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A COMPRESSIVE STUDY ON FAULT DETECTION AND DIAGNOSIS FOR RELIABLE OPERATION OF HVAC, ENERGY BUILDINGS AND MACHINERIES

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Abstract

In Heating, Ventilation, and Air Conditioning (HVAC) systems, faults can be occurred due to various reasons such as drift deviation, valve/fan failure,water clogging,air filter obstruction, temperature sensor failure and so on. Similarly in electrical machineries faults can be occurred due to multiple causes such as phase reversal, over or under voltage, starter open/short circuit, bearing problems, insulation breakdown, overloading, thermal unbalance, environmental as well as other technical issues. The faults analysis at various stages of electrical systems are critically important for reliable operation of the system. In view of reliability and safety operations of modern sophisticated electrical systems, faults analysis and its diagnosis are necessary to avoid unaccountable losses. The faults at various stages, its causes, methods of detection and diagnosis, fault classifications are included in this work. The comment on effectiveness methods of detection of fault and diagnosis are included for electrical systems. In the industries, systems are incorporated with monitoring capacity for detection of faults at easy and early stage. This paper mainly focused on advancements in fault detection and diagnosis (FDD) methods with short review of various recent methods. This includes system information representation,methods of FDD, description of faults, fault classification, and decision actions related to maintenance, providing a systematic overview of the current state of FDD. Furthermore, the paper underscores the pivotal roles of FDD in electrical systems, emphasizing its effectiveness in identifying faulty states and taking pre-emptive actions against potential failures or accidents. The discussion extends to developments of current research in FDD approaches for electrical machineries with system monitoring, accompanied by short review of diverse and valuable FDD methodologies. The study concludes by addressing comments on recent trends, future directions, challenges, and prospective solutions in the hybrid and dynamic landscape of FDD.

Keywords: Fault types and classification, Fault detection and diagnosis (FDD), HVAC, Electrical machines, Energy buildings, Reliability

1. Introduction

In the era of Industry 4.0, processes are evolving smart systems these are well equipped with advanced sensing devices to collect process related data for fault detection and process monitoring. As industries embrace full automation, meticulous supervision, involving process maintenance, control and corrective actions, becomes imperative to ensure operational efficiency [1]-[2]. Maintaining reliable and optimal performance in industrial processes is a challenge, often susceptible to various faults, is a key challenge. Among the array of FDD in process supervision techniques, is important issue of control methodology. Industries seek to enhance their process performance by leveraging advanced FDD capabilities, which primarily involve monitoring process behavior and uncovering faults, their characteristics, and root causes [3]- [4]. Efficient and accurate detection and diagnosis tools are crucial for sustaining high process yield and throughput. FDD has garnered substantial attention across diverse industrial sectors and academia over several decades, offering benefits such as cost reduction, improved quality, and enhanced productivity [5]. This is particularly evident in safety-critical applications like robotics, autonomous vehicles, surveillance, and manufacturing systems, where FDD plays a pivotal role in ensuring human safety and preventing infrastructure loss. Modern systems and equipment demand the integration of FDD not only for safety but also for increased production and reliable operation. A robust FDD system, as highlighted in recent research, encompasses overall system health monitoring, diverse malfunction handling, and precise fault identification and localization for safe component removal. Over the past three decades, extensive work has been conducted on FDD, resulting in various techniques. These range from approaches of model based such as structural graphs and observer-based to approaches of data-driven employing classification, pattern recognition, and neural networks. Model-based FDD relies on accurate mathematical models, making it suitable for smaller systems with explicit models but susceptible to disturbances and uncertainties. In contrast, method of data-driven extract information from predicted signals to predict faults, with approaches of signal-based divided into statistical methods. The advent of technology has brought intelligent systems to the forefront, posing challenges in developing knowledge bases from raw historic information. The representation of information based includes knowledge explicit through production rules or expert systems and knowledge implicit in machine learning (ML) classifiers. Earlier reviews, have focused on model-based or data-driven FDD techniques, spectral approaches, and deep learning. This review provides a comprehensive overview, encompassing both traditional and signal processing based FDD approaches, with a specific emphasis on artificial intelligence-based methods. Covering the fundamental elements of FDD systems and prevalent techniques, this article contributes valuable insights to the FDD field for HVAC and electrical machineries. Challenges in real-time datasets includes the presence of outliers, which are often detected using unsupervised methods. In the approach of semi supervised learning which leverages both unlabelled and labelled data, providing a better choice. Data-driven FDD methods have gained significant attention across diverse industries, playing a pivotal role in monitoring of complex industrial process. The effectiveness of these approaches relies on the quality of historical data and the analytical models employed [6]. While various data-driven FDD methods exist, PCA-based and PLS-based approaches stand out for their simplicity and efficiency in detecting and diagnosing process faults. In literature of data-driven methodologies, it has been focused on PLS-based and PCA-based monitoring of process schemes. Many academicians have addressed modifications necessary for successful implementation and proposed an integrated adaptive residual generation technique to address uncertainty issues. The control techniques of fault-tolerant and data driven based FDD methods have been developed by Wang et al. [7], discussing their advances and general developments. In the work, researcher presented application example and outlined direction of research work, highlighting issues of FDD [8]. It is details by the Yin et. al [9] that data driven process was fundamental monitoring and diagnosis of faults including PLS, PCA, ICA and FDA. The study covered characteristics, computational complexities, design, and algorithms of these data-driven methods. In another work of Qin [11] provided data driven approaches and applications. In the study of it has been discussed the modelling on the basis of latent variable and fault detection work which are approaches for diagnosis and identification. Sensors are often limited to data transmission and sensing capabilities. Periodically, they send sensed data to a remote node that houses FDD blocks. They then wait for that node to make a determination on the presence of faults. With the aforementioned limitations in mind, we suggest a distributed sensor-fault detection and diagnosis system such that, immediately following data sensing, the sensor's fault detection block starts to function. This will conserve the energy used for periodic data transfer to and from a remote node in addition to providing a speedy determination regarding the existence of a malfunction. Additionally, this plan will offer chances to alert users or automatically halt system operations prior to a monetary loss or harm to human life. On the other hand, a central node implements the fault diagnosis block. Due to the fact that diagnosis is not time-sensitive, data exchanges between nodes may cause delays in the system. The use of this strategy minimizes the sensor's computing burden. In actuality, diagnosis is computationally expensive because, in contrast to detection models that just distinguish between normal and abnormal conditions, the model must learn higher-level representations in order to distinguish among the fault types. A central node hosts problem diagnostics in the suggested distributed system design, whereas sensor nodes handle fault detection. The fault detection and reliability or model operation are active area not only in the industrial systems but also in the multidisciplinary fields[10]-[11].

This paper organised into the following sections: Section 1, included the introduction about the fault classification, FDD methods with overview of general faults category. Section 2, where a short discussion made on the work of fault categorization and various methods if FDD for general applications which includes categories from the general industrial processes. The survey on the major techniques for HVAC and energy buildings is included in Section 3 while Section 4 contains survey of electrical machineries. The paper ends with some remarks and conclusions which is part of Section 5.

2. Fault Categorisation and Detection Methods

Beyond system representation and redundancy, the selection of an appropriate FDD system is heavily influenced by the nature of faults. A primary classification categorizes faults into software, hardware, communication and networking faults. Hardware faults encompass sensor, actuator, plant/process, and structural faults. Software faults include bit-flips, subroutine execution failures,runtime issues, and other software malfunctions. Networking and communication faults involve protocol incompatibility, packet transmission failures, and non-recoverable data packets. The general block diagram of industrial process control system is shown in Fig. 1. In the control theory, various academicians had been contributed to control the process using modified controller [12, 13, 14], with advances in control strategies [15, 16]. There are many types of faults and malfunctions which are based on industrial systems and described below in short

- Sensor Category
  In sensor category, there are faulty components due to current/voltage sensor, speed, position sensor, absolute encoder type sensors or in general the fault components because of sensors which are used in industrial systems. The fault descriptions may include one or more reasons such as additive and/or multiplicative fault, abrupt voltage, power failure dropout, encoder fault, open circuit fault, multiple hard and soft failures and so on.

