

Review

State-of-the-Art Methodologies for Self-Fault Detection, Diagnosis and Evaluation (FDDE) in Residential Heat Pumps

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Abstract

The European Union's 2050 targets for decarbonization and electrification are promoting the widespread integration of heat pumps for space heating, cooling, and domestic hot water in buildings. However, their energy and environmental performance can be significantly compromised by soft faults, such as refrigerant leakage or heat exchanger fouling, which may reduce system efficiency by up to 25%, even with maintenance intervals every two years. As a result, the implementation of self-fault detection, diagnosis, and evaluation (FDDE) tools based on operational data has become increasingly important. The complexity and added value of these tools grow as they progress from simple fault detection to quantitative fault evaluation, enabling more accurate and timely maintenance strategies. Direct fault measurements are often unfeasible due to spatial, economic, or intrusiveness constraints, thus requiring indirect methods based on low-cost and accessible measurements. In such cases, overlapping fault symptoms may create diagnostic ambiguities. Moreover, the accuracy of FDDE approaches depends on the type and number of sensors deployed, which must be balanced against cost considerations. This paper provides a comprehensive review of current FDDE methodologies for heat pumps, drawing insights from the academic literature, patent databases, and commercial products. Finally, the role of artificial intelligence in enhancing fault evaluation capabilities is discussed, along with emerging challenges and future research directions.

Keywords: heat pumps; fault detection and diagnosis; fault evaluation; state-of-the-art review; patents



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1. Introduction

The energy demand for heating and cooling in the building sector has significantly increased in recent years, accounting for nearly 30% of global final energy consumption [1]. To cope with the newer decarbonization targets [2] fixed by the European Union, and to consider the rise in the employment of renewable energies that will occur in the future [3], electric heat pumps will represent a promising solution for the replacement of traditional fossil fuel boilers. The number of heat pumps, particularly air-to-air and air-to-water types, has in fact significantly increased [4] in Europe, reaching a stock of almost 24 million, especially air-to-air and air-to-water types. However, although these systems represent a

more sustainable alternative for space heating and domestic hot water compared to fossil fuel systems, and given that they are already the most commercially available solution for space cooling, several challenges arise regarding the containment of direct and indirect environmental impact to be compliant with the decarbonization targets fixed for 2050. In regard to the direct impact, the presence of refrigerant leakages represents a huge contribution, especially if high global warming potential (GWP) fluids are employed. In this sense, the new 2024 F-gas regulation [5] has imposed new limitations in the use of fluorinated and high-GWP refrigerants in several refrigeration and air-conditioning applications. For instance, in domestic applications, split air-conditioning and heat pumps with a capacity lower than 12 kW will not be able to use fluorinated gases after a definitive ban planned for the 1 January 2035. After that, only natural refrigerants will be allowed, such as propane. On the other hand, the indirect impact is influenced by the overall performance of the heat pump, for which threshold values are set by the ecodesign regulation [6] depending on the specific system. Heat pump performance may also be enhanced by the exploitation of renewable sources; for instance, with PV panels directly producing electricity [7], or using multiple sources to optimize the thermodynamic cycle operations [8]. However, regulations do not take into account performance divergences from rated values over time due to operational faults, which results in extra-energy consumption and operational costs for such systems. Faults in heat pump systems can be divided into two different categories [9]: hard and soft ones. Hard faults are anomalies that compromise the continuous operations of machines (e.g., compressor failure, fan failure, fault to the control, and electronics). Soft faults do not compromise the machine operations but cause a degradation in performance that may significantly lead to unidentified extra-energy consumption. In particular, undetected soft faults, such as refrigerant leakage or heat exchanger fouling, can lead to significant energy efficiency losses and increased operational costs, even in systems that initially meet stringent ecodesign performance standards.

In this framework, it becomes crucial to use tools able to provide a complete fault detection, diagnosis, and evaluation (FDDE) in order to prevent degradation in performance and schedule maintenance operations. Particularly, fault detection (FD) refers to the detection of a generic anomaly, fault diagnosis (FDD) refers to the identification of the specific occurred fault, whereas fault evaluation (FDDE) refers to the quantification of the exact fault intensity. In terms of fault evaluation, having a tool able to precisely evaluate a fault intensity will provide the possibility to having scheduled maintenance operations, with operators that in advance may know where to intervene on the machine, such as by simply cleaning the heat exchangers, by recharging the refrigerant in the piping system, or by replacing a specific component.

However, there are still several challenges, especially for FDD and FDDE, for which a specific diagnosis and evaluation could be ambitious. Firstly, the evolution of residential heat pumps towards variable-speed components, multifunctional operation (heating, cooling, DHW), and integration with renewable sources has increased system complexity, making traditional fault detection strategies often inadequate or too expensive. The need for reliable FDDE solutions is also reflected in recent research efforts and industrial innovations. However, many existing commercial systems are still limited to simple fault alerts or generic maintenance recommendations, lacking the ability to quantify the fault severity or to discriminate between multiple overlapping faults. As a matter of fact, it may happen that different faults are affecting in a similar way the operations of machines, making it impossible to adequately conduct a fault diagnosis and evaluation without the employment of specialized sensors. This latter point is also crucial for offering cost-affordable FDDE solutions [10], and this could be particularly challenging, especially for small-sized machines, where the cost of the monitoring system could strongly affect the total cost of the entire

systems. For instance, the easiest way to evaluate a refrigerant leakage would be to install a lever sensor in a charge accumulation point, whereas direct measures of air and water flow rates will quickly diagnose and evaluate issues of heat exchanger fouling, measures which are usually taken in large-capacity systems. However, this could not be feasible for small residential-size units, both for reasons of space and because the cost of such sensors could be even higher than the ones of the entire systems. So, cheap, space-saving, and easy-to-install measures should be employed, such as pressures and temperatures, for FDDE purposes in residential units [11].

Another challenge related to FDDE tools regards the methodology on which they rely. As a matter of fact, there can be physics-based or machine learning-based methodologies [12], each of them with some advantages and disadvantages. In the case of physics-based tools, they rely on simulation models describing the exact physical behavior of the machine, requiring adequate knowledge of phenomena to develop such tools. Conversely, machine learning tools are mostly based on data, without the requirement of thorough knowledge of physical phenomena. In this sense, physics-based models can be more generalizable [13]; however, they can suffer from low accuracy if some physical phenomena are neglected, or in the case of high computational time, sometimes non-compatible with a real-time FDDE procedure. Otherwise, machine learning-based tools can be quite fast and accurate [14], but they require large amounts of data for training, and they perform well only for the systems for which they are calibrated. A good compromise would be the use of gray-box FDDE approaches, which take advantage of some characteristics of the physics-based ones but with dedicated calibrations of the experimental data.

