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Review

Advances in Fault Detection and Diagnosis for Thermal Power Plants: A Review of Intelligent Techniques

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Abstract: Thermal power plants (TPPs) are critical to supplying energy to society, and ensuring their safe and efficient operation is a top priority. To minimize maintenance shutdowns and costs, modern TPPs have adopted advanced fault detection and diagnosis (FDD) techniques. These FDD approaches can be divided into three main categories: model-based, data-driven-based, and statistical-based methods. Despite the practical limitations of model-based methods, a multitude of data-driven and statistical techniques have been developed to monitor key equipment in TPPs. The main contribution of this paper is a systematic review of advanced FDD methods that addresses a literature gap by providing a comprehensive comparison and analysis of these techniques. The review discusses the most relevant FDD strategies, including model-based, data-driven, and statistical-based approaches, and their applications in enhancing the efficiency and reliability of TPPs. Our review highlights the novel and innovative aspects of these techniques and emphasizes their significance in sustainable energy development and the long-term viability of thermal power generation. This review further explores the recent advancements in intelligent FDD techniques for boilers and turbines in TPPs. It also discusses real-world applications, and analyzes the limitations and challenges of current approaches. The paper highlights the need for further research and development in this field, and outlines potential future directions to improve the safety, efficiency, and reliability of intelligent TPPs. Overall, this review provides valuable insights into the current state-of-the-art in FDD techniques for TPPs, and serves as a guide for future research and development.

Keywords: thermal power plant; fault detection and diagnosis (FDD); boiler tube leakage; turbine; data-driven method; model-based method; and signal-based methods

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1. Introduction

TPPs continue to play a crucial role in the generation of electricity globally, with 83% of the world's electricity production being generated from fossil fuels, 12.6% from renewable sources, and 6.3% from nuclear energy, as per the British Petroleum Statistical Review of World Energy 2021 [1]. Despite the increasing popularity of renewable energy, thermal power generation remains essential in supporting the variable output of renewables, and maintaining energy security. As the demand for electricity continues to grow, TPP equipment is becoming larger and more complex, which in the event of a fault can pose challenges. Quickly diagnosing and repairing faults can be difficult, due to a lack of information and manpower, leading to prolonged downtime and increased production losses [2]. A previous literature survey shows that identifying faults in boilers and turbines is a time-consuming process that often requires expert experience and technical support from the original manufacturer [3]. To address these challenges, the use of FDD techniques in TPPs has been proposed as a solution. The implementation of these techniques has the potential to improve the safety, efficiency, and reliability of TPP operations, ultimately reducing downtime and production losses. FDD techniques help to quickly and accurately detect and diagnose faults, reducing the time needed to repair equipment, and minimizing the impact on production [4]. In addition to the boiler and turbine sections, other sections in thermal power plants can experience faults. For instance, scaling and fouling can occur in the cooling system of thermal power plants, leading to reduced heat transfer efficiency and negatively impacting overall plant performance [5–7]. The generator and electrical equipment may also be prone to faults, such as insulation breakdown, voltage instability, and rotor winding issues [8]. Additionally, the fuel system may also have potential faults, including fuel quality issues such as high moisture content or impurities that can cause combustion problems and damage to the combustion chamber or exhaust system [9]. The emission control system may also experience faults, such as a malfunctioning scrubber or catalytic converter, leading to violations of environmental regulations and affecting the overall efficiency of the power plant [10]. Although the majority of the literature on fault detection and diagnosis in thermal power plants focuses on the boiler and turbine sections, it is crucial to consider potential faults in other areas. Addressing these faults can improve efficiency and reliability, reduce maintenance costs, and ensure compliance with environmental regulations.

FDD is an important process that is used to identify and isolate faults in a system. This process starts with the detection of faults, followed by isolation to determine the location of the fault, and then identification, which involves calculation of the fault's time-variant characteristics. The FDD methods can be divided into three categories: model-based methods [11,12], data-driven methods [13], and statistical methods [14]. Model-based methods are efficient solutions for simple fault detection problems. However, they can be challenging to apply to complex industrial processes. In such cases, data-driven approaches and statistical methods have become popular. These methods involve the use of machine learning algorithms [15], ANN [16], and multivariate statistical techniques, such as PCA [17]. The concept of e-maintenance [18,19], also known as condition-based maintenance, has recently been introduced. This system uses advanced FDD methods to identify faults in TPPs. These methods use real-time data from advanced data acquisition systems to detect and diagnose faults. TPPs are equipped with various acoustic emissions [20,21] and process monitoring sensors [22], which generate a large amount of data. These data can be used for performance monitoring and intelligent FDD by learning from the stored historical data. Boiler tube leakage and turbine failures are the major equipment faults in TPPs [23,24]. According to a survey conducted from 2013 to 2017 [22,25], boiler tube leaks were the most common cause of failure in TPPs, constituting 54% of the total power plant outages. Among these leaks, water wall tube leakage was the dominant type, followed by the second superheater, first reheater, and first superheater, as shown in Figure 1. The cost of repairing these leaks can range from USD 2 to 10 million per leak [26]. Therefore, the implementation of intelligent FDD methods is essential for TPPs to ensure safe and reliable equipment operation and to reduce maintenance costs.