- Actuator or final control element category
  This category can be based on electrical, mechanical or hydraulic or pneumatic elements. Faults can be because of armature and field winding, fault in stator winding, defect in insulation, rotor and bearing faults, rotor axis misalignment, gear box defects, fault in electrohydrostatic aerospace actuators. The description of actuators can be found by means

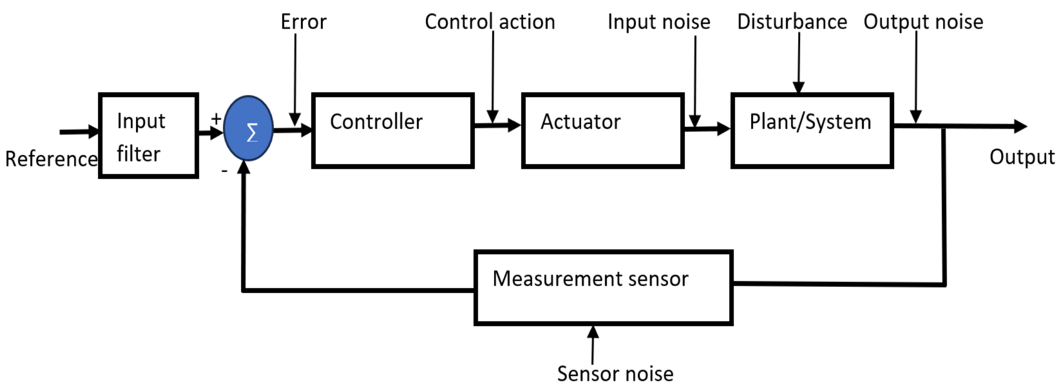

Figure 1: *General block diagram of industrial process with faults and/or disturbance points*

of drift, open and short circuit faults, magnetic fields degradation associated with windings. There can be loss of effectiveness of actuators, defects or faults in inner-race, outer-race and ball problem/ damage, excessive wear of bearing, less lubrication and problem in axis of rotor. Also, mechanical imbalance of rotor and broken motor bar are causes of faults. Friction and leakage losses are also said to be cause of regular faults in case of mechanical systems.

- Controller or Control action category
  Transient faults arise from sudden changes within the system and can be disappear after some time. Permanent faults cause lasting damage, requiring repair or replacement. Intermittent faults cycle between active and inactive states, while incipient faults exhibit gradual or slowly changes in the state variables of faulty components. This comprehensive categorization aids in understanding and addressing various types of problems in faults and malfunctions that may impact systems.

- Plant/Process category
  The faulty components under the category of plant/ process includes engine, part of plant, intelligent in automatic wind turbine, robotic manipulator, centrifugal pump malfunction, chemical/petrochemical plant or any specific units etc. The fault description includes various reasons such as misconduct of diagnosis in engine, leakage in tank, disengagement in DC motor, mechanical and electrical motor faults, transducers, final control elements and faults in torque converter additive magnitude joint faults, bearing defects, open and short circuit faults, duct and damper leaking fan and sensor failures.

- Software and hardware category
  The faults may be bit-flips, execution failure in routine functioning, faults of structural functioning in network, faults in communication network. The bit-flips can cause detection as well as correction of mainly leading faults and dependently faults, error probe and fault prone attributes. The network part is due to network faults on chip switches. The faulty nodes in source to destination transmission leads to communication faults which can be main reason to loss of signal or information. Any faulty controller output, electronic throttle controller and electric power steering controller included in this category. Fault description of controller response is partial loss of control effectiveness, degradation of throttle damping and return spring and friction loss prognosis. Another classification focuses on the dynamics and nature of faults, distinguishing between permanent, transient, incipient and intermittent faults.

In view of system representation,information and redundancy considerations, the next crucial factor in selecting appropriate FDD systems is the categorization of faults. A common classification divides faults into software,hardware communication and networking faults. Hardware faults encompass sensor, actuator, plant/process, and structural faults. Software faults include bit-flips, sub-routine execution failures, runtime issues, and other software malfunctions. Networking and communication faults involve protocol incompatibility, packet transmission failures, and non-recoverable data packets. The recent work of FDD methods are summarized in Table 1 with short remark and applicable domain. The FD methods available in the literature are shown in Fig.2.

Intelligent manufacturing has garnered substantial interest from both academia and industry in recent times. Intelligence is essential to the chemical and petroleum industries for both productivity and safety. This explains the recent decades' rapid development of FDD. A vast amount of measurement data is accessible to extract the useful information for process monitoring and optimization schemes because of the use of advanced computer and information technologies. Numerous applications involve the installation of sensors in hard-to-reach locations, which makes tasks like battery replacement or recharging challenging. In actuality, certain locations such as deep within woods to track weather patterns and identify fires or other possible calamities are more frequently equipped with limited-resource sensors than easily accessible ones. Furthermore,

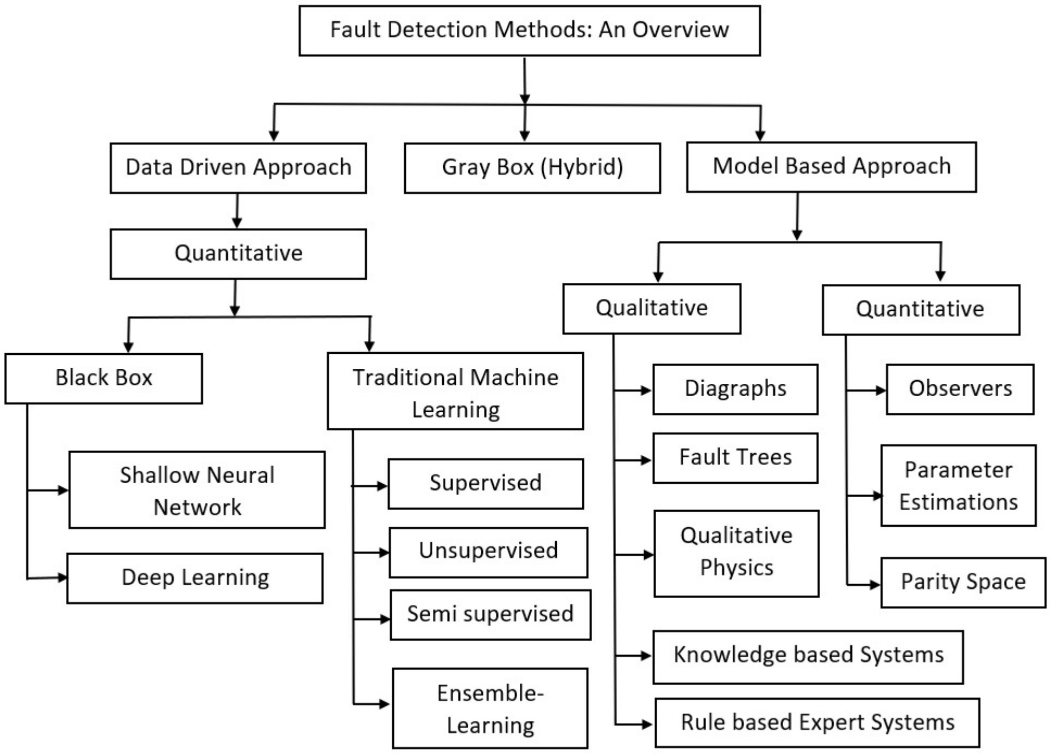

Figure 2: *Fault detection methods*

their battery life, memory, and processing power are all constrained. Therefore, while building FDD systems for such sensors, the following issues should be met.

- Smart Fault Detection: It is important to find errors as soon as they arise and before they cause significant losses. If these errors could be predicted, that would be much better for reliable operation of the system.
- Low Computation Cost: Because sensors have limited energy and computational capacity, FDD systems must operate effectively using the available resources.

3. Domestic and HVAC Applications

For more than 20 years, there has been active study into FDD for applications involving air conditioning (AC) systems. Still, the vast majority of techniques were created for commercial structures. Although a lot of this work is applicable to the domestic marketplace, there are certain possibilities and problems specific to this industry that should be thought to be apart of the industrial refrigeration and commercial HVAC systems. A fault in the measurement of mixed air temperature, for instance, could affect the data gathered by fans,coils, dampers and elements of airflow loop, thereby affecting the condition of the indoor environment. The anomalous airflow supply to building zones caused by the problems related to the chilled water supply could have an adverse effect on the chiller water supply by means of the control loop. Additionally, it's feasible that other subsystems servicing the same zone make up for the effects of one system defect (such as an inadequate air supply to the zone). With the exception of fault propagation, identification and compensation, there are some fault symptoms become more difficult to identify and isolate than others because they are less evident than others. One instance is the faults of the Variable air volume (VAV) terminals, which could be hard to find because there aren't enough sensors [51], [52]. Finally, the possibility of many faults occurring simultaneously during HVAC system operation makes FDD more difficult to understand because of contradicting or mutually worsening fault symptoms.