Therefore, taking into account all the challenges arising with FDDE strategies within the heat pump sector, the main target of this work is to provide a literature review of state-of-the-art works dealing with soft faults on heat pumps and methodologies for FDDE, focusing in detail on several key aspects and identifying the most common occurring faults, different approaches, advantages, limitations, and issues that may occur. There are already several works in the literature making an overview of FDDE tools for heat pump systems [15,16]. However, to the best of the authors' knowledge, a comprehensive review of state-of-the-art FDDE tools for use in heat pumps, including literature works, available patents, and products, is currently unavailable.

2. State-of-the-Art Literature

Table 1 shows the state-of-the-art works reviewed in this paper, divided into methodology employed, application, and fault analyzed. Among the reviewed works of the literature, some of them deal with the development of FDDE methods, whereas others deal with the investigation of the effect of several soft faults on the system measured parameters and performances. FDDE methods can be broadly categorized into physics-based (PB) and data-driven (AI-based) approaches: PB methods typically rely on fundamental thermodynamic laws (e.g., mass and energy balances) and component-level models. On the other hand, AI-based methods include supervised learning algorithms such as support vector machines (SVMs), neural networks, or ensemble methods, which classify operational data into fault categories. With regard to works analyzing the effect of faults on measured variables, the main aim is to identify the main influencing parameters on the machine, to be used as FDDE symptoms, and these can be categorized depending on methodology, which can be experimental or numeric depending on if the soft fault investigated is experimentally or virtually reproduced. The applications investigated can be of various types related to air conditioning, including air source heat pumps (split or rooftop), air-to-water systems, VRV/VRF, or chillers (with some papers referring to generic schematics without specifying the typology of the system).

Table 1. List of literature papers reviewed in this work, between 2005 and 2024, divided by methodology, application, fault analyzed, and main objective.

Work	Methodology *	Application	Faults Analyzed **	Effect on Performance/Variables	FDD	Simultaneous Faults
Chen et al. [17,18]	E	VRV/VRF	CF, DEV, EF, RL, RO	Yes	No	No
Llopis-Mengual and Navarro-Peris [19]	PB	Air-to-Air heat pump	CF, CVL, EF, RL, RO	Yes	No	Yes
Llopis-Mengual and Navarro-Peris [20]	E	Air-to-Water heat pump	CF, EF, RL, RO	Yes	No	No
Mauro et al. [11,21]	PB	Air source heat pump (split)	CF, EF, RL	Yes	No	Yes
Uddin et al. [22]	E/ML	Packaged rooftop units	CF, CVL, EF, LL, NC, RL, RO	No	Yes	No
Aguilera et al. [23]	PB	Two-stage ammonia w-to-w heat pump	EF	No	Yes	No
Chen et al. [24]	ML	Residential air conditioners	CF, CVL, EF, LL, NC, RL, RO	No	Yes	No
Cheng et al. [25,26]	ML	VRV/VRF	D4V, DEV, RL, RO	No	Yes	No
Hu and Yuill [27]	E	Heat Exchanger	NC, RL, RO	Yes	No	Yes
Jounay et al. [28]	PB	Air-to-water heat pump	RL	No	No	No
Mauro et al. [29]	ML/PB	Air source heat pump (split)	CF, EF, RL	No	Yes	Yes
Bellanco et al. [30]	E	Water-to-Water heat pump	CVL, EF, LL, RO	Yes	No	No
Han et al. [31]	ML	VRV/VRF	CF, CLF, EF, RL, RO	No	Yes	No
Hu et al. [32,33]	E	Air source heat pump (split)	EF, LL, NC, RL, RO	Yes	No	No

Table 1. Cont.

Work	Methodology *	Application	Faults Analyzed **	Effect on Performance/Variables	FDD	Simultaneous Faults
Hu et al. [34–36]	E	Air source heat pump (split)	EF, LL, NC, RL, RO	Yes	No	Yes
Llopis-Mengual et al. [37]	PB	Air-to-Water heat pump	CF, CVL, RL, RO,	Yes	No	Yes
Zhang et al. [38]	ML	VRV/VRF	CLF, D4V, DEV, RL, RO	No	Yes	No
Zhou et al. [39]	E	VRV/VRF	CF, EF, NC, RL, RO	Yes	No	Yes
Wang et al. [40]	ML	VRV/VRF	CLF, D4V, RL, RO	No	Yes	No
Zhou et al. [41]	ML	VRV/VRF	CLF, D4V, DEV, EF, RL	No	Yes	No
Behfar and Yuill [42]	PB	Walk-in Freezer	CVL, EF, LL	Yes	No	Yes
Ebrahimifakhar et al. [43]	ML/PB	Air source heat pumps (Rooftop)	CF, CVL, EF, LL, NC, RL, RO	No	Yes	No
Kim and Braun [44]	E/PB	Rooftop unit	CVL, RL, RO, CF, EF, DEV	No	Yes	Yes
Eom et al. [45]	E/ML	Air source heat pumps (Generic)	RL, RO	No	Yes	No
Yuill et al. [46,47]	E	Air source heat exchangers	CF, EF	Yes	No	No
Mehrabi and Yuill [48,49]	LD	Air source heat pumps (Split/rooftop)	CF, CVL, EF, LL, NC, RL, RO	Yes	No	No
Noel et al. [50]	E	Air-to-water heat pump	EF, CF, RL, RO	Yes	No	No
Du et al. [51]	LD	Air source heat pumps (Split)	CF, CVL, EF, LL, RL, RO	Yes	No	No
Payne et al. [52–54]	E	Air source heat pump (Split)	CF, CVL, D4V, EF, LL, NC, RL, RO	Yes	No	No
Kim and Braun [55]	PB	Different split and packaged units	RL	No	Yes	No

Table 1. Cont.