In recent years, AI and machine learning have gained prominence as effective tools for fault detection and diagnosis (FDD) in thermal power plants. They offer a significant advantage in handling and processing large amounts of data from various sources, such as sensors and control systems [27,28]. By analyzing and interpreting these data in real-time, AI algorithms can identify potential faults, providing valuable insights into the performance of the power plant. Machine learning algorithms can continuously learn and adapt to new data, improving their accuracy and effectiveness over time. These algorithms can be applied to various FDD techniques, including model-based, data-driven, and statistical-based approaches. For example, in model-based approaches, AI algorithms can develop more accurate and robust models of the thermal power plant to detect and diagnose faults [29]. Similarly, in data-driven approaches, AI algorithms can analyze historical data to identify patterns and anomalies that may indicate potential faults in the power plant [30]. However, challenges exist in implementing AI and machine learning for FDD in thermal power plants. There is a need for large amounts of high-quality data to train the algorithms effectively, and advanced computing capabilities to handle the computational complexity of these algorithms. Despite these challenges, several successful applications of AI and machine learning have been reported, such as Cui et al. [31] who developed a machine learning system for early fault diagnosis and warning of temperature deviation in power plant boiler reheater. The system can predict and issue alarms when the deviation exceeds a certain threshold, thus improving the efficiency and safety of power plants. The study findings showed that the model can identify the influencing factors of temperature deviation and provide reference guidance for the operation of power plant boilers. Dhini et al. [32] developed a fault diagnosis system for steam turbines in thermal power plants using extreme learning machine-radial basis function networks (ELM-RBF). Tested with real fault data, the system demonstrated high accuracy and fast computation, with ELM-RBF being faster than backpropagation neural networks (BPNN) without significant loss of accuracy. The proposed system can prevent unplanned breakdowns and accurately classify potential faults, improving the efficiency and safety of thermal power plants. Therefore, the use of AI and machine learning for FDD in thermal power plants holds great promise for improving the efficiency and reliability of these systems. In addition to AI-based approaches, recently, new technologies such as IoT, IoE, and smart grids are gaining increasing attention in sustainable energy development. They have the potential to significantly improve energy efficiency, reduce carbon emissions, and enable efficient integration of renewable energy sources into the grid [33–35].