3.1. Domestic Applications

This subsection reviews various methods of FDD for AC systems with fault types and evaluates it with appropriate methods. Opportunities for advancement exist in the field of applying these techniques to the domestic and residential market, such as: (a) Taking into account the degree of fault diagnosis (FD) that is most economical in the residential market. (b) Reducing the number of sensors needed for FDD. The two most widely acknowledged advantages of accurately identifying and treating issues with AC systems are: (1) lower energy usage and (2) lower maintenance expenses. But even with these advantages, the expense of applying FDD techniques in the domestic AC industry has not been considered worthwhile. This study is primarily focused on developing cutting edge FDD techniques for domestic air conditioning systems and exploring ways to lower costs of these methods. But the goal of this subsection is to lay out a more thorough grasp of the advantages that efficient FDD offers. The person living in the house stands to gain the most from lower energy usage, and the owner benefits most from lower maintenance expenses. Nonetheless, FDD offers the owner and occupant additional significant advantages. The home-owner may gain more from the contented tenants than from lower maintenance expenses, and the tenant may profit more from the dependable comfort that FDD may offer than from lower electrical bills. Moreover, there is a lengthy value chain for ACs, and the home-owner and occupant are just two of the participants. FDD does, however, also help a great deal of other organizations. A straightforward illustration of the AC value chain and the advantages

Table 1: *Short summary of data driven and knowledge/model based approaches for FDD*

Approach	Method	Literature work	Remark/Applicability
Data driven	PCA/ICA	[17, 18, 19, 20, 21]	Complex processes Nonlinear fault diagnosis Minimization of false alarms
-	CVA	[22], [23],[24, 25], [25]	Time domain approach Consistent performance
-	Data type	[26], [27],[28],[29]	Biochemical/nuclear ANN& Wavelet transform Very complex systems
Model based	Observer type	[30],[31],[32]	Sliding mode observer Non linear processes Parameter varying processes
-	Parity equation	[33],[34],[35]	Parity relation of input-output Use of optimisation Time varying system
-	Supervised learning	[36],[37],[38],[39]	Use of support vector machine Grid search,genetic algorithm Efficient algorithms
-	Unsupervised learning	[40],[41],[42]	Online fault detection Use of CNN Hybrid fault detection
-	AI based	[43],[44],[45],[46]	Real time systems Smart NN based approach Predicted fault detection
-	Knowledge based	[47],[48],[49],[50]	Neuro-fuzzy and BN approach Use of fault isolation Advanced algorithm for FDD

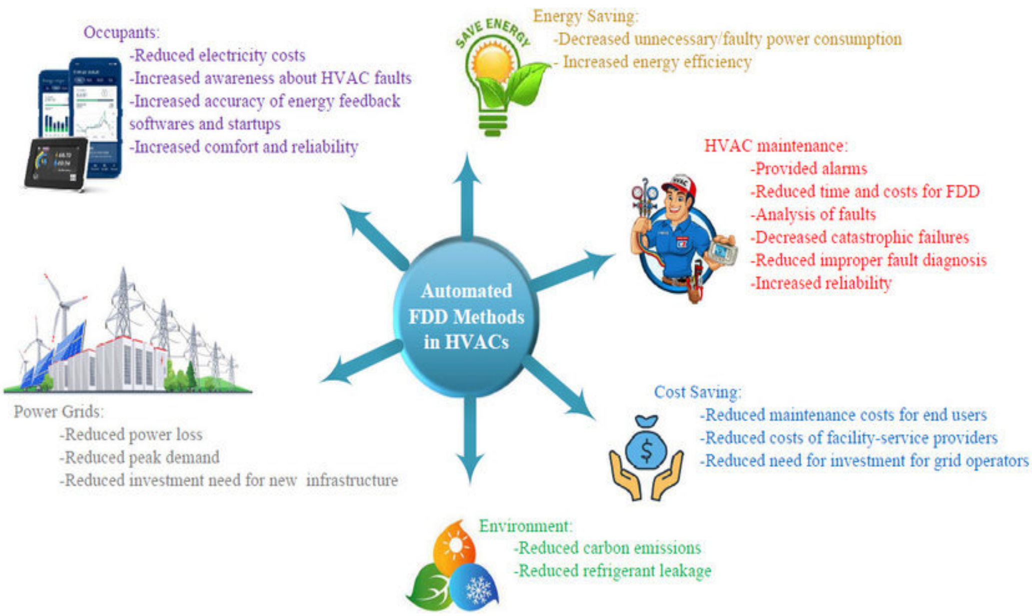

Figure 3: *Benefits of automated FDD methods in HVAC applications[53]*

that FDD offers to its different organizations can be found in Fig. 3. Peak demand will drop as a result of lower AC loads, which will substantially reduce the demands on the companies that generate, transmit, and distribute power. Efficient FDD techniques may also enhance the commissioning of AC systems and give personnel a way to confirm the efficacy of their work. Home-owners may reduce the burden on the AC service sector during the hot/summer by identifying problems before they become apparent and taking appropriate action during the shoulder seasons. In addition, the home-owner's repair expenses would go down. Effective FDD techniques could offer input on system design and sales to the dealer and manufacturer, allowing them to determine which systems have a track record of dependability and where improvements can be made. Lastly, by lowering carbon emissions from power plants and refrigerant leakage, better AC operations have a major positive environmental impact. In order for FDD to be widely adopted in the domestic cum residential sector, it is necessary to comprehend the advantages of this diagnosis at every stage of the value chain. The increased costs of the FDD system must be covered by someone, and if these benefits are attained, several parties may have to split the cost. Electric grid operators can, for instance, offer consumers who install the FDD system a financial rebate as a sort of incentive. Manufacturers may also provide the dealer with a cheaper FDD-enabled system. In order to get input, the dealer, installer, and service provider may also provided access to the available FDD data. The research described below shows that there is scope for considerable progress in the areas considering following points.

- Reduced maintenance costs
  In Downey and Proctor's work [72], almost 13,000 air conditioners, both home and commercial, were examined. The study's took into account a number of variables pertaining to the state of air conditioners, including performance and operational parameters, indoor environmental conditions, and interior building circumstances where cooling constraints were important considerations among other things. The authors concluded that whereas 57% of the systems did not meet refrigerator level specifications, 65% of domestic/residential and 71% of light commercial systems needed maintenance as well as repairing. Breuker and Braun's work examined frequent rooftop AC defects and their effects, and it assessed the relative cost of servicing for each fault through analysis of record. The influence of performance indicators in terms of simple issue detection and timely, affordable repair was the author's main concern. It was determined that the average impact of the faults on

cooling capacity and coefficient of performance (COP) indices were significant because they raise energy costs and/or cause building occupants to feel less comfortable and because they offer a standard measurement for comparing the effects of various faults. Additionally, according to a database available in the literature of 6000 separate fault cases, it was noted that 24% of total repair expenses were attributable to compressor faults.

- Reduced electricity costs
According to Proctor and Downey's analysis in [73], normal HVAC servicing practices fail to address two crucial parameters that affect equipment performance, which is why air conditioners and heat pumps perform below their designed capacity and efficiency. Two factors that the authors examined were inadequate airflow and an inaccurate refrigerant charge. Researchers have noted that domestic air conditioners work at least 17% less efficiently than what is stated on their efficiency ratings. According to the authors of [74], duct leakage, poor indoor air flow, and inaccurate refrigerant charges were among the most common errors. Furthermore, the authors found that only fixing issues with charges and ventilation might result in an average 16% boost in efficiency. According to [73], residential air conditioners function at a minimum of 17% less efficiently than their rated capacity. According to the authors of [74], duct leakage, poor indoor air flow, and inaccurate refrigerant charges were among the most common errors. Furthermore, the authors found that only fixing issues with charges and ventilation might result in an average 16% boost in

Table 2: *Short summary of recent work (2020-2024)on FD methods for AC systems*

Fault	Method	Ref.	System
Drift deviation	Kernel PCA and double layer long-short term memory	[54]	HVAC
Coil valve dampers	ANN,GA & multilinear regression	[55]	AHU
Leakage and fouling	On field measurement	[56]	Heat pumps
Gas & liquid line restrictions	CPA	[57]	AC with microtube condenser
Failures in valve Liquid floodback(compressor)	PCA & hybrid data mining	[58]	VRF AC
Compressor liquid & refrigerant charge	SVM,shallow NN deep learning	[59]	VRF AC
Fan failure, damper stuck water clogging, air duck leakage	COP-deep learning SVM,multilayer perception	[60]	AC
Several faults	IoT & cyber physical system	[61]	HVAC
Refrigerant charge faults & condenser fouling	Virtual sensors & fault impact	[62]	HVAC
Valve,fan, temp sensors	Grey box	[63]	HVAC
Air temperature sensors	Hybrid approach	[64]	HVAC
Air filter obstruction	Physical based	[65]	HVAC
Chiller faults	AI-twin architecture	[66]	HVAC
Valve & temperature	learning based	[67]	chilled beam
chiller faults	Convolutional network	[68]	HVAC chiller
Condenser/evaporator fouling	ML	[69]	Roof top units
Fouling of condenser reduced water flow,refrigerant	Adaptive NN	[70]	Chiller
Condenser fouling reduced water flow,refrigerant	Feature recognition Spectral regression	[71]	Chiller

efficiency.