Work	Methodology *	Application	Faults Analyzed **	Effect on Performance/Variables	FDD	Simultaneous Faults
Han et al. [56,57]	LD	Chillers	CF, EF, NC, RL, RO	No	Yes	Yes
Li and Braun [58]	PB	Different systems	RL	No	Yes	No
Li and Braun [59]	PB	Different systems	CF, CVL, EF, LL, NC, RL, RO	No	Yes	No
Namburu et al. [60]	LD	Chillers	CF, DEV, EF, NC, RL, RO	No	Yes	No
Kim and Kim [61]	E	Air source heat pumps (Generic)	CVL, CF, EF, RL	Yes	Yes	No

* Methodology: E: experimental; LD: data from literature; ML: numerical machine learning-based; PB: numerical physics-based. ** Faults analyzed: CF: condenser fouling; CLF: compressor liquid floodback; CVL: compressor valve leakage; D4V: defective 4-way valve; DEV: defective expansion valve; EF: evaporator fouling; LL: liquid line restriction; NC: non-condensable in the refrigerant; RL: refrigerant leakage/undercharge; RO: refrigerant overcharge.

It is worth clarifying that the 46 articles reviewed in this work were selected based on the authors' expert knowledge of the most active research groups in the field of FDDE for heat pumps. The papers span from 2005 to 2024, with a particular focus on the last decade, which has seen an increased number of contributions combining experimental analysis and physics-based and AI-based fault detection strategies.

To give an estimation of the number of published papers across the years, research on the Scopus database was conducted, as shown in Figure 1. Particularly, the following constraints were included: the words “heat”, “pump”, and “fault” should appear in the title, abstract, or keywords, whereas the words “detection”, “diagnosis”, or “evaluation” should appear in all the other fields. The results show a great increase in the number of works between 2012 and 2014, when several experimental activities were conducted. Moreover, a further increase occurred in the last 2–3 years, between 2022 and 2024, due to the increased attention paid to artificial intelligence and machine learning tools, which has re-increased the attention of scientific research on such topics.

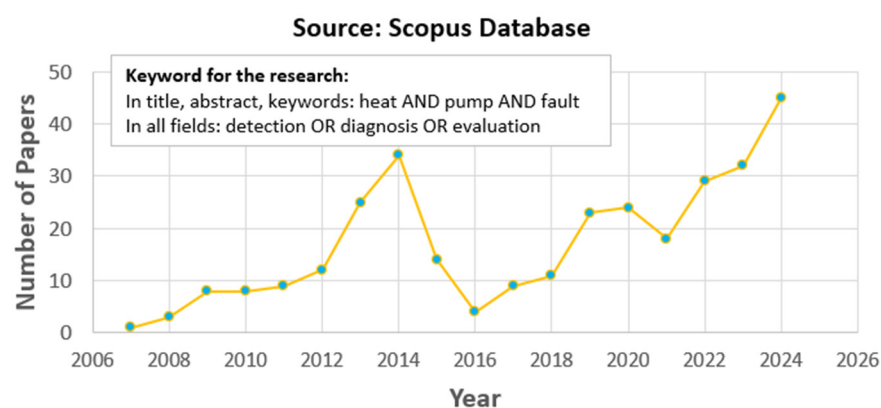


Figure 1. Evolution of number of papers published according to the Scopus database, using research keywords “heat”, “pump”, and “fault” in the title, abstract, and keywords and “detection”, “diagnosis”, or “evaluation” for all the other fields.

A geographical representation of the most active countries and institutions is also reported in Figure 2, with an indication for each country of the number of papers which have been reviewed in this work. It can be noticed that most of the papers come from the US and China. In Asia, there are some works coming from South Korea, whereas in Europe, the situation is more fragmented, with more research groups dealing with the FDDE in the heat pump topic, though with a lower number of published papers.



Figure 2. Most active countries and institutions in the world with papers published on the heat pump FDDE topic and corresponding numbers of papers published.

2.1. Common Soft Faults on Heat Pump Systems

Soft faults can be divided into operational and installation ones. Operational failures can typically accumulate their fault intensity across time, until they reach a certain level which becomes incompatible with the machine operation (e.g., refrigerant leakage, condenser and evaporator fouling, compressor valve leakage). Refrigerant leakage (RL) may typically occur through piping seals, welds, and curves due to manufacturing defects, and the leakage rate may vary depending on the situation, being slow but steady or strong due to accidental ruptures [11]. This rate may vary from 2 to 15% of the initial charge for chillers and from 1 to 10% for residential and commercial heat pumps [62]. Condenser and evaporator fouling (CF; EF) is related to the accumulation of dirt and dust on the heat exchanger plates (if water type) or fins (if air type), causing a penalization both in the fault-free area of the secondary fluids and in the available heat transfer surface [23]. Compressor valve leakage (CVL) instead refers to the bypass of a certain refrigerant flow rate due to the wear or aging of seals or a non-perfect seal of suction and discharge valves, in a way that the circulating flow in the system piping is lower than the one elaborated by the compressor [19]. A similar effect could also be caused by a defective four-way valve (D4V) [30].

Conversely, installation faults are mostly caused by poor installation and assembly made by technicians who have not been properly trained, causing the following problems: Liquid line restriction (LL) is typically a blockage caused by a clogged filter-drier by impurities or debris accumulated before or during the installation [34]. This causes a strong and unintentional pressure reduction in the refrigerant, bringing about in some cases a two-phase flow at the inlet of the expansion valve. The presence of non-condensable gases (NC) (mostly air) is typically caused by a non-correct gas expulsion from piping during the charge operation [16]. Air accumulates in the condenser, mostly penalizing heat transfer [59]. A non-correct charge operation can also lead to refrigerant undercharge and overcharge (RO), in which the refrigerant charge is lower or exceeds the optimal value [40]. Less common faults are the defective expansion valve (DEV) in which the valve may remain stuck in a certain small-opening or large-opening position [17,18], and the compressor liquid floodback (CLF), occurring in multi-evaporator direct expansion systems (VRV/VRF), where a sudden user load variation can cause a large amount of liquid refrigerant at the compressor inlet [31].

A list of the common faults occurring in heat pumps and air conditioning systems, both hard and soft types, is provided in Figure 3, whereas a statistic reporting the number of papers studying each of the reviewed soft faults is reported in Figure 4a. Among the possible soft faults investigated, the operational ones are the most critical. As a matter of fact, while installation faults may typically be identified in the first hours of operation, the operation may remain unidentified for long periods, causing a high extra-energy consumption. Among these, faults related to single components, such as compressor valve leakage and defective expansion valve, can be identified by providing detailed simulation models and monitoring the compressor and expansion valve, whereas heat exchangers (HEX) fouling and refrigerant leakage are typically the most difficult to deal with.

