
TU/AC articles			One-step FDD	
501 [233]	2021	Variable refrigerant flow	BPNN-DT	
39 [234]	2020	Variable refrigerant flow	CF (consists of RF + ET) + IT	
48 [92]	2020	Variable refrigerant flow	DT; SVM (best for single faults); CL; SNN; DNN (best for multiple faults)	
50 [235]	2020	Variable refrigerant flow	GMM-PCA	
51 [236]	2020	Variable refrigerant flow	1-D CNN; ensemble 1-D CNN	
96 [64]	2020	Fan coil	DT	
550 [99]	2020	Fan coil	K-means + multiclass SVM	
140 [237]	2019	Variable refrigerant flow	CBA + ARM	
187 [238]	2018	Variable refrigerant flow	DBNN	
285 [239]	2017	Variable refrigerant flow	BPNN	
TU/AC articles			Two-step FDD	
962 [240]	2019	Sensor; water-source heat pump	PCA + Q statistic + T2 statistic + threshold	Subtractive clustering + K-means clustering + Q statistic + T2 statistic + threshold

Table A4. Energy distribution: air-handling unit.

Ref	Year Published	Component	Fault Detection	Fault Diagnosis
	AHU articles		FD	
119 [241]	2019	VAV	Ruleset	
149 [188]	2019	VAV; fan	XGBoost + threshold	
156 [128]	2019		Chernoff bound	
637 [121]	2019	Electricity use	Chernoff bound	
975 [242]	2019	VAV; heating coil; cooling coil; sensor	NB; RF; DT	
256 [71]	2017	All air system; gas furnace; vapor-compression air conditioner	Deviation in ARX model parameter identified; deviation in ARMAX Model parameter identified	
260 [243]	2017		SVR + GP with residuals	
344 [52]	2016		Residuals + threshold (t-statistics)	
1014 [244]	2015		PCA; LDA; KDA; SSLDA; SSKDA	
401 [141]	2014		Wavelet + PCA + Q-residuals + threshold	
408 [58]	2014		Pattern matching + PCA + Q-residuals + threshold	
476 [245]	2012		BN	
1569 [147]	2011		DYBN + HMM + graphical model + agglomerative clustering algorithm	
1219 [246]	2010	Sensor	FCD	
1671 [247]	2002		SSQZ; performance index + ruleset; residual analysis + threshold	
1543 [248]	2001	VAV	RARX + frequency analysis	
1545 [249]	2001	Dual-duct system; sensor; control; heating coil; cooling coil	Feedforward controller from static model + PI controller + residuals + threshold	
1662 [108]	2001	DCV	ANN	
1854 [116]	1998	VAV	ARX; AFMM	
1985 [250]	1996	VAV	GDE	
1896 [251]	1996	Cooling coil	RBF network + residuals + threshold	
1841 [252]	1995	Dampers; heating coil; cooling coil	Constraint suspension	
1905 [253]	1994	Control; sensor	Performance index + threshold (mean and standard deviation)	
	AHU articles		One-step FDD	
2 [8]	2021	Economizer control; outside air damper; chilled-water and hot-water valve; supply fan	Trend analysis (manual)	

Table A4. *Cont.*

Ref	Year Published	Component	Fault Detection	Fault Diagnosis
3 [254]	2021	Fan	CS-ELM	
5 [255]	2021		MCNN	
13 [143]	2021		SAE	
45 [49]	2020		Ruleset	
57 [256]	2020	Sensor	AE-BI	
82 [93]	2020		RF; SVM; MLP; KNN; DT	
94 [257]	2020	Sensor	AANN	
540 [258]	2020	Sensor; calibration	BI	
562 [120]	2020	DCV; IAQ	DBN	
134 [145]	2019		EK-UFI	
636 [259]	2019	Sensor	DNN	
971 [260]	2019		GMR	
176 [181]	2018	Sensor	Penalty function + residuals	
217 [131]	2018		HMM	
1031 [132]	2018		HMM + K-means clustering	
235 [73]	2017		Semantic model mean vote	
274 [146]	2017		Dynamic HMM	
278 [125]	2017		BN	
316 [72]	2016		APAR	
812 [261]	2016	Cooling coil; sensor	Fuzzy logic model with residuals	
373 [97]	2015		SVM-ARX	
821 [142]	2015		NARX-TDNN	
823 [262]	2015	VAV; sensor	Probabilistic graphical model	
1587 [134]	2011		WNN	
1676 [129]	2011	Chiller valve; cooling coil	Fuzzy model + degree of belief	
1408 [133]	2009	VAV sensors	WNN	
1436 [48]	2008	Room level; fan	Ruleset + performance index + residuals + threshold	
1465 [263]	2006		Residuals + RS + ANN	