- Improved commissioning
  Commercial and industrial buildings were analyzed by Rogers and Rasmussen [75] for power usage and 15-minute peak demands. The writers noted that a specific and effective side The refrigerant charge is wrong in over 60% of domestic ACs [73]. Furthermore, 47% of home systems are excessive, in comparison to the suggested sizing computation [74].

- Reduced peak demand
  Reduced efficiency results in higher levels of peak demand and total energy consumption. The summertime peak demand levels in Texas are approximately 25 % greater than the wintertime peak levels [75], mostly because of chiller loads and air conditioning.

The specifics of FDD techniques based on quantitative models are provided in [76]. Process fault diagnosis has a plethora of literature covering anything from statistical techniques to artificial intelligence (AI) and analytical procedures. From a modeling standpoint, certain techniques necessitate precise process models, semi-quantitative models, or qualitative models. On the other side of the spectrum, some methods just use historical process data and do not require any kind of model information. Furthermore, based on process information, various search strategies can be used to carry out diagnostics. Any candidate who is not an expert in these tactics will frequently find it challenging to navigate such a confusing array of alternatives and methodologies. The fault diagnosis techniques are categorized into three main types and are covered in three sections. According to [76], there are three types of model-based approaches: process history, quantitative model, and qualitative model. The researchers also provided a general mathematical framework that included a multi-step, complete FDD algorithm in addition to this categorization. In addition, it examined unprocessed measurements to produce helpful characteristics that were applied to identify certain issues. In general, the three-part review is a useful tool for comprehending the whole FDD methodology. Nevertheless, the review lacked relevant application-related information. According to [77], equipment that is not adequately maintained, deteriorated, or managed wastes between 15 and 30 percent of the energy utilized in commercial buildings. A large portion of this waste might be avoided if automated condition-based maintenance were widely used. The foundation for condition-based maintenance of engineered systems is provided by prognostics and automated FDD. Applications for energy building systems, such as HVAC and refrigeration have been researched and showcased. However, a plenty of of research and development has been done in the past ten years with the goal of creating FDD techniques for HVAC and refrigeration systems. In the work of [78] provides an overview of automated FDD research conducted since 2004 that is pertinent to the commercial building industry. The evaluation divides automated FDD techniques into three categories and updates an earlier review that was carried out in 2004. A selection of automated FDD examples from the major category are examined in order to determine which approaches are best suited for system construction and to comprehend the advantages and disadvantages of each approach. Additionally described in the dispersion of studies based on HVAC systems and automated FDD techniques. The current article can be used as a reference by industries and researchers to choose an acceptable automated FDD approach.

3.2. Applications in Energy Buildings

There must be Recognize the difficulties and complexity of FDD. There are three levels of complexity associated with this FDD problem: (1) building complexity, which arises from the existence of different building types and characteristics; (2) HVAC complexity, which arises from the intricate coupling of components of HVAC to meet various building needs; and (3) fault complexity of HVAC system, which arises from complex and variable fault symptoms. More than 40% of a building's energy is used by the HVAC system, one of the most significant mechanical systems. Problems with HVAC system operation can lead to interior environmental problems, such as low indoor air quality and thermal comfort, which can have an impact on occupant health and productivity. [79], [80], and [[81]]. The study conducted by Jasmin et al. [79] examined the impact of a flexible space layout design on energy demand and thermal comfort within a contemporary open-plan office setting. The scholars evaluated the suitability of four control zoning methodologies in conjunction with three distinct HVAC systems, radiant ceiling,mechanical ventilation and a thermally active building system using dynamic thermal modelling. According to their findings, mechanical ventilation systems required a more intricate control plan to maintain thermal comfort, whereas thermally active and radiant ceilings building systems offer potential options for flexible office spaces for a typical location.

In the meantime, broken or malfunctioning HVAC systems waste a lot of energy and reduce the energy efficiency of buildings. According to estimates, problems with the HVAC system and lighting systems together might raise the use of these sectors by 4 % which is $\approx$ 18%, or 0.35 and 1.7 quads of US yearly consumption, respectively [82]. Given the complexity in HVAC systems with several coupling components and the intricate interactions between HVAC systems, buildings, and inhabitants, maintaining fault-free functioning of HVAC systems is difficult. The development of computer methods,such as the emergence of deep learning methods and building management systems which are utilizing more affordable sensors to support building operations allowing for the potential application of FDD. A promising method for guaranteeing HVAC system faultlessness. FDD techniques are typically categorized into three types : process history based, quantitative model-based, as well as qualitative model-based [83]. Simplified or detailed physics based models are typically useful in quantitative model based approaches to monitor variations between measured system status and anticipated system operation conditions. Qualitative model based techniques typically follow expert guidelines or fundamental FDD concepts. Process history based techniques rely on data, as they examine system sensing data directly to identify and diagnose HVAC system operating conditions. More broadly, knowledge-based approaches can be b roadly defined as quantitative and qualitative model based methods that draw from engineering or physics knowledge in FDD. Data-driven techniques can be defined as FDD methods that solely rely on system sensing data. Zhao et al.s work [84] includes a thorough literature review of AI based fault detection and diagnosis (FDD) methods for energy systems built in the 20 years between 1998 and 2018, summarizing the benefits and drawbacks of the available AI-based techniques and outlining the most crucial areas for future research.

There are numerous types of structures for both residential and commercial purpose, including multi-family or single-family and cottages type (e.g., office, school, shopping center). These buildings serve a variety of purposes, which contributes to different building operation patterns throughout the day. Additionally, the physical characteristics of buildings vary greatly between designs and vintages, including window-to-wall ratios, zone configurations, and insulation levels. Ultimately, the behaviour of building occupants varies and is stochastic, resulting in a variety of characteristics for the load profile. Each of these results in distinct patterns and demands for heating and cooling; hence, building with HVAC interactions change, which in turn adds to the inherent FDD complexity. Examples of applications of FDD include campus buildings [85], manufacturing buildings [86], commercial buildings in hot [87], [88], mild [89], uncertain climates [[90]], etc. The intricacy of HVAC systems needs to be examined, as they have different types, capacities, and modes of operation that are driven by the growth of HVAC techniques and the various requirements for preserving the indoor environment [91]. Variable air volume, variable refrigerant flow, and direct expansion systems are common system types found in existing buildings; Table 2 provides examples of these systems to which FDD has been applied. These days, HVAC systems are typically made up of a broad range of closely coupled sub-systems (such as air handling units chillers, cooling towers, air distribution systemsand so on.) to effectively maintain the typical indoor environment of buildings [92], [93]. Therefore, in order to achieve FDD, the established technique must take into account the interdependencies, or mutual influence caused by controlling feedback loops which couple HVAC sub-systems, in addition to properly handling probable software and hardware errors within the sub-systems. The inconsistent design of the HVAC system, its real functioning, and the FDD mechanism further exacerbate the issue. HVAC systems frequently operate under unanticipated circumstances while they are in use (such as an oversized or undersized system). Moreover, rather of being used for FDD, the sensor elements in HVAC systems are made for feedback control of HVAC during regular operation. Each of them adds to the FDDs HVAC system's complexity. The symptom complexity of system problems is a direct outcome of the buildings and HVAC systems. In particular, the process of detecting and diagnosing faults with symptom propagation and compensation is complicated by the interdependencies between sub-systems and within sub-system components [85], [93].

The significance of FDD in HVAC systems for ensuring building energy performance and occupant service has garnered attention from the building HVAC research community on a regular basis. The developed FDD techniques were summarized and categorized in a number of previous assessments. For instance, in their FDD application, Katipamula and Brambley had divided FDD techniques into the three categories previously described and have included a brief discussion of the advantages and disadvantages of each kind of method [77]. There was also discussion on how these methods could be applied to particular HVAC & R(Refrigeration) areas. In a further investigation, Yu et. al. and colleagues have integrated and synthesized FDD research from 2005 to 2017 with the identical classification [94]. Yu et al [94] have examined analytical-based, knowledge based, and data driven approaches specifically for FDD of Air Handling Units (AHUs). Frank and colleagues [95] evaluated the obstacles and difficulties facing FDD in small commercial buildings. In their analysis of the progress made in each stage of the FDD process data sources, feature creation, fault detection, and fault diagnosis Shi and Brien [96] have identified a number of issues that need to be resolved in subsequent FDD studies. The applications of AI-based methods in FDD have garnered a lot of attention lately, and numerous writers have talked about the crucial next research projects in the subject of FDD. Mirnaghi and Haghighat [97] have examined data-driven methods that combine supervised, unsupervised, and hybrid learning for large-scale HVAC system fault diagnosis and repair. Li and neill [98] have concentrated on examining FDDs fault modeling for HVAC systems.