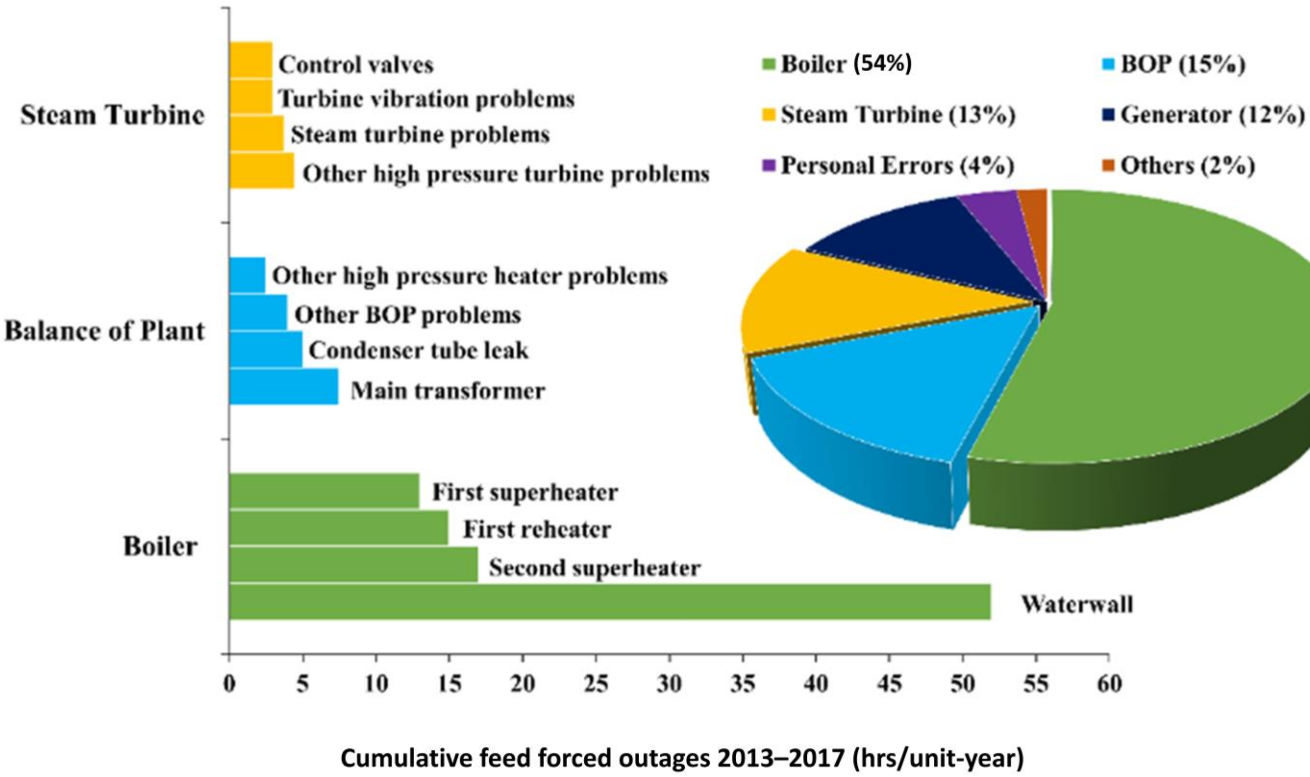

Figure 1. Graph Depicting the Severity of Power Plant Faults and their Resulting Percentage of Outages [22].

This survey provides a comprehensive overview of the current advancements in FDD techniques and their practical applications in modern TPPs. The aim of this review is to bring the challenges faced by TPPs to the attention of the FDD research community, and to summarize the different FDD approaches and their applications in identifying faults in key power plant equipment, such as boilers and turbines. The FDD methods are categorized into three types: model-based methods, data-driven methods, and statistical methods. The survey focuses on the real-world applications of these methods in detecting faults in power plant equipment, and provides a detailed explanation of the principles behind these approaches, practical examples of their use, and a discussion of future trends and areas for further development. Based on our review of the literature, there is a clear gap in the research on the use of intelligent techniques for fault detection and diagnosis in thermal power plants (TPPs). While there has been significant research on fault detection and diagnosis in TPPs, particularly on model-based and data-driven approaches, there is a lack of comprehensive analysis and comparison of these techniques. Our paper addresses this gap by providing a systematic review of the most relevant FDD strategies, including model-based, data-driven, and statistical-based approaches, as well as their classifications and applications in improving the efficiency and reliability of TPPs. By highlighting the novel and innovative aspects of these techniques, our review emphasizes their importance in the sustainable development of the energy sector and their potential to ensure the long-term viability of thermal power generation. Overall, our paper provides valuable insights into the state-of-the-art in FDD for TPPs and identifies opportunities for further research and development in this field.

2. TPP Equipment and Common Faults: An Overview

This section presents an overview of the major equipment, critical faults, and their causes in the TPP.

2.1. Major Equipment in TPPs

The TPPs are facilities that produce electricity by harnessing heat from sources such as coal, natural gas, oil, and nuclear reactions. These plants include several critical pieces of equipment that are crucial to the energy generation process, for which equipment includes boilers, steam turbines, generators, and condensers [36]:

1. Boiler

The boiler is one of the most important pieces of equipment in a TPP, and is responsible for heating the water that will be turned into steam and used to drive the turbine. Boilers are typically fueled by coal, natural gas, or oil, and can reach temperatures of over 1000 degrees Celsius. The heat generated in the boiler is used to convert water into steam, which is then transported to the turbine through a series of pipes [37].

2. Steam Turbine

The steam turbine is the next key piece of equipment in a thermal power plant, and uses the steam generated by the boiler to produce mechanical energy, which is then used to drive the generator. Turbines come in a variety of sizes and shapes, but the basic principle behind them all is the same. They work by using steam to spin a rotor, which is connected to a shaft that drives the generator. The faster the steam flows, the more energy the turbine can produce [38].

3. Generator

The generator is the next piece of equipment in the TPP process. It takes the mechanical energy generated by the turbine, and converts it into electrical energy that can be used to power homes and businesses. Generators use magnetic fields to produce electrical currents, which are then fed into the electrical grid to be distributed to users. Generators can range in size from small units that are used to power individual homes, to large units that can generate hundreds of megawatts of electricity [39].

4. Condenser

The condenser is a critical component in the operation of a TPP. It is used to cool the steam produced by the turbine, condensing it back into the water, so that it can be reused in the boiler. The steam is typically condensed by running it through a series of tubes, which are surrounded by cool water that is pumped in from a nearby source, such as a river or lake [40].

These major pieces of equipment in a TPP play a crucial role in the energy generation process. From the boiler that heats the water to the turbine that produces mechanical energy, to the generator that converts that energy into electricity, each of these pieces of equipment must work together seamlessly to produce the energy that powers homes and businesses. Additionally, condensers play an important role in maintaining the efficiency of the energy generation process, helping to prevent damage to the equipment, and keeping the plant running smoothly. Figure 2 shows a schematic diagram of a coal-fired thermal power plant, which is a type of power plant that generates electricity by burning coal to produce steam that drives a turbine connected to a generator. The process begins with the coal being transported to the plant and fed into a boiler, where it is burned at high temperatures to produce steam. The steam then flows through a series of pipes and turbines, where it expands and turns the blades, generating mechanical energy that is then converted into electrical energy by the generator. After the steam passes through the turbines, it is cooled and condensed back into water and returned to the boiler to repeat the cycle. The diagram also includes other essential components of the power plant, such as the cooling tower and transformer [22].