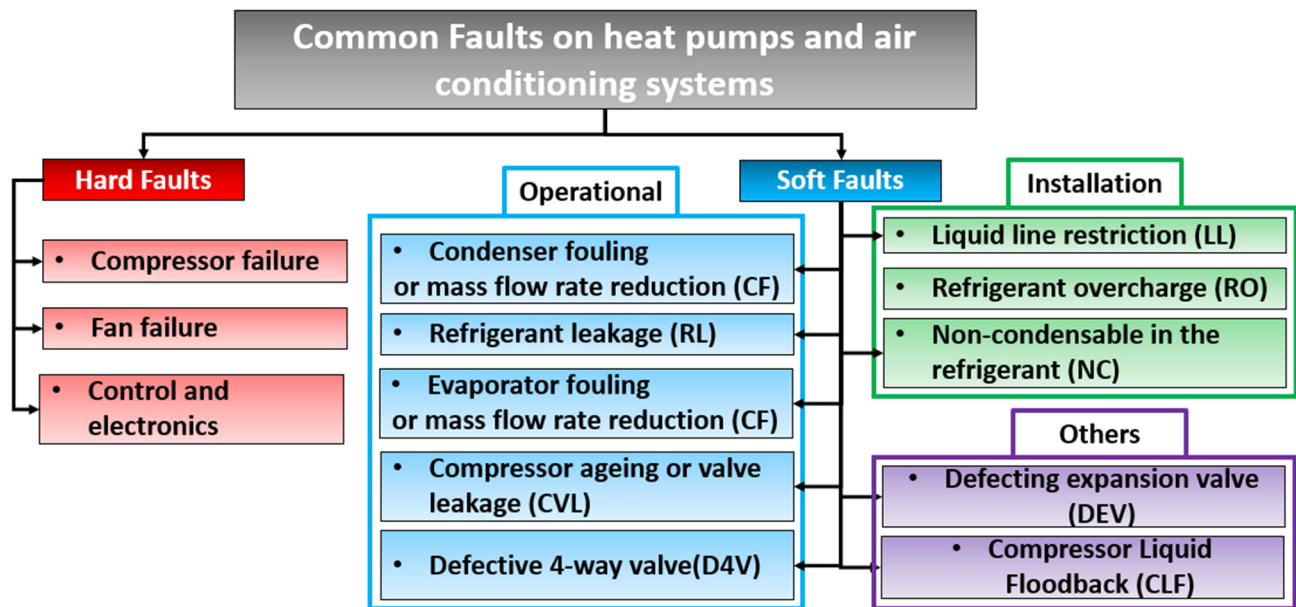


Figure 3. List of common faults on heat pumps and air conditioning systems, divided into hard and soft failures, with the latter divided in turn into operational faults, installation faults, and others.

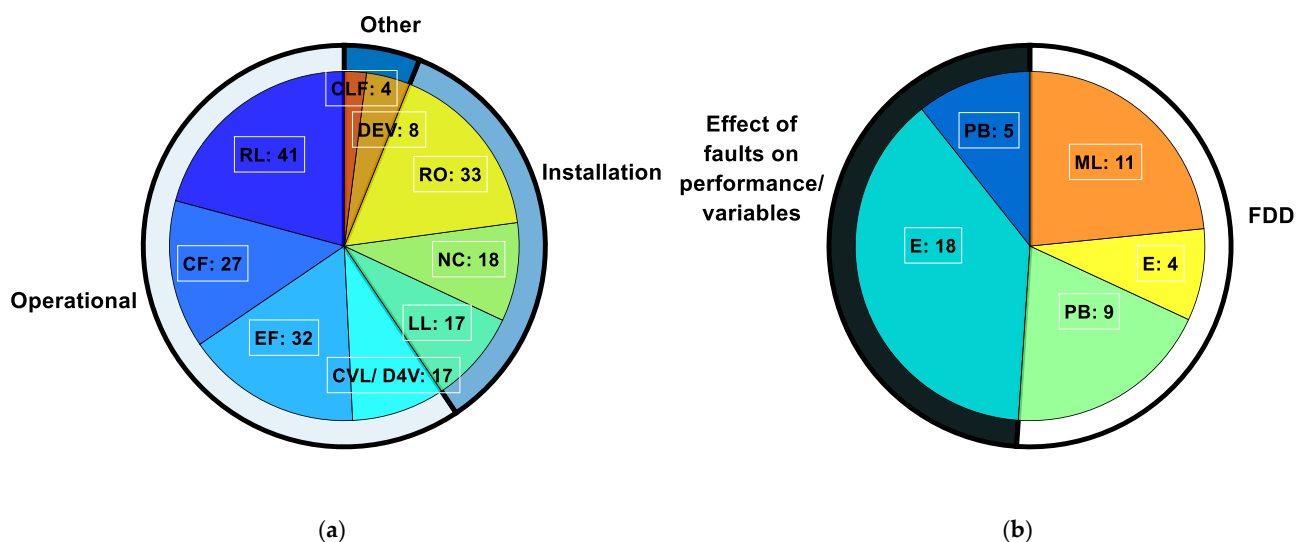


Figure 4. Classification of the paper reviewed in this work. (a) The kinds and typologies of investigated faults. (b) Main objective of the paper and methodology. In brackets, the number of papers is provided.

2.2. Experimental Investigations and Numerical Analysis of Mostly Influenced Parameters by Faults

Among the works shown in Table 1, some of them do not present a complete FDDE methodology but rather analyze the effects of specific faults on system performance and monitored variables. These studies are essential to understand which faults are critical and which variables are most influenced, supporting the design of efficient and cost-effective FDDE strategies. Most of them are based on experimental case studies, whereas others are based on calibrated physical models. The scopes are twofold: to determine the capacity and performance penalization and to understand which are the most influenced measured variables on the thermodynamic cycle, with the aim of informing fault detection and diagnostic procedure. In terms of system performance degradation, Zhang et al. [17] identified cooling capacity and coefficient of performance (COP) degradation up to, respectively, 30–40% and

10–20% for HEX fouling, whereas Llopis Mengual and Navarro Peris [20] obtained heating capacity and COP penalization up to 30% in the case of refrigerant leakage. Similarly, Du et al. [51] identified capacity and performance degradation up to 40% for undercharge faults, almost unchanged performance for overcharge, and a 20–30% decrease for HEX fouling for five different split units, whereas the same authors in Cho et al.’s paper [54] tried to obtain generalized performance degradation curves related to a single fault occurring.