4. Applications in electrical machinery

In industrial processes, dependability and safety are essential components. Numerous industries depend heavily on rotating machinery, which is prone to malfunction because of its lengthy operating lifespan and difficult working circumstances [99]. The various faults occurs in electrical machineries is enlisted in Fig. 4 and the detailed information is enlisted in the work of Asad et. al. [100] and [101]. The vibration signals of rolling element bearings always appear as low signal noise ratio, nonstationary statistical parameters while operating under demanding conditions (such as time-varying speed and load, high shocks), which makes diagnostic techniques challenging. To ensure smooth functioning under erratic situations, faults in various electrical machinery components must be found. A few instances of rotating machinery parts are motors, engines, shafts, bearings, gears, pumps, and blades. Qu et al. [102] have developed and tested AE-based methodologies and acoustic emission (AE) sensors for gearbox failure diagnosis. For the diagnosis of gearbox faults, AE-based methods demand far larger sampling rates than vibration analysis-based methods. It is therefore debatable whether, at the same sampling rate, an AE-based technique would perform better or at least as well as vibration analysis-based techniques. The first known attempt to compare the gearbox fault detection performance of AE and vibration analysis based methodologies using the same sampling rate was made by the authors in their comparative study for gearbox tooth damage level diagnostics using AE and vibration measurements. The study also mentioned that the lab experiments are conducted using a gearbox test rig to seed and test partial tooth cut faults. After conducting a comparative analysis, the authors concluded that, as compared to the vibration-based technique, the AE-based approach has the ability to distinguish between different levels of gear tooth damage. Mechanical resonance can easily impair vibration signals, but AE signals operate more steadily. The researcher concludes that vibration signal condition indicators are inconsistent with the extent of gear tooth damage because vibration is less sensitive than AE to minute tooth damage in the low speed range, making it challenging to identify gear faults.

Sakthivel et al.'s work [103] focuses on vibration-based problem diagnostics for single-block centrifugal pumps. Experiments have been conducted on the pump under various fault scenarios as well as in good working order. Drawn pump characteristic graphs show discharge vs. efficiency under both ideal and unfavorable situations. Aithors noted that the pump's efficiency is high when everything is working properly, and for any malfunction, it falls into a range of values that is significantly lower than when everything is working properly. It is clear that if any of the study's studied pump flaws were present, the pump's efficiency would drop precipitously. Therefore, it is imperative that this fault identification investigation be completed. Additionally, in the same work, a mono-block monoblock centrifugal pump is used to model six classical states: normal, bearing fault, impeller fault, seal fault, impeller and bearing fault together, and cavitation. Using the C4.5 decision tree approach, a set of features has been retrieved and classified in the simulation. It is noted that based on the discussion and findings, it is safe to conclude that the C4.5 algorithm and vibration signals are suitable options for real-world defect diagnosis of monoblock centrifugal pumps. By Haidong et al. [104], a novel technique for rolling bearing fault diagnosis termed deep wavelet auto-encoder (DWAE) with extreme learning machine (ELM) was presented for intelligent rolling bearing fault detection. The study utilized wavelet function as a nonlinear activation function to create a wavelet auto-encoder (WAE) that is capable of efficiently capturing signal properties. To improve the capacity for unsupervised feature learning, a DWAE including several WAEs was built, and ELM was chosen as the classifier to precisely identify various bearing problems. The technique was used to examine the experimental vibration signals from the bearings. According to the authors' data, the created method is more effective than both standard deep learning methods and traditional methods in eliminating the need for human feature extraction. Haidong et al. [104] note that combining the wavelet function with deep learning and extreme learning machine improves fault diagnosis of rotating bearings greatly. Vibration signature analysis has historically been used to identify shafting system misalignments. The temperature increase at the source is also caused by these misalignments. couplings and bearings. Mohanty et al.'s contribution [105] describes an experimental investigation that used a thermal imaging camera to measure the shaft couplings' temperature in order to discover misalignment in systems early on. In order to identify flaws, the effects of load, speed, and misalignment on the different types of couplings and their temperature rise have been investigated. Before the temperature of the coupling achieves its steady state value, it is utilized to measure the misalignment in the system. In order to correlate with the thermal imaging, vibration

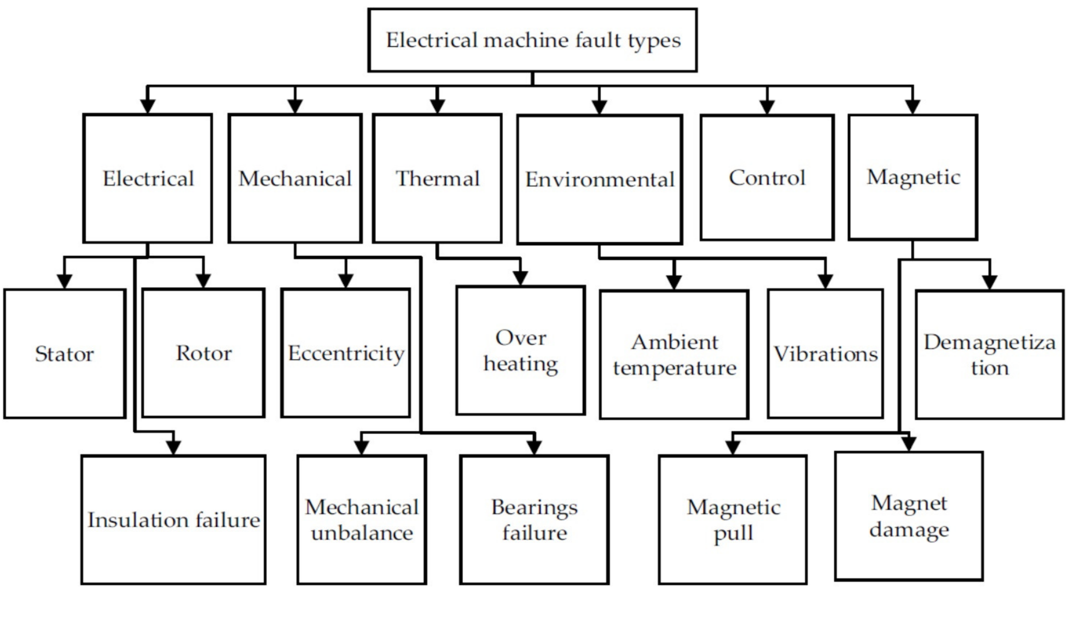

Figure 4: *Fault types in electrical machines [100]*

measurements at the bearing locations under various load and speed circumstances were also made using accelerometers and single point laser vibrometers. The recorded transient spatial temperature distribution on the couplings, the researchers discovered, also points to the shafting system's misalignment. The approach can be applied to automated thermography-based detection systems to identify misalignments from far-off places where traditional vibration monitoring would be challenging. Notably, the method can be applied to windmill gearbox problem detection at elevated positions where traditional contact type instrumentation would be very laborious.

Kubiak and colleagues conducted the failure analysis of the 150 MW gas turbine blades [106]. The 150 MW gas turbine used as the study's basis experienced a forced breakdown due to abnormally strong vibrations, which reduced output power to nearly nil. The analyzers' diagnostic task is to identify the primary reason behind the blades' failure. Additional research revealed that low cycle fatigue was the initial cause of the blade failure, which resulted in a crack that spread throughout the securing pin hole (stress raiser) at the blade's root.A few suggestions are made in light of the study to prevent gas turbineblades faults and failures. In light of the need for and impact of condition monitoring and fault diagnosis in induction motors (IMs) as well as the need for further study, Choudhary et al. [107] provided a state-of-the-art review that details various IM fault types and their corresponding diagnostic approaches. Numerous surveillance The methods that are available for diagnosing IM faults have been noted and shown. The researchers announced that there is a lot of potential for the use of non-invasive data collection methods in autonomous, timely maintenance scheduling and failure aspect prediction of dynamic machinery.The shortcomings of traditional sensors and monitoring schemes will be addressed by the use of non-invasive type instruments, which will remove the requirement to attach the sensor on the machine and provide speedy measurement, non-intrusiveness, and high accuracy. The thermal imaging approach is thought to be an effective tool for online instant messaging monitoring without human intervention when compared to other non-invasive techniques. For practical applications, combining infrared thermal imaging techniques with artificial intelligence-based methods can speed up decision-making even more.

An oil monitoring approach for engine wear evaluation was examined in the work of Bin Fan et al. [108]. The oil samples underwent quick on-site analysis using online visual ferrograph (OLVF). The wear debris concentration for the abnormal engines was discovered to have a low index of particle coverage area (IPCA) by the authors. Large debris was also infrequently seen on OLVF ferrrograms, which was congruent with the findings of analytical ferrography. The cause of this was examined and addressed. In order to reduce the number of manual confirmations that require disassembling the oil pans, the researchers looked into an oil monitoring technique of wear evaluation for the 9-min engine hot tests. Oil samples from engines are quickly analyzed on-site using OLVF. However, the authors also mentioned that it is challenging to collect the larger wear debris by sampling at half of the oil level because of the short operating duration and the elimination of wear debris. Low concentration of the small wear debris is also a sign of abnormal wear during the 9-min hot test. The amount of small debris in the oil samples from the normal engines is greater than that of the abnormal engines.