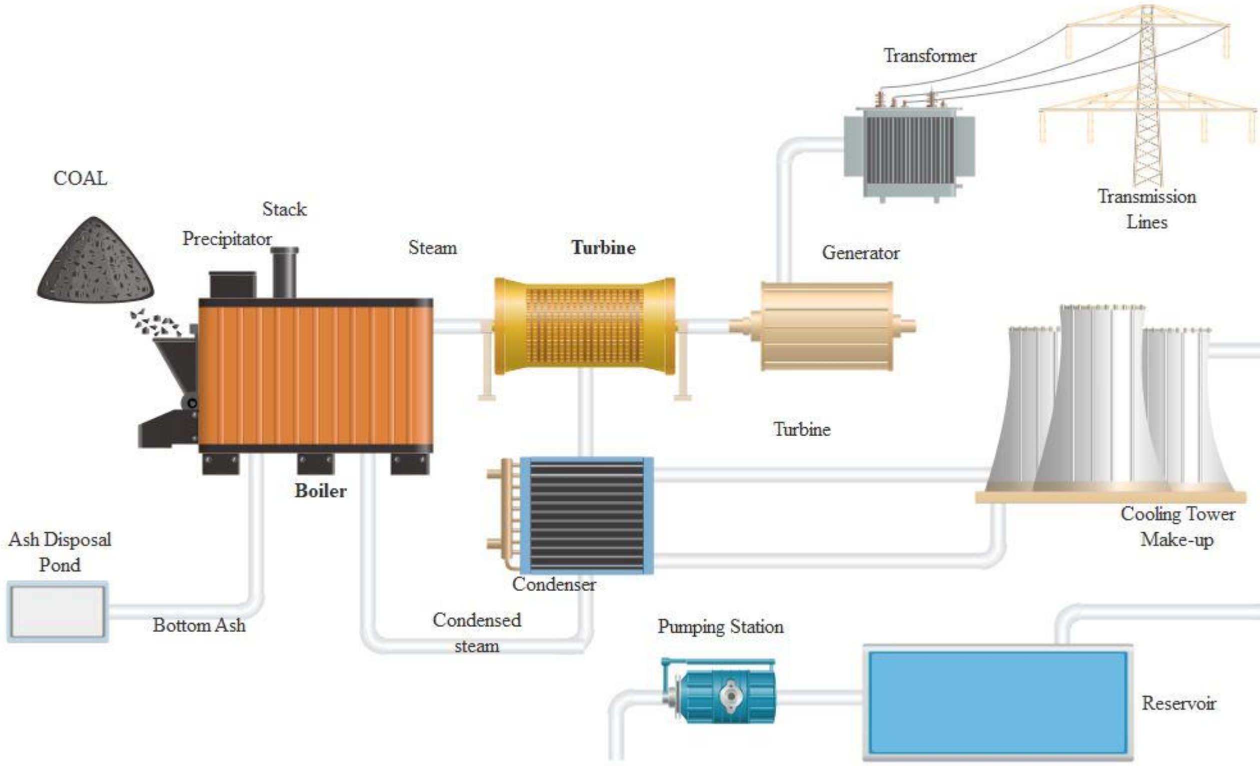

Figure 2. Schematic of the coal-fired TPP representing major equipment [22].

2.2. Common Faults in TPPs

This section summarizes in detail the two major equipment faults (boiler tube leakage and steam turbine failure) in the TPP.

2.2.1. Steam Turbine Faults

The steam turbine is a critical component in the energy generation process, converting the energy from steam into mechanical energy that can be used to generate electricity. The turbine converts high thermal energy from high-pressure vapor at high temperatures into rotational energy through a series of moving blades. This process involves multiple stages of energy conversion as the vapor passes through static blades. The rotation of the turbine rotor, connected to the generator's axle, ultimately produces electrical energy [41]. Steam turbine fault detection is an important aspect of maintaining the efficient operation of a

TPP. Any faults in the steam turbine can result in reduced efficiency, increased downtime, and potentially catastrophic failure. Several common faults can occur in steam turbines, which include blade failure, bearing failure, and rotor imbalance [42]. These faults can cause vibrations and other symptoms that can be detected and monitored using a range of diagnostic tools and techniques. Figure 3 offers an overview of the different faults that may occur in steam turbines, which are further explored in the following sections.