In the case of multiple faults occurring, Hu et al. [34] obtained a cooling capacity and COP penalization up to 30% and 24% for double faults, 34% and 29% for triple faults, and 38% and 34% for quadruple faults.

Mehrabi and Yuill [48] and Bellanco [30] identified for single faults as the most influenced parameters the evaporator temperature for evaporator fouling, the condensing temperature and compressor frequency for compressor valve leakage, and evaporator superheating and condenser subcooling for liquid line restriction and refrigerant overcharge. Similarly, Mehrabi and Yuill [49] and Noel et al. [50] identified as the most influenced parameters the condenser and evaporator temperatures for the condenser fouling and both condenser and evaporator temperature, subcooling, and EEV opening in the case of refrigerant leakage. An overview of works analyzing the effect of faults on performance and measured variable on the machine, divided per methodology, is provided in Figure 4b. Finally, a qualitative trend of some measured variables depending on the occurred faults is reported in Table 2, in accordance with the works of Llopis Mengual and Navarro Peris [19], and of Hu and Yuill [36]. Symbol “↑” means an increase in the variable with the fault compared to the fault-free case, symbol “↓” denotes a decrease, whereas “—” reflects a weak dependence between the measured variable and the fault. Other experimental works reviewed in this paper are qualitatively in accordance with the trends presented in Table 2. However, more quantitative deviations may also depend on the typology of the system investigated, as also better clarified below.

Table 2. Main relationships (“↑”: positive; “↓”: negative; “—”: negligible) between the measured variables of condensing temperature (T_{co}), evaporating temperature (T_{ev}), condenser outlet subcooling (ΔT_{sc}), evaporator outlet superheating (ΔT_{sh}), compressor discharge temperature (T_{dis}), mass flow rate ($\dot{m}_{ref}$), capacity ($\dot{Q}$), compressor power consumption ($\dot{W}_{comp}$), and some soft faults according to Llopis Mengual and Navarro Peris [19] and to Hu and Yuill [36].

	T_{co}	T_{ev}	ΔT_{sc}	ΔT_{sh}	T_{dis}	$\dot{m}_{ref}$	$\dot{Q}$	$\dot{W}_{comp}$
EF	—	↓	—	—	↑	—	—	↑
CF	↑	—	↑	—	↑	—	—	↑
CVL	↓	↑	—	—	↑	↓	↓	↑
RL	↓	↓	↓	↑	↑	↓	↓	↑
RO	↑	—	↑	—	↑	—	—	↑

2.3. Physics-Based and AI-Based FDDE Techniques

Some studies in Table 1 developed fault detection and diagnosis algorithms, mostly relying on pressure and temperature measurements on the heat pump system, both on the refrigerant size and on the water/air size depending on the typology of the system investigated. These can be categorized depending on the type of approaches employed for the FDD, which can be physics-based (relying on physical equations) or artificial intelligence (AI)-based (by calibrating machine learning algorithms). Among the physics-based works, Braun et al. [44,55,59] introduced the concept of virtual sensors, defined as a feature either directly measured or derived from other measured parameters, which depend uniquely on individual faults. The presence of a fault can be determined whenever the

value assumed by the virtual sensor differs from an expected value coming from fault-free operations. Li and Braun [44] developed three virtual sensors for the evaluation of the refrigerant mass flow rate using a compressor map (as a function of the evaporator and condenser temperature), using an energy balance with the power consumption, and using semi-empirical correlation from the electronic expansion valve to decouple compressor aging/valve leakage and defective EEV faults. The same authors in Li and Braun's paper [59] developed virtual sensors for condenser and evaporator fouling based on the determination of a virtual condenser/evaporator air volumetric flow rate; however, it was still influenced by the presence of other faults, and for liquid line restriction, by measuring the pressure drop between the filter upstream and downstream. Regarding the refrigerant leakage/overcharge faults, in [55,58], a refrigerant charge virtual sensor was developed. It consists of evaluating the ratio of the mass difference between the actual and rated amount of refrigerant on the total rated as a function of the superheating and of the subcooling by using two different coefficients calibrated ad hoc on the investigated system. Finally, Kim and Kim [61] developed a rule-based FDD algorithm for a generic vapor compression system by using compressor speed and analyzing residuals between fault-free and faulty data. Depending on whether faulty variables are above or below fault-free ones, this algorithm was able to diagnose single faults such as condenser and evaporator fouling, refrigerant leakage and overcharge, and compressor valve leakage.

Conversely, other works make use of data-driven techniques, calibrated on real experimental or numerical data, often based on machine learning tools. In FDD problems, it is common to employ classification techniques, able to predict a faulty or fault-free class. As an example, Ebrahimifakhar et al. [43] and Uddin et al. [22] demonstrate the applicability of several machine learning (ML) classification tools in rooftop units with several standalone faults, obtaining for the best algorithm (support vector machine, SVM) an accuracy of about 96.2%. Similar considerations were made in the work of Mauro et al. [29] for domestic air source heat pumps, where several ML-FDDE strategies (artificial neural networks, k-nearest neighbors) for single and simultaneous faults of HEX fouling and refrigerant leakage were tested. Similar data-driven tools were investigated also for VRF/VRF systems by Chen et al. [25,31,40], and for chillers by Han et al. [56], where a sensitivity analysis on the input data has also been carried out.

Among the two physics-based and AI-based methodologies, PB methods rely on thermodynamic models and are generally interpretable and applicable to a wide range of similar systems [13]. However, they often require accurate component modeling and may struggle in capturing complex multi-fault behaviors or unmodeled dynamics, being also computational costly for real-time FDDE predictions. This aspect was also observed in our previous work [29], in which we found that physics-based models, based also on multiple interpolation, can have very high computational time, making them unfeasible for producing real-time results. On the other hand, AI-based methods can capture non-linear patterns and learn from complex data relationships, being interesting when a low calculation time is needed [14,63]. Nonetheless, they require large and diverse datasets for training, are often system-specific, and may lack interpretability. Moreover, they are strictly related to the system for which they are calibrated and typically underperform with different machines. This was observed in Chen et al.'s work [24], where an SVM classifier trained on a certain system performs poorly if applied to a different one. Another issue is the presence of imbalanced training data, that typically occurs when training data comes from experiments, reducing the prediction accuracy up to 43%, as observed in [41]. Finally, both physics-based and ML-based methods can suffer from single- and multiple-fault indeterminacy, as better clarified in the following section.