5. CONCLUSIONS

In this study, FDD approaches for typical applications of electrical applications is reviewed to study the impact of early diagnosis of the faults. The various approaches of FDD for domestic applications, HVAC and electrical machineries applications are studied with the contributions of academicians and researchers from the literature. A disturbance or fault rejection strategy is main focus of the this paper for the reliable and maintaince free operation of the HVAC and electrical machines. In this study, recent techniques has been incorporated in view to design and implement the FDD methods. The approaches of FDD included are admittance as per earlier techniques due to fast FD algorithm with use of computational facilities on the ground of soft faults. Recent algorithms have improved fault detection strategy which will not affected due to parameter uncertainties and model mismatch in operational reliability of the system or modelling.

The study uses to generates minimum fouling in the system performance by considering the sensor, actuator and control signal.

The presented review includes

- The work which have been contributed for domestic applications in recent years
- The work which focuses on FDD of HVAC systems and its major failures due to non maintenance/repairing of the systems.
- The contribution which clearly mention that the routine maintenance can reduce the cost of expenses to avoid replacing the equipment.
- The study includes typical faults and its mitigation by advanced FDD methods with

It has been mentioned that the performances of the any system obtained through FDDs have been interest of reliability operation of the systems. The detection of fault can be made by parallel simulations or by means of dynamic identifications either through data driven or knowledge based approach. The FDD implied dynamically for the HVAC or any other devices to avoid any malfunction would be interest of the researcher through the use of advanced techniques such as deep learning, machine learning or AI approaches. In future work, the hybrid concepts can be useful for the FDD of sensors and other components of the industrial complex systems. There are the opportunities and challenges for the real time applications at micro level in the focused domains including defence, sensitive chemical and petrochemical as well as other industries.

References

[1] Liang Ming and Jinsong Zhao. Review on chemical process fault detection and diagnosis. In *2017 6th international symposium on advanced control of industrial processes (AdCONIP)*, pages 457–462. IEEE, 2017.

[2] Xian Du. Fault detection using bispectral features and one-class classifiers. *Journal of Process Control*, 83:1–10, 2019.

[3] Inseok Hwang, Sungwan Kim, Youdan Kim, and Chze Eng Seah. A survey of fault detection, isolation, and reconfiguration methods. *IEEE transactions on control systems technology*, 18(3):636–653, 2009.

[4] Rolf Isermann. *Fault-diagnosis systems: an introduction from fault detection to fault tolerance*. Springer Science & Business Media, 2005.

[5] Karim Salahshoor, Mojtaba Kordestani, and Majid S Khoshro. Fault detection and diagnosis of an industrial steam turbine using fusion of svm (support vector machine) and anfis (adaptive neuro-fuzzy inference system) classifiers. *Energy*, 35(12):5472–5482, 2010.

[6] Nassim Laouti, Nida Sheibat-Othman, and Sami Othman. Support vector machines for fault detection in wind turbines. *IFAC Proceedings Volumes*, 44(1):7067–7072, 2011.

[7] Wang Hongm, Chai Tian-You, Ding Jin-Liang, and Martin Brown. Data driven fault diagnosis and fault tolerant control: some advances and possible new directions. *Acta Automatica Sinica*, 35(6):739–747, 2009.

[8] Shen Yin, Steven X Ding, Adel Haghani, Haiyang Hao, and Ping Zhang. A comparison study of basic data-driven fault diagnosis and process monitoring methods on the benchmark tennessee eastman process. *Journal of process control*, 22(9):1567–1581, 2012.

[9] S Joe Qin. Survey on data-driven industrial process monitoring and diagnosis. *Annual reviews in control*, 36(2):220–234, 2012.

[10] Ramgopal Dhaka, Bhoopendra Pachauri, and Anamika Jain. Two-dimensional srgm with delay in debugging by considering the uncertainty factor and predictive analysis. *Reliability: Theory & Applications*, 16(SI 2 (64)):82–94, 2021.

[11] Amitkumar Patil, Gunjan Soni, Anuj Prakash, and Mangey Ram. Intelligent valve fault diagnosis approach for reciprocating compressor based on acoustic signals. *Reliability: Theory & Applications*, 16(SI 2 (64)):35–47, 2021.

[12] GM Malwatkar, SH Sonawane, and LM Waghmare. Tuning pid controllers for higher-order oscillatory systems with improved performance. *ISA transactions*, 48(3):347–353, 2009.

[13] SR Shiledar, GM Malwatkar, IS Jadhav, and GV Lakhekar. Design of discrete sliding mode controller for higher order system. *Reliability: Theory & Applications*, 16(SI 1 (60)):90–97, 2021.

[14] GM Malwatkar, AA Khandekar, VG Asutkar, and LM Waghmare. Design of centralized pi/pid controller: interaction measure approach. In *2008 IEEE Region 10 and the Third international Conference on Industrial and Information Systems*, pages 1–6. IEEE, 2008.

[15] VS Biradar and GM Malwatkar. Second order sliding mode control for robust performance of the systems. *Reliability: Theory & Applications*, 17(4 (71)):358–370, 2022.

[16] Shaktikumar R Shiledar and Gajanan M Malwatkar. A compressive study on discrete time sliding mode control with advances and applications. *International Journal of Systems, Control and Communications*, 13(4):283–310, 2022.

[17] Jinane Harmouche, Claude Delpha, and Demba Diallo. Incipient fault detection and diagnosis based on kullback–leibler divergence using principal component analysis: Part i. *Signal processing*, 94:278–287, 2014.

[18] Evan L Russell, Leo H Chiang, and Richard D Braatz. Fault detection in industrial processes using canonical variate analysis and dynamic principal component analysis. *Chemometrics and intelligent laboratory systems*, 51(1):81–93, 2000.

[19] Gang Li, S Joe Qin, and Tao Yuan. Data-driven root cause diagnosis of faults in process industries. *Chemometrics and Intelligent Laboratory Systems*, 159:1–11, 2016.

[20] Sang Wook Choi, Changkyu Lee, Jong-Min Lee, Jin Hyun Park, and In-Beum Lee. Fault detection and identification of nonlinear processes based on kernel pca. *Chemometrics and intelligent laboratory systems*, 75(1):55–67, 2005.

[21] Xi Sun, Horacio J Marquez, Tongwen Chen, and Muhammad Riaz. An improved pca method with application to boiler leak detection. *ISA transactions*, 44(3):379–397, 2005.

[22] Shallon Stubbs, Jie Zhang, and Julian Morris. Fault detection in dynamic processes using a simplified monitoring-specific cva state space modelling approach. *Computers & Chemical Engineering*, 41:77–87, 2012.

[23] Benben Jiang, Dexian Huang, Xiaoxiang Zhu, Fan Yang, and Richard D Braatz. Canonical variate analysis-based contributions for fault identification. *Journal of Process Control*, 26:17–25, 2015.

[24] Benben Jiang, Xiaoxiang Zhu, Dexian Huang, and Richard D Braatz. Canonical variate analysis-based monitoring of process correlation structure using causal feature representation. *Journal of Process Control*, 32:109–116, 2015.

[25] Cristobal Ruiz-Cárcel, Yi Cao, D Mba, Liyun Lao, and RT Samuel. Statistical process monitoring of a multiphase flow facility. *Control Engineering Practice*, 42:74–88, 2015.

[26] Xi Zhang and Karlene A Hoo. Effective fault detection and isolation using bond graph-based domain decomposition. *Computers & chemical engineering*, 35(1):132–148, 2011.

[27] Kamal Hadad, Meisam Pourahmadi, and Hosein Majidi-Maraghi. Fault diagnosis and classification based on wavelet transform and neural network. *Progress in nuclear energy*, 53(1):41–47, 2011.

[28] P Konar and P Chattopadhyay. Bearing fault detection of induction motor using wavelet and support vector machines (svms). *Applied Soft Computing*, 11(6):4203–4211, 2011.

[29] Kris Villez, Babji Srinivasan, Raghunathan Rengaswamy, Shankar Narasimhan, and Venkat Venkatasubramanian. Kalman-based strategies for fault detection and identification (fdi): Extensions and critical evaluation for a buffer tank system. *Computers & chemical engineering*, 35(5):806–816, 2011.

[30] Yunkai Wu, Bin Jiang, Ningyun Lu, Hao Yang, and Yang Zhou. Multiple incipient sensor faults diagnosis with application to high-speed railway traction devices. *ISA transactions*, 67:183–192, 2017.