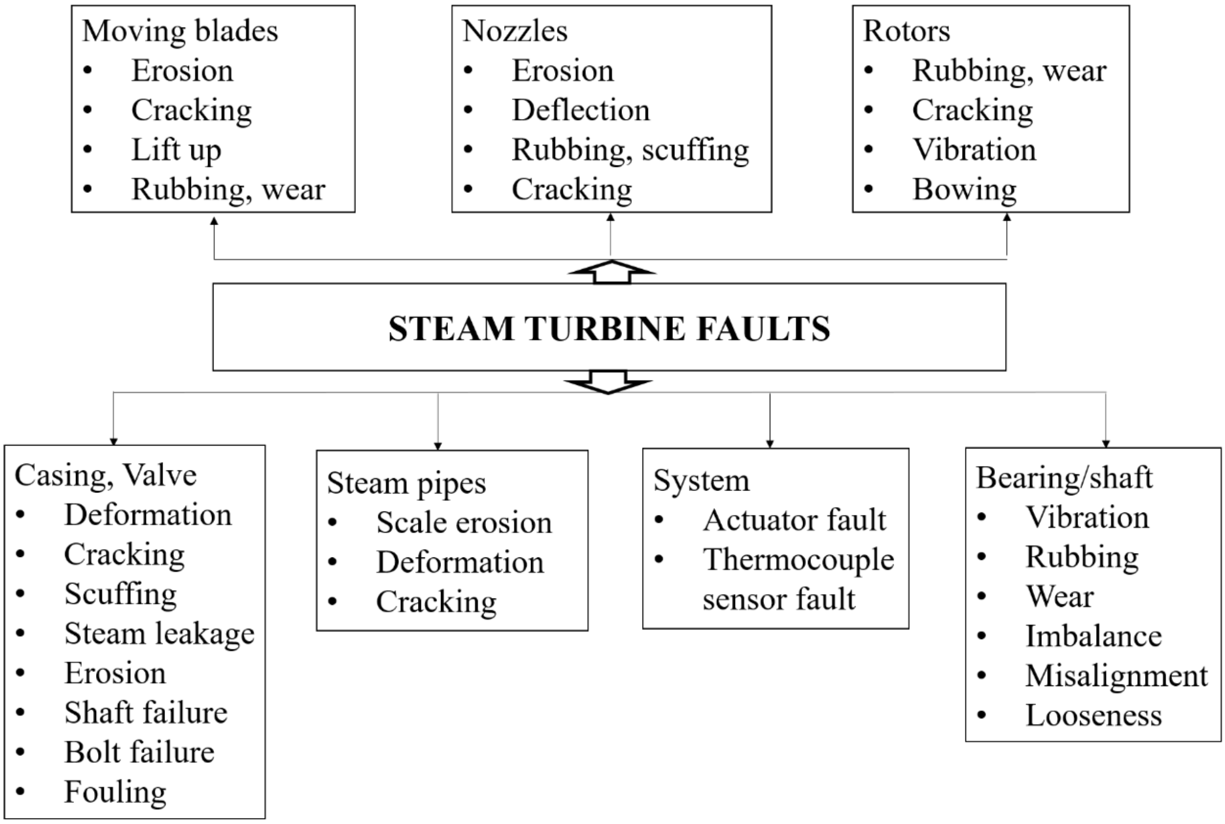

Figure 3. Steam turbine fault types and the causes of failures.

1. Unbalancing and misalignment

Unbalance is a frequent cause of vibration in steam turbines, but can be resolved by proper balancing of the components. Vibrations in overhung and flexible rotors are mainly radial, i.e., horizontal, vertical, or axial. The magnitude of unbalance is proportional to the amplitude of vibrations. Misalignment, such as the bearing not being aligned with the shaft, between bearings, or with the clamping halves, can result in excessive stress on the bearing, leading to damage due to fatigue. A bent shaft can also cause misalignment. Radial and axial vibrations are important in determining misalignment, with axial vibration being the key factor. The three types of misalignment are angular, parallel, and their combination [43].

2. Mechanical looseness

Mechanical looseness can compromise the operation of a steam turbine, affecting its power production. Regular monitoring can be costly in terms of reducing maintenance downtime, but if a fault is diagnosed, it offers sufficient notice to prepare for necessary corrective actions [44].

3. Actuator Fault

A faulty actuator can impact the turbine controller's output, causing a slower response to the required flow rates. A broken spindle can lead to leakage in the overflow valve, reducing turbine performance [45].

4. Thermocouple sensors fault

A malfunction in the thermocouple sensor in the steam path of the turbine can result in gradually increasing or decreasing readings over time [46].

5. Fouling fault

Accumulated deposits in the steam route can cause deviations in the steam velocity, resulting in pressure drops, reduced turbine capacity and efficiency, and extra rotor thrust. Uneven fouling can lead to unbalanced rotors and vibration issues. The deposits can cause nozzles and blades to deviate from their original configuration, and increase the resistance to the flow of steam [47].