2.4. FDDE Indeterminacy in the Case of Single Faults and Compensation Effects by Modern Components

Among all the different FDD algorithms, several problems of indeterminacy may occur in the case of the identification of standalone occurring faults. Modern residential and commercial heat pumps increasingly adopt variable-speed compressors, electronic expansion valves (EEVs), and refrigerant accumulators or receivers. These components enable enhanced efficiency and control but also introduce significant complexity in fault detection and diagnosis. As a matter of fact, machines are able to compensate for the presence of some faults, leading to negligible or no evident effect on the measured variables of the thermodynamic cycle. In this way, it would be possible to detect, diagnose, and eventually precisely evaluate a fault only when its fault intensity has arrived at a certain limit for which these control parameters arrive to their maximum value, delaying a scheduled maintenance intervention.

One example regards the thermostatic expansion valve (TXV), which compared to the fixed orifice system (FXO), can regulate, compensating for the effect of some faults. For instance, in the work of Hu et al. [34] and of Kim and Braun [44], the presence of a TXV is able to delay the identification of liquid line blockage, by operating at a higher valve opening until the blockage reaches such a high fault intensity that its position becomes fully open. The same aspect was observed in Pelella et al.'s work [21] for refrigerant leakage where despite the presence of a low-quality saturated vapor entering at the expansion valve inlet, the valve is able to work at an enhanced opening section until an increased refrigerant leakage leads the valve to be fully open. Refrigerant leakage can also be compensated by the presence of a liquid receiver at the inlet of the compressor [20] or at the outlet of the condenser [11], which can operate as a buffer in some less severe operating conditions, making the thermodynamic cycle indifferent from small leakages [44], as long as the receiver itself remains non-empty. Finally, a sort of compensation effect could also be reached in a system characterized by a variable compressor speed [61], which in some cases increases to guarantee the user capacity. However, this operation will modify the thermodynamic cycle of the machine itself, making faults identifiable if a proper monitoring of the machine variable is considered. A framework of the main reasons for the FDDE indeterminacy in the case of single faults is provided in the upper part of Figure 5.

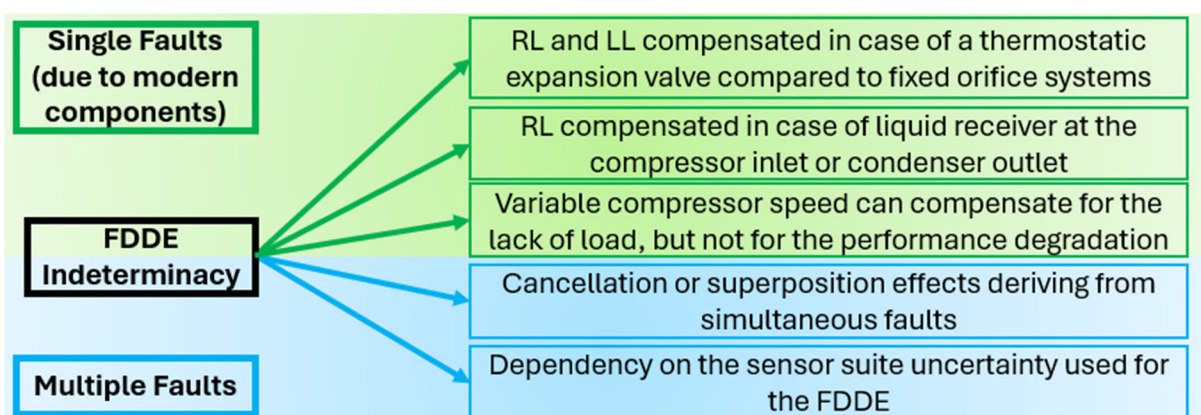


Figure 5. List of main reasons for the FDDE indeterminacy for single and multiple faults.

2.5. FDDE Indeterminacy in the Case of Multiple Simultaneous Faults

In the case of multiple faults, an indeterminacy can derive from some superposition effects that faults may have on each measured variable. For instance, according to Pelella et al. [11], the simultaneous effects of a refrigerant leakage, causing a reduction in the condenser temperature, can be compensated by the increasing effect of a condenser fouling.

Similarly, an evaporator temperature decrease could be caused by an evaporator fouling and enhanced by a refrigerant leakage. Zhou et al. [41] even observed a COP increase when double fault occurred (e.g., RO and CF).

To assess these superposition/cancellation effects, Hu et al. [34] define a difference variable comparing the overall impact of combined faults to the sum of impacts of the same standalone faults. They obtained that the simultaneous fault interaction is typically lower compared to summing single-fault effects. This is emphasized by the possible uncertainty of the sensors and measuring instruments employed for the FDDE, as outlined in Pelella et al.'s work [11], which may increase the fault diagnosis and evaluation indeterminacy zone. A framework of the main reasons for the FDDE indeterminacy in the case of multiple simultaneous faults is provided in the lower part of Figure 5.

2.6. Impact of Number of Sensors and Their Configuration on the FDDE's Accuracy

In the reviewed works, some studies stand out which, despite not directly analyzing the effect of faults on the measured variables, examine the effect of number of sensors and their configuration on the accuracy of FDDE. Among them, it is worth mentioning the case study of Han et al. [57]. This work, which is based on the literature data coming from the ASHRAE 1043RP Project [9], developed a machine learning algorithm, specifically an SVM, to predict the occurrences of several soft faults on chillers. In particular, they employed a genetic algorithm on subsets of 6, 7, 8, and 9 measures on a total of the 64 available, including temperatures, pressures, flow rates, valve positions, heating and cooling rates, electrical powers, and setpoints, in order to optimize the number of sensors to install, achieving an optimal balance between FDDE accuracy and cost. The results were presented in terms of correct rate and false alarm rate predictions, and they suggest that a number of features at least equal to the number of faulty classes investigated should be considered for the FDDE (in their paper of eight features). In this way, overall, a correct rate of about 99.5% was achieved, and a false alarm rate lower than 1% was also achieved. A similar investigation was also conducted by Namburu et al. [60], which developed FDD algorithms based on SVM or statistical methodologies. They conducted an optimization of the sensor selection, by means of a genetic algorithm, considering two different cases: a first case optimizing only the prevision accuracy and a second case in which also the sensor total cost was minimized. In the first case, on a total amount of 48 sensors, the best accuracy was obtained with 24 measurements, whereas this number decreases to 8 for the second case, being also in this case equal to the number of faulty classes investigated. However, both works dealt with the fault diagnosis of single occurring faults, without mentioning the possibility of analyzing multiple occurring faults.