Table A4. *Cont.*

Ref	Year Published	Component	Fault Detection	Fault Diagnosis
1469 [264]	2006	Sensor	PCA	
1516 [265]	2002	Preheating process	In situ testing under specific conditions	
1830 [130]	1999	Sensor; cooling coil	Fuzzy model + degree of belief	
1850 [113]	1999	Outdoor air ventilation and economizer operation	Ruleset	
1851 [266]	1999	VAV	ANN; K-nearest; nearest prototype; rule-based; Bayes classifier	
1853 [114]	1999	VAV; cooling coil	Ruleset	
AHU articles			Two-step FDD	
44 [144]	2020		aSAX + cSpade (in transient period); aSAX + CART (in nontransient period)	aSAX + CART (in nontransient period)
168 [267]	2018		Parity relation (residuals)	Profile estimation (residuals)
872 [268]	2014	Sensor	Combined BPNN + threshold	Subtractive clustering analysis
1034 [51]	2012	Rooftop unit	Relation between variables	Correlation with reference
1212 [269]	2011	VAV	PCA + correlation analysis + threshold	FD on sublevel
1531 [270]	2011	VAV; cooling coil; fan	Analytical model + residuals + threshold; electrical power analysis	Expert knowledge; parameter estimation + threshold [144]
1229 [271]	2010		BPNN	ENN + WA
1351 [272]	2010	VAV	PCA + residuals + threshold	FD on sublevel
1412 [273]	2009		Residuals	Ruleset
1273 [274]	2007	VAV; sensor	PCA + Q-statistics + threshold	FDA + Mahalanobis distance
1268 [275]	2006	VAV; sensor	PCA	Contribution plots and JAA (joint-angle analysis)
1444 [276]	2006	Cooling coil; fan	Performance index + residual analysis	SVM
1452 [277]	2006	VAV; chiller	PCA + SPE + threshold	Expert ruleset + joint-angle point
1615 [90]	2005	Sensor	PCA + Q-statistics + threshold	PCA + Q-contribution plot + Ruleset + fault pattern + residuals
1502 [278]	2004	Heating coil; cooling coil	RCMAC + residuals + ruleset	Ruleset
1498 [89]	2003	Sensor	PCA + Q-statistics + threshold	Q-statistic + Q-contribution plot + expert ruleset
1537 [279]	2001		Residuals + t-distribution	Magnitude of residuals + expert knowledge

Table A5. Energy distribution: terminal unit/Air-conditioning system.

Ref	Year Published	Component	Fault Detection	Fault Diagnosis
	TU/AC articles		FD	
8 [41]	2021		RC model + residuals	
1326 [135]	2001	Room level	Model + residuals +threshold	
	TU/AC articles		One-step FDD	
83 [42]	2020	VAV; damper	Residuals	
224 [43]	2018	VAV; damper	Residuals	
264 [280]	2017	Sensor; cooling coil	DC + residuals + threshold	
864 [119]	2014	VAV	DBN	
	TU/AC articles		Two-step FDD	
328 [281]	2016	VAV; damper	Fuzzy logic	Fuzzy logic + ANN

Table A6. Energy use: Whole building.

Ref	Year Published	Component	Fault Detection	Fault Diagnosis
	WB articles		FD	
4 [282]	2021	Energy	EDA-LSTM	
24 [55]	2021	Electricity	DBSCAN + K-means + CART	
574 [47]	2020	Sensors; actuators; BMS; zone	Expert rules from inverse RC model	
150 [283]	2019	Energy	CPD	
647 [123]	2019	Energy use	Change-point model; CART; ANN	
619 [284]	2019	HVAC; sensor; control	PCA; PCA-wavelet	
190 [61]	2018	Energy	CART + aSAX	
361 [136]	2015	Electricity; lighting; total active power	CART + GESD; K-means + GESD; DBSCAN; MLP-BEM	
366 [117]	2015	Energy	Residuals	
370 [285]	2015	Energy	K-means + QARM; PAM + QARM; hierarchical clustering + QARM; EWKM + QARM; fuzzy c-means clustering + QARM	
1459 [286]	2006	Energy	Outlier detection	
1852 [287]	1999		Belief network (collection of NNs)	
1922 [107]	1992	Electricity	ANN	
	WB articles		One-step FDD	
69 [288]	2020	Sensor; HVAC	ARR	
222 [289]	2018	HVAC	FEMA	

Table A6. *Cont.*

Ref	Year Published	Component	Fault Detection	Fault Diagnosis
811 [102]	2016	Meters; electricity	WASVM	
440 [290]	2013	Energy; total; refrigeration; lighting; HVAC; boiler	ANN + residuals	
441 [291]	2013	Energy	RDP	
909 [50]	2013	Energy	Graphical network mode + anomaly score	
	WB articles		Two-step FDD	
19 [54]	2021	Energy	ANN + CART + "Follow the leader" clustering + residuals	ANN + profile + threshold
517 [292]	2020	Energy	SVM with threshold	SVM
987 [44]	2018	Room level; heating system; AHU	RC model + residuals + threshold	Ruleset
870 [293]	2014	Energy	EnergyPlus model + PCA + Q-residuals	Contribution from variables (covariance)
1380 [294]	2009	Sensor; heating/cooling system billing	PCA + SPE + threshold	SVI + threshold

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