Traditionally, to maintain the efficient operation of a TPP, various methods of fault detection have been utilized for steam turbines, including the following:

1. Vibration analysis: This involves measuring the vibration levels of the steam turbine components, and analyzing the data to detect any deviations from the normal operating conditions. Vibration analysis can help identify faults, such as unbalance, misalignment, or mechanical looseness [48].
2. Thermography: This involves using thermal cameras to measure the temperature of the steam turbine components and detect any anomalies. Thermography can help to identify faults, such as a broken spindle or fouling [49].
3. Acoustic monitoring: This involves listening for changes in the sound produced by the steam turbine, and analyzing the data to detect any deviations from the normal operating conditions. Acoustic monitoring can help to identify faults, such as mechanical looseness or bearing damage [50].
4. Oil analysis: This involves testing the lubricating oil for contaminants or other signs of wear and tear, and analyzing the data to detect any anomalies. Oil analysis can help identify faults, such as actuator malfunction or a thermocouple sensor fault [51].

2.2.2. Boiler Tube Leakage

Boiler tube leakage in a TPP can be a serious issue, as it can lead to reduced efficiency, increased downtime, and even catastrophic failure. Boiler tubes, which are used to carry hot gases from the combustion process to the steam turbine, are subjected to high temperatures and pressures. Over time, these tubes can become damaged, leading to leakage, and ultimately reducing the efficiency of the power plant. There are several reasons why boiler tubes may leak. One common cause is corrosion [52,53], which can occur as a result of exposure to high temperatures and corrosive chemicals, such as those found in the combustion gases. Other factors that can lead to boiler tube leakage include mechanical stress, thermal stress, and improper maintenance [54]. The consequences of boiler tube leakage can be significant. Leaks can reduce the efficiency of a power plant, as they allow hot gases to escape, instead of being directed to the steam turbine. This can lead to increased fuel consumption and decreased output, ultimately affecting the bottom line of the power plant. Additionally, leaks can cause damage to other components in the system, such as the steam turbine, increasing the likelihood of unscheduled downtime and repair costs.

The most dominant occurrence of boiler tube leakage lies in the water wall tube section [55]. Waterwall tubes are a critical component in a TPP, as they are responsible for containing and directing the flow of hot water and steam. However, water wall tubes are also subjected to high temperatures and pressures, and over time they can become damaged and leak. Waterwall tube leakage can have serious consequences, including reduced efficiency, increased downtime, and even catastrophic failure. There are several causes of waterwall tube leakage in a TPP. Another common cause of waterwall tube leakage is thermal stress, which occurs when the tubes are subjected to repeated fluctuations in temperature. This can cause the tubes to expand and contract, leading to cracking and eventual failure. In addition to these causes, there are other factors that can contribute to waterwall tube leakage; these include mechanical fatigue [56], erosion [57], and inadequate design. For example, if the waterwall tubes are not properly supported, they may be subjected to excessive stress and vibrations, leading to cracking and failure.

Yang et al.'s study on coal quality discovered that the high ash content in the coal used in TPPs leads to corrosion in the water wall tubes. They proposed that proper coal blending could help to minimize this corrosion [58]. Additionally, Xue et al. analyzed the boiler water, and found that the presence of NaOH causes corrosion-induced perforations and leakage in the water wall tubes. To prevent these leakages, it is important for power plant inspectors to regularly monitor the water quality and perform necessary tests to ensure the tubes do not leak [59]. Similarly, superheater and reheater tubes in a steam power plant are constantly exposed to high temperatures and pressures, making them susceptible to damage and leakage over time. Purbolaksono et al. found localized short-term overheating to be the main cause of failure in primary superheater tubes [60]. Khalil et al. looked into the reasons behind failures in both cold and hot reheater tubes, and concluded that poor maintenance practices and improper feed water chemistry were the main contributing factors [61]. These findings highlight the importance of proper maintenance and monitoring to ensure the longevity and reliable operation of superheater and reheater tubes in a power plant.

Boiler tube leakage in power plants can have serious consequences. Leaks reduce the efficiency of the plant, as hot water and steam escape, instead of being directed to the steam turbine. This results in higher fuel consumption, reduced output, and negative impact on the plant's financial performance. Furthermore, leaks can cause damage to other system components, such as the steam turbine, leading to unplanned downtime and costly repairs. To minimize the risk of tube leakage, it is crucial to conduct regular inspections and maintenance of the waterwall tubes [62]. This includes checking for signs of corrosion or damage, replacing damaged tubes, and cleaning to remove corrosive build-up. Proper operation within design parameters is also important to avoid overloading the system, and reduce the risk of leakage.

To detect and prevent boiler tube leaks, several traditional fault detection techniques that are commonly used in TPPs are

1. Ultrasonic Testing: High-frequency sound waves are used to detect faults in the tubes. The location and size of the leak can be determined by transmitting sound waves through the tube wall [63].
2. Eddy Current Testing: Magnetic fields are used to detect faults in the tubes. The location and size of the leak can be determined by inducing an eddy current in the tube wall [64].
3. Leak Detection Dye: A water-soluble dye is injected into the steam system, and the location of the dye observed as it leaks out of the tubes. This can provide visual indication of the location and size of the leak [65].
4. Pressure Testing: The pressure drop in the steam system is measured over time. A sudden drop in pressure can indicate a leak in the tubes.
5. Thermographic Imaging: Infrared cameras are used to detect changes in temperature in the tubes. The location and size of the leak can be determined by detecting changes in temperature [66].