3. Patents and Products for the FDDE

3.1. List of Patents

In this work, a total of 18 patents related to FDDE tools for refrigeration and air conditioning appliances were reviewed. A comprehensive list of patents is provided in Table 3, where indications about each patent code, application field, and current assignee are provided. It should be noted that most of the filed patents come from the US, China, and Japan, with some exceptions. Moreover, most of the patents are filed generically for vapor compression systems, without detailing a specific application field, whereas some others are specifically developed for heat pump or air-conditioning, refrigeration and HVAC systems, or single components (e.g., P2). Finally, most of the patents belong to the main refrigeration and air conditioning manufacturers (Carrier Corp. (Palm Beach Gardens, FL, USA), Copeland (Houston, TX, USA), Mitsubishi (Tokyo, Japan), Daikin Industries (Osaka, Japan), and Whirlpool (Benton Harbor, MI, USA)), with few exceptions.

Table 3. List of the patents reviewed in this work, with corresponding application field and current assignee.

Patent	Reference	Code	Application	Owner/Assignee
P1	[64]	US9435576B1	Air conditioners and heat pumps	Mainstream Engineering Corp., Rockledge, FL, USA
P2	[65]	US7469546B2	Condenser in a refrigeration cycle	Copeland
P3	[66]	US7494536B2	HVAC system	Carrier Corp.
P4	[67]	US9261542B1	Air conditioners and heat pumps	Advantek Consulting Services, Eden Prairie, MN, USA
P5	[68]	US6701725B2	Vapor compression (generic)	Mcloud Technologies, Vancouver, BC, Canada
P6	[69]	US10712036B2	HVAC system	N.A.
P7	[70]	CN100529604C	Vapor compression (generic)	Carrier Corp.
P8	[71]	JP5249821B2	Refrigerators	Mitsubishi
P9	[72]	EP2812640B1	Vapor compression (generic)	Carrier Corp.
P10	[73]	US10208993B2	Refrigerators	Whirlpool Corp.
P11	[74]	JP4265982B2	Vapor compression (generic)	Mitsubishi
P12	[75]	US7631508B2	Vapor compression (generic)	Purdue Research Foundation, West Lafayette, IN, USA
P13	[76]	JPH08219601A	Refrigerators	Hitachi Ltd., Tokyo, Japan
P14	[77]	WO2001097114A1	Air conditioner	Daikin Industries Ltd.
P15	[78]	JP2005345096A	Refrigerators	Mitsubishi
P16	[79]	US11248829B2	Heat Pump	Mitsubishi
P17	[80]	AU2014313328B2	Air conditioner	Mitsubishi
P18	[81]	JP3610812B2	Vapor compression (generic)	Daikin Industries Ltd.

A detailed technical and methodological classification of the reviewed patents is conducted in Table 4, by categorizing them depending on the kind of operational fault (both soft and hard type). Three different implemented methodologies are identified, including a simple fault detection (or the patent deals with a single occurring fault), a fault diagnosis among different fault typologies, and a precise fault evaluation. Moreover, methods based on low-cost and easy-to-install measurements are shown in bold.

Among the investigated patents, most of them developed single refrigerant leakage detectors. Patents P7 and P18 developed a method to detect refrigerant leakage based on the measure of the actual value of the evaporator superheat. Similarly, P17 is based not only on the evaporator superheating but also on the temperature difference between compressor outlet and condensing, whereas patent P8 provides the monitoring and identification of anomalies with the direct measures of the air, water, and refrigerant temperatures, as well as the compressor behavior. Only two patents (P9 and P12) are able to evaluate the actual level of refrigerant charge, so the refrigerant leaked. However, they do not consider any

effect which may derive from the occurrence of other faults, leading to a misclassification of the faulty condition.

Table 4. Classification of patents (P1 to P19) reviewed in this work for kind of fault and methodology.

Fault *	Detection (or Only 1 Fault Investigated)	Diagnosis	Evaluation
Refrigerant Leakage	P7, P8, P16, P17, P18	P1, P2, P11, P13, P14, P15	P9, P12
Condenser Fouling		P1, P2, P13, P15	
Evaporator Fouling	P3	P1, P2, P13, P15	
Others	P6, P7	P1, P2	
Hard Faults		P10, P11, P14, P15, P17	
Performance Estimation		P4, P5	

* In **bold** if low-cost and easy-to-install measures are employed.

Other patents are instead able to provide a diagnosis among different typologies of faults, including refrigerant leakage, condenser, and evaporator fouling. Patents P1, P13, and P15 rely on measures of temperatures, pressures, voltages, and currents and compare online measured values with threshold considered as symptoms for different faulty conditions. A similar procedure was developed by patent P11, which however discriminates refrigerant leakage and other hard faults without including heat exchanger fouling, whereas patent P3 uses mostly pressure and temperature measurements to detect an evaporator fouling condition. No evaluation of the precise fault intensity is conducted for HEX fouling faults, whereas the patent P10 deals also with the diagnosis of hard faults, such as the compressor failure or the rupture of condenser and evaporator coil fans.

Finally, only two patents (P4 and P5) are able to evaluate the system performance (COP) directly from measured data.

Most of the reviewed patents rely on easy-to-install measures, apart from patent P2, which necessitates the employment of temperature and relative humidity sensors, air volumetric flowmeters, and power meters to discriminate among refrigerant leakage, condenser fouling, and evaporator fouling, patent P16, which employs a refrigerant leakage detector in water, and patents P8 and P10, which monitor the compressor status (e.g., frequency, on/off). It should be clarified that the presence of expensive and redundant measurements can be justified in cases when the reliability of the heating/cooling service is more important than the investment cost of the system itself, especially in medical product conservation, food storage, and military applications.