[31] Farzin Piltan and Jong-Myon Kim. Bearing fault diagnosis using an extended variable structure feedback linearization observer. *Sensors*, 18(12):4359, 2018.

[32] Emanuel Bernardi and Eduardo J Adam. Observer-based fault detection and diagnosis strategy for industrial processes. *Journal of the Franklin Institute*, 357(14):10054–10081, 2020.
[33] Hendrik M Odendaal and Thomas Jones. Actuator fault detection and isolation: An optimised parity space approach. *Control Engineering Practice*, 26:222–232, 2014.
[34] Maiying Zhong, Yang Song, and Steven X Ding. Parity space-based fault detection for linear discrete time-varying systems with unknown input. *Automatica*, 59:120–126, 2015.
[35] Achmad Widodo and Bo-Suk Yang. Support vector machine in machine condition monitoring and fault diagnosis. *Mechanical systems and signal processing*, 21(6):2560–2574, 2007.
[36] Jonghyuck Park, Ick-Hyun Kwon, Sung-Shick Kim, and Jun-Geol Baek. Spline regression based feature extraction for semiconductor process fault detection using support vector machine. *Expert Systems with Applications*, 38(5):5711–5718, 2011.
[37] Tribeni Prasad Banerjee and Swagatam Das. Multi-sensor data fusion using support vector machine for motor fault detection. *Information Sciences*, 217:96–107, 2012.
[38] Yingchao Xiao, Huangang Wang, Lin Zhang, and Wenli Xu. Two methods of selecting gaussian kernel parameters for one-class svm and their application to fault detection. *Knowledge-Based Systems*, 59:75–84, 2014.
[39] Chen Jing and Jian Hou. Svm and pca based fault classification approaches for complicated industrial process. *Neurocomputing*, 167:636–642, 2015.
[40] Shiyong Zhong, Qiaojun Wen, and Zhiqiang Ge. Semi-supervised fisher discriminant analysis model for fault classification in industrial processes. *Chemometrics and Intelligent Laboratory Systems*, 138:203–211, 2014.
[41] Jueun Kwak, Taehyung Lee, and Chang Ouk Kim. An incremental clustering-based fault detection algorithm for class-imbalanced process data. *IEEE Transactions on Semiconductor Manufacturing*, 28(3):318–328, 2015.
[42] Ki Bum Lee, Sejune Cheon, and Chang Ouk Kim. A convolutional neural network for fault classification and diagnosis in semiconductor manufacturing processes. *IEEE Transactions on Semiconductor Manufacturing*, 30(2):135–142, 2017.
[43] Joe-Air Jiang, Cheng-Long Chuang, Yung-Chung Wang, Chih-Hung Hung, Jiing-Yi Wang, Chien-Hsing Lee, and Ying-Tung Hsiao. A hybrid framework for fault detection, classification, and location-part ii: implementation and test results. *IEEE transactions on power delivery*, 26(3):1999–2008, 2011.
[44] Ihab Samy, Ian Postlethwaite, and Da-Wei Gu. Survey and application of sensor fault detection and isolation schemes. *Control Engineering Practice*, 19(7):658–674, 2011.
[45] S Sina Tayarani-Bathaie and K Khorasani. Fault detection and isolation of gas turbine engines using a bank of neural networks. *Journal of Process Control*, 36:22–41, 2015.
[46] Likun Ren and Weimin Lv. Fault detection via sparse representation for semiconductor manufacturing processes. *IEEE Transactions on Semiconductor Manufacturing*, 27(2):252–259, 2014.
[47] David Leung and Jose Romagnoli. An integration mechanism for multivariate knowledge-based fault diagnosis. *Journal of Process Control*, 12(1):15–26, 2002.
[48] Roozbeh Razavi-Far, Hadi Davilu, Vasile Palade, and Caro Lucas. Model-based fault detection and isolation of a steam generator using neuro-fuzzy networks. *Neurocomputing*, 72(13-15):2939–2951, 2009.
[49] Kim Verbert, R Babuška, and Bart De Schutter. Combining knowledge and historical data for system-level fault diagnosis of hvac systems. *Engineering Applications of Artificial Intelligence*, 59:260–273, 2017.
[50] Mihiran Galagedarage Don and Faisal Khan. Dynamic process fault detection and diagnosis based on a combined approach of hidden markov and bayesian network model. *Chemical Engineering Science*, 201:82–96, 2019.
[51] Fu Xiao, Yang Zhao, Jin Wen, and Shengwei Wang. Bayesian network based fdd strategy for variable air volume terminals. *Automation in Construction*, 41:106–118, 2014.

[52] Haitao Wang, Youming Chen, Cary WH Chan, and Jianying Qin. An online fault diagnosis tool of vav terminals for building management and control systems. *Automation in Construction*, 22:203–211, 2012.

[53] Amir Rafati, Hamid Reza Shaker, and Saman Ghahghahzadeh. Fault detection and efficiency assessment for hvac systems using non-intrusive load monitoring: A review. *Energies*, 15(1):341, 2022.

[54] Xiuying Yan, Ting Guan, Kaixing Fan, and Qing Sun. Novel double layer bilstm minor soft fault detection for sensors in air-conditioning system with kpca reducing dimensions. *Journal of Building Engineering*, 44:102950, 2021.

[55] Narges Torabi, H Burak Gunay, William O'Brien, and Ricardo Moromisato. Inverse model-based virtual sensors for detection of hard faults in air handling units. *Energy and Buildings*, 253:111493, 2021.

[56] F Pelella, L Viscito, and AW Mauro. Soft faults in residential heat pumps: Possibility of evaluation via on-field measurements and related degradation of performance. *Energy Conversion and Management*, 260:115646, 2022.

[57] Yifeng Hu and David P Yuill. Impacts of common faults on an air conditioner with a microtube condenser and analysis of fault characteristic features. *Energy and Buildings*, 254:111630, 2022.

[58] Yuzhou Wang, Zhengfei Li, Huanxin Chen, Jianxin Zhang, Qian Liu, Junfeng Wu, and Limei Shen. Research on diagnostic strategy for faults in vrf air conditioning system using hybrid data mining methods. *Energy and Buildings*, 247:111144, 2021.

[59] Zhenxin Zhou, Guannan Li, Jiangyu Wang, Huanxin Chen, Hanlu Zhong, and Zihan Cao. A comparison study of basic data-driven fault diagnosis methods for variable refrigerant flow system. *Energy and Buildings*, 224:110232, 2020.

[60] Noor Asyikin Sulaiman, Md Pauzi Abdullah, Hayati Abdullah, Muhammad Noorazlan Shah Zainudin, and Azdiana Md Yusop. Fault detection for air conditioning system using machine learning. *IAES International Journal of Artificial Intelligence*, 9(1):109, 2020.

[61] Sana Ullah Jan, Young Doo Lee, and In Soo Koo. A distributed sensor-fault detection and diagnosis framework using machine learning. *Information Sciences*, 547:777–796, 2021.

[62] Woohyun Kim and Je-Hyeon Lee. Fault detection and diagnostics analysis of air conditioners using virtual sensors. *Applied Thermal Engineering*, 191:116848, 2021.

[63] Akshay Ranade, Gregory Provan, Alie El-Din Mady, and Dominic O'Sullivan. A computationally efficient method for fault diagnosis of fan-coil unit terminals in building heating ventilation and air conditioning systems. *Journal of Building Engineering*, 27:100955, 2020.

[64] Hesam Hassanpour, Prashant Mhaskar, John M House, and Timothy I Salsbury. A hybrid modeling approach integrating first-principles knowledge with statistical methods for fault detection in hvac systems. *Computers & Chemical Engineering*, 142:107022, 2020.

[65] Antonio Gálvez, Alberto Diez-Olivan, Dammika Seneviratne, and Diego Galar. Fault detection and rul estimation for railway hvac systems using a hybrid model-based approach. *Sustainability*, 13(12):6828, 2021.

[66] Xiang Xie, Jorge Merino, Nicola Moretti, Pieter Pauwels, Janet Yoon Chang, and Ajith Parlikad. Digital twin enabled fault detection and diagnosis process for building hvac systems. *Automation in Construction*, 146:104695, 2023.

[67] Liping Wang, James Braun, and Sujit Dahal. An evolving learning-based fault detection and diagnosis method: Case study for a passive chilled beam system. *Energy*, 265:126337, 2023.

[68] Cunxiao Shen, Hanyuan Zhang, Songping Meng, and Chengdong Li. Augmented data driven self-attention deep learning method for imbalanced fault diagnosis of the hvac chiller. *Engineering Applications of Artificial Intelligence*, 117:105540, 2023.