3. FDD Approaches in Intelligent TPPs

The FDD is a crucial process in identifying faults within a system. It involves detecting faults, determining their location, and characterizing them based on size and other attributes [67]. The two main categories of FDD methods are model-based and model-free, with the latter further divided into data-driven and statistical methods, as shown in Figure 4. Model-based FDD [68] involves using a mathematical model to predict normal system behavior, and comparing it to actual observations to detect and diagnose faults. However, its implementation can be limited by the requirement of an accurate model, which can be difficult to obtain [69]. In contrast, data-driven FDD [70] methods identify correlations between system measurements to detect and diagnose faults. These relationships are established by training an empirical model using normal, fault-free data, and evaluating the estimation residuals of new measurements to identify faults. On the other hand, statistical-based methods compare features extracted from a signal to the desired normal baseline values to make FDD decisions [71]. Both data-driven and statistical-based methods have been widely adopted across various industries for FDD purposes.

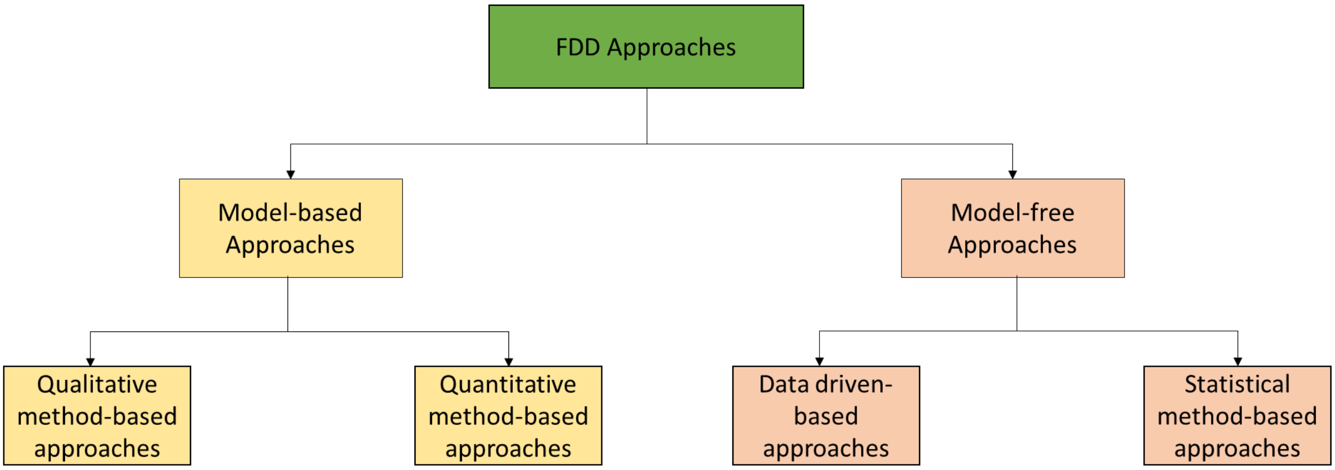

Figure 4. Diagram of Various Fault Detection Techniques in Power Plant Systems.

3.1. FDD Approaches for Steam Turbine

In this section, we delve into the application of FDD approaches, including both model-based methods and model-free methods, in the context of steam turbine TPPs.

3.1.1. Model-Based Fault Detection

Model-based fault detection is a widely used approach to detect and diagnose faults in steam turbines in TPPs [72]. This approach involves the use of mathematical models to simulate the behavior of the steam turbine system, and to identify any deviations from normal operating conditions that may indicate the presence of a fault. The first step in model-based fault detection is to develop a mathematical model of the steam turbine system that accurately represents its behavior under normal operating conditions. This model can be based on physical laws, empirical data, or a combination of both. The model should include all of the important components and interactions of the steam turbine system, such as the steam flow rate, temperature, pressure, and power output. Once the model has been developed, it can be used to monitor the behavior of the steam turbine system in real-time. The model can be compared to the actual operating data from the steam turbine system, and any deviations from the model predictions can be used to identify potential faults. For example, if the model predicts a certain steam flow rate, and the actual steam flow rate is significantly different, this may indicate the presence of a fault, such as a leak in the steam flow system.

Similarly, if the model predicts a certain power output, and the actual power output is significantly lower, this may indicate the presence of a fault, such as an inefficient turbine blade [73]. Model-based fault detection offers several advantages over other fault detection approaches. For example, it provides a more comprehensive and accurate view of the steam turbine system, it can be more sensitive to subtle changes in the system behavior, and it can be used to diagnose the root cause of faults, which can be useful for maintenance and repair purposes. In summary, model-based fault detection is a valuable tool for detecting and diagnosing faults in steam turbines in TPPs. By using mathematical models to simulate the behavior of the steam turbine system, it provides a more comprehensive and accurate view of the system, which can be used to identify and diagnose faults, and to improve the efficiency and reliability of the steam turbine system. Figure 5 illustrates the model-based fault detection approaches for thermal power plants. It depicts the types of models, including non-linear, linearized, LPV, and Fuzzy T-S models, and their corresponding approaches such as set membership, fault estimation, neural network, and fuzzy inference. The figure also shows how residual generation and evaluation are used to detect and diagnose faults in the power plant, thereby improving its efficiency and reliability. The residual evaluation is carried out using threshold check and feature extraction, along with Bayesian approaches, which ensures the accurate detection and diagnosis of faults. In summary, the techniques presented in Figure 5 are critical in enabling prompt corrective action and ensuring the long-term viability of thermal power generation.