3.2. List of Products

Some measures for the detection and diagnosis of anomalies are already included in some commercialized products of some heat pump, refrigeration, and air conditioning manufacturers. Table 5 lists eight different commercialized products (from p1 to p8) for several low- and high-capacity applications. Again, most of the products belong to well-known manufacturers such as Daikin, Carrier, Danfoss (Nordborg, Denmark), and Copeland. Among the heat pump systems on the market, most of them dispose of a monitoring system, based on error code able to communicate to the final user a diagnosis of a specific kind of fault, typically of hard type and rarely of soft type. For instance, the manufacturer of products p1 and p2 gives an error code whenever several problems occur, including dirty air filters, clogged drain line, wiring problems, frozen or overheating evaporator coils, refrigerant undercharge and overcharge, broken fan motor, and anomalies in pressures. The same is also implemented by products p3 where the machine is able to

provide error codes to final users, related to over voltages, high-temperature protection, refrigerant leakage detection, high- and lower-pressure protection, defective sensors, etc. Similarly, product p8 provides machines with smart thermostats, able to collect data and guarantee flexible scheduling and maintenance service for both some hard and soft faults. Product p7 instead consists of a three-sensor based platform that can be mounted to several air conditioning system types, independently from the manufacturer, and that enables continuous machine monitoring, especially to optimize performance and comfort and reduce performance degradation deriving from some soft faults such as dust accumulation.

Table 5. List of market products (p1 to p9) reviewed in this work.

Product	Manufacturer	Application	Hard Faults	Soft faults	Fouling	Leakage	ML-Based	Generic Maintenance (Not Specified)
p1 [82]	Daikin	Mini-split	Yes	Yes	Yes	Yes	No	No
p2 [83]	Daikin	Split, VRV, Chiller	Yes	Yes	Yes	Yes	No	No
p3 [84]	Carrier	Split	Yes	Yes		Yes	No	No
p4 [85]	Danfoss	Generic HVAC	No	No	No	No	No	Yes
p5 [86]	Danfoss	Supermarkets	No	No	No	Yes	No	Yes
p6 [87]	Danfoss	Cold display cabinets	No	No	No	No	No	Yes
p7 [88]	Smart AC Houston, TX, USA	Residential Air-to-air	No	Yes	Yes	No	Yes	No
p8 [89]	Copeland	Residential Air-to-air	Yes	Yes	Yes	No	(?)	No

Conversely, some of the reviewed products do not deal with the specific detection and diagnosis of soft faults such as HEX fouling, refrigerant leakage, or hard faults but rather consider a generic maintenance and monitoring service without specifying the type of fault that occurred. For instance, for HVAC systems, product p4 offers control intelligent solutions by using smart sensors, remote control, and optimization of occupancy patterns and usage profiles.

Similar IoT monitoring infrastructures are also developed for some refrigeration applications regarding supermarkets food retail (p5) and cold display cabinets (p6), providing indications in terms of energy consumption, service call, and food loss.

However, despite most of the reviewed products available on the market already carrying out some hard/soft fault detection and eventually diagnosis, none of them mention the possibility of a fault evaluation, which in any case can be challenging, especially in the case of multiple simultaneous faults.

4. Conclusions

In this paper, several literature works, patents, and available products on the market were reviewed. The main outcomes are provided as follows:

- Forty-six literature papers were reviewed, both analyzing the effect of faults on system performance/measured variables and developing FDDE algorithms. Each work was categorized based on the fault investigated and on the methodology employed. From the literature, it emerges that soft faults, such as refrigerant leakage and heat exchanger fouling, are among the most critical due to their frequent occurrence and subtle impact on performance, which often goes undetected over long periods. While many studies address fault detection and diagnosis, relatively few focus on fault evaluation, which is crucial for predictive maintenance and real-time control adaptation.

- Main limitations of actual FDDE tools are highlighted, related to a diagnosis and evaluation indeterminacy both in the case of single and multiple faults occurring. A significant research gap remains in the integration of modern components (e.g., variable-speed compressors, EEVs, receivers), which introduce non-linear and adaptive behaviors that complicate FDDE in the case of single faults. For instance, the presence of TXV and refrigerant charge accumulators can limit the effect of some faults such as refrigerant leakage and liquid line restriction on the measured parameters. In the case of multiple faults, cancelation and superposition effects can cause the underperformance of FDDE tools, which are worsened by sensors' uncertainty.
- Eighteen literature patents and eight market products from main machine manufacturers were reviewed and, overall, a lack of precise fault evaluations, especially when more than one fault occurs simultaneously, is noticed.
- Therefore, future research should focus on several aspects, including the following:
- Developing hybrid FDDE models that combine physics-based insights with data-driven flexibility.
- Designing cost-effective and scalable sensor architectures suitable for small residential systems.
- Improving fault evaluation accuracy by incorporating sensor uncertainty and interaction effects and overcoming indeterminacy situations derived by modern components for single faults and by superposition and cancelation effects for multiple faults.
- Encouraging regulatory alignment, recognizing in-service performance degradation as a key criterion in system evaluation.

All these elements will play a key role in future scenarios where heating and cooling will be offered as a service. In such contexts, heating and cooling demands will no longer be met by merely purchasing a standalone unit but rather through a comprehensive service package offered by service providers that includes installation, usage on loan, intelligent control, and maintenance. Consequently, the development of FDDE strategies could facilitate smart management and maintenance, particularly in small-capacity systems where the use of cost-effective sensors is essential.

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We confirm that we have given due consideration to the protection of intellectual property associated with this work and that there are no impediments to publication, including the timing of publication, with respect to intellectual property. In so doing, we confirm that we have followed the regulations of our institutions concerning intellectual property. We understand that the corresponding author is the sole contact for the Editorial process (including the Editorial Manager and direct communications with the office). He is responsible for communicating with the other authors about the progress, submissions of revisions, and final approval of proofs. We confirm that we have provided a current, correct email address that is accessible by the corresponding author.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
CF	Condenser Fouling
CLF	Compressor Liquid Floodback
COP	Coefficient of Performance
CVL	Compressor Valve Leakage
D4V	Defective 4-way Valve
DEV	Defective Expansion Valve
E	Experimental
EEV	Electronic Expansion Valve
EF	Evaporator Fouling
FD	Fault Detection
FDD	Fault Detection and Diagnosis
FDDE	Fault Detection, Diagnosis and Evaluation
FXO	Fixed Orifice
GWP	Global Warming Potential
HEX	Heat Exchanger
HVAC	Heating, Ventilation and Air Conditioning
LD	Literature Data
LL	Liquid Line restriction
ML	Machine Learning
NC	Non-condensable in the refrigerant
PB	Physics-Based
RL	Refrigerant Leakage
RO	Refrigerant Overcharge
SVM	Support Vector Machine
TXV	Thermostatic Expansion Valve
VRV/VRF	Variable Refrigerant Volume/Flow

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