[69] Mohammed G Albayati, Jalal Faraj, Amy Thompson, Prathamesh Patil, Ravi Gorthala, and Sanguthevar Rajasekaran. Semi-supervised machine learning for fault detection and diagnosis of a rooftop unit. *Big Data Mining and Analytics*, 6(2):170–184, 2023.

[70] Ke Yan and Xiaokang Zhou. Chiller faults detection and diagnosis with sensor network and adaptive 1d cnn. *Digital Communications and Networks*, 8(4):531–539, 2022.

[71] Xi Bai, Muxing Zhang, Zhenghao Jin, Yilin You, and Caihua Liang. Fault detection and diagnosis for chiller based on feature-recognition model and kernel discriminant analysis. *Sustainable Cities and Society*, 79:103708, 2022.

[72] Mark S Breuker and James E Braun. Common faults and their impacts for rooftop air conditioners. *Hvac & R Research*, 4(3):303–318, 1998.

[73] John Proctor and Tom Downey. Transforming routine air conditioner maintenance practices to improve equipment efficiency and performance. In *Proceedings of the 1999 international energy program evaluation conference*, pages 1–12, 1999.

[74] Chris Neme, Steven Nadel, and John Proctor. Energy savings potential from addressing residential air conditioner and heat pump installation problems. American Council for an Energy-Efficient Economy Washington, DC, 1999.

[75] Austin P Rogers and Bryan P Rasmussen. Opportunities for consumer-driven load shifting in commercial and industrial buildings. *Sustainable Energy, Grids and Networks*, 16:243–258, 2018.

[76] Venkat Venkatasubramanian, Raghunathan Rengaswamy, Kewen Yin, and Surya N Kavuri. A review of process fault detection and diagnosis part i quantitative model based methods. *Computers & chemical engineering*, 27(3):293–311, 2003.

[77] Srinivas Katipamula and Michael R Brambley. Methods for fault detection, diagnostics, and prognostics for building systems a review, part i. *Hvac& R Research*, 11(1):3–25, 2005.

[78] Woohyun Kim and Srinivas Katipamula. A review of fault detection and diagnostics methods for building systems. *Science and Technology for the Built Environment*, 24(1):3–21, 2018.

[79] Jasmin Anika Gärtner, Francesco Massa Gray, and Thomas Auer. Assessment of the impact of hvac system configuration and control zoning on thermal comfort and energy efficiency in flexible office spaces. *Energy and Buildings*, 212:109785, 2020.

[80] Pawel Wargocki, Jan Sundell, W Bischof, G Brundrett, Povl Ole Fanger, F Gyntelberg, SO Hanssen, P Harrison, A Pickering, Olli Seppänen, et al. The role of ventilation and hvac systems for human health in nonindustrial indoor environments. a supplementary review by euroven group. In *9th International Conference on Indoor Air Quality and Climate*, 2002.

[81] Olli Seppanen, William J Fisk, and QH Lei. Effect of temperature on task performance in office environment. 2006.

[82] Kurt W Roth, Detlef Westphalen, Patricia Llana, and Michael Feng. The energy impact of faults in us commercial buildings. 2004.

[83] Jianli Chen, Liang Zhang, Yanfei Li, Yifu Shi, Xinghua Gao, and Yuqing Hu. A review of computing-based automated fault detection and diagnosis of heating, ventilation and air conditioning systems. *Renewable and Sustainable Energy Reviews*, 161:112395, 2022.

[84] 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. *Renewable and Sustainable Energy Reviews*, 109:85–101, 2019.

[85] Debashis Dey and Bing Dong. A probabilistic approach to diagnose faults of air handling units in buildings. *Energy and Buildings*, 130:177–187, 2016.

[86] Qianjun Mao, Xi Fang, Yunpeng Hu, and Guannan Li. Chiller sensor fault detection based on empirical mode decomposition threshold denoising and principal component analysis. *Applied Thermal Engineering*, 144:21–30, 2018.

[87] Shengwei Wang and Jianying Qin. Sensor fault detection and validation of vav terminals in air conditioning systems. *Energy conversion and management*, 46(15-16):2482–2500, 2005.

[88] Cheng Fan, Fu Xiao, and Chengchu Yan. A framework for knowledge discovery in massive building automation data and its application in building diagnostics. *Automation in Construction*, 50:81–90, 2015.

[89] Guannan Li, Yunpeng Hu, Huanxin Chen, Haorong Li, Min Hu, Yabin Guo, Shubiao Shi, and Wenju Hu. A sensor fault detection and diagnosis strategy for screw chiller system using support vector data description-based d-statistic and dv-contribution plots. *Energy and Buildings*, 133:230–245, 2016.

[90] Ding Li, Donghui Li, Chengdong Li, Lin Li, and Long Gao. A novel data-temporal attention network based strategy for fault diagnosis of chiller sensors. *Energy and Buildings*, 198:377–394, 2019.

[91] Zhimin Du, Ling Chen, and Xinqiao Jin. Data-driven based reliability evaluation for measurements of sensors in a vapor compression system. *Energy*, 122:237–248, 2017.

[92]

[93] Fu Xiao, Shengwei Wang, Xinhua Xu, and Gaoming Ge. An isolation enhanced pca method with expert-based multivariate decoupling for sensor fdd in air-conditioning systems. *Applied Thermal Engineering*, 29(4):712–722, 2009.

[94] Yuebin Yu, Denchai Woradechjumroen, and Daihong Yu. A review of fault detection and diagnosis methodologies on air-handling units. *Energy and Buildings*, 82:550–562, 2014.

[95] Stephen Frank, Xin Jin, Daniel Studer, and Amanda Farthing. Assessing barriers and research challenges for automated fault detection and diagnosis technology for small commercial buildings in the united states. *Renewable and Sustainable Energy Reviews*, 98:489–499, 2018.

[96] Zixiao Shi and William O'Brien. Development and implementation of automated fault detection and diagnostics for building systems: A review. *Automation in Construction*, 104:215–229, 2019.

[97] Maryam Sadat Mirnaghi and Fariborz Haghighat. Fault detection and diagnosis of large-scale hvac systems in buildings using data-driven methods: A comprehensive review. *Energy and Buildings*, 229:110492, 2020.

[98] Yanfei Li and Zheng Oneill. A critical review of fault modeling of hvac systems in buildings. In *Building Simulation*, volume 11, pages 953–975. Springer, 2018.

[99] Ming Zhao, Jing Lin, Xiaoqiang Xu, and Xuejun Li. Multi fault detection of rolling element bearings under harsh working condition using imf based adaptive envelope order analysis. *Sensors*, 14(11):20320–20346, 2014.

[100] Bilal Asad, Toomas Vaimann, Anton Rassolkin, Ants Kallaste, and Anouar Belahcen. A survey of broken rotor bar fault diagnostic methods of induction motor. *Electrical, Control and Communication Engineering*, 14(2):117–124, 2018.

[101] Siddique Akbar, Toomas Vaimann, Bilal Asad, Ants Kallaste, Muhammad Usman Sardar, and Karolina Kudelina. State-of-the-art techniques for fault diagnosis in electrical machines: Advancements and future directions. *Energies*, 16(17):6345, 2023.

[102] Yongzhi Qu, David He, Jae Yoon, Brandon Van Hecke, Eric Bechhoefer, and Junda Zhu. Gearbox tooth cut fault diagnostics using acoustic emission and vibration sensors a comparative study. *Sensors*, 14(1):1372–1393, 2014.

[103] NR Sakthivel, V Sugumaran, and S Babudevasenapati. Vibration based fault diagnosis of monoblock centrifugal pump using decision tree. *Expert Systems with Applications*, 37(6):4040–4049, 2010.

[104] Shao Haidong, Jiang Hongkai, Li Xingqiu, and Wu Shuaipeng. Intelligent fault diagnosis of rolling bearing using deep wavelet auto-encoder with extreme learning machine. *Knowledge-Based Systems*, 140:1–14, 2018.

[105] AR Mohanty and S Fatima. Shaft misalignment detection by thermal imaging of support bearings. *IFAC-PapersOnLine*, 48(21):554–559, 2015.

[106] J Kubiak, G Urquiza, JA Rodriguez, G González, I Rosales, G Castillo, and J Nebradt. Failure analysis of the 150 mw gas turbine blades. *Engineering Failure Analysis*, 16(6):1794–1804, 2009.

[107] Anurag Choudhary, Deepam Goyal, Sudha Letha Shimi, and Aparna Akula. Condition monitoring and fault diagnosis of induction motors: A review. *Archives of Computational Methods in Engineering*, 26:1221–1238, 2019.

[108] Bin Fan, Song Feng, Yitong Che, Junhong Mao, and Youbai Xie. An oil monitoring method of wear evaluation for engine hot tests. *The International Journal of Advanced Manufacturing Technology*, 94:3199–3207, 2018.