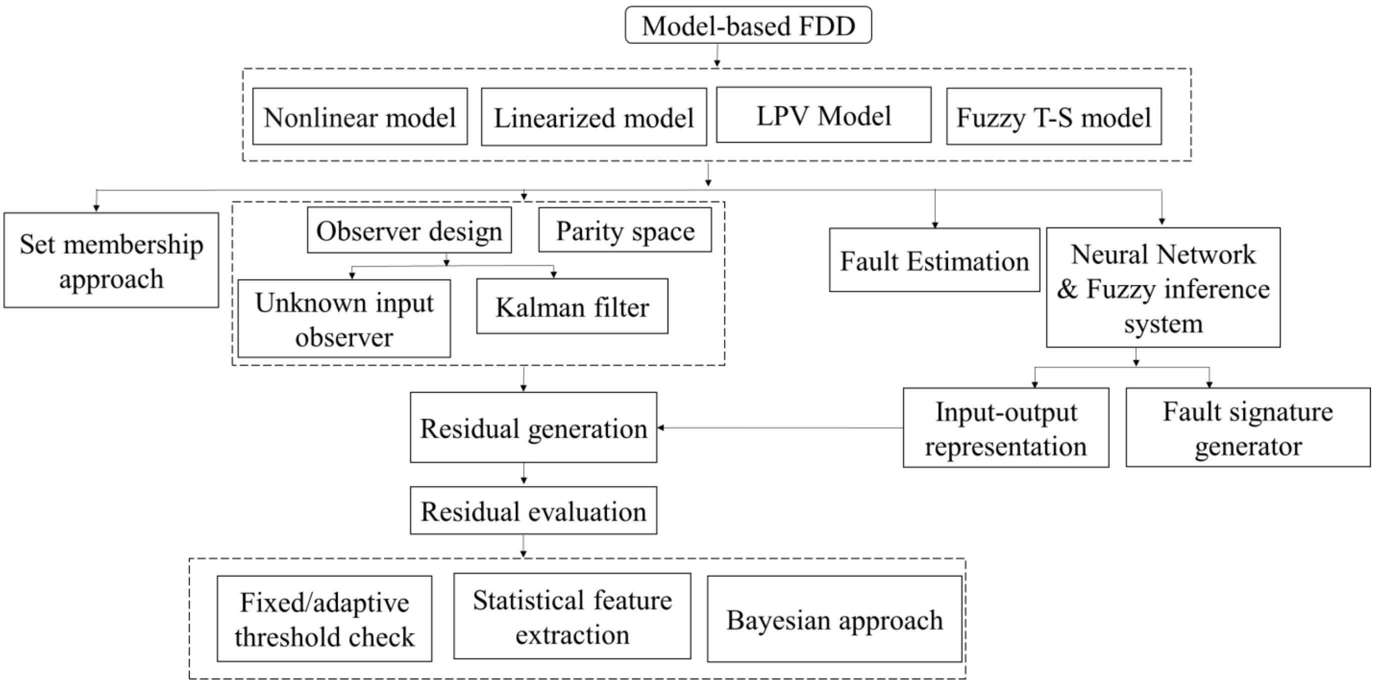

Figure 5. Illustration of Model-Based Fault Detection TPP Systems.

The application of FDD approaches in steam turbine TPPs has received significant attention in recent years. Researchers have proposed a variety of model-based approaches to improve the accuracy of FDD in steam turbines. Table 1 shows the different types of model-based approaches and the corresponding faults that they can detect and diagnose. For example, Salashoor et al. combined a support vector machine (SVM) classifier and an adaptive neuro-fuzzy inference system (ANFIS) classifier to improve the FDD assignments [74]. Another study proposed an FDD system based on the ANFIS technique for four different faults in steam turbines [75]. The proposed system was tested for its effectiveness in diagnosing 12 major faults under various noise and data manipulation conditions. Li et al. presented a Moving Exponential Double-Sided Sensitivity filter (MEDSS filter) based on the Kalman filter, which enhanced the FDD of the regular sinusoidal synthesis (SS) method [76]. The effectiveness of the model was validated through simulations and real-world case studies. Sha et al. proposed an improved Locality-Preserving Projection (ILPP) scheme using the Riemannian metric for the diagnosis of fouling faults in steam turbines [77]. The results of this method showed significant improvement, compared to other existing approaches. Huang et al. proposed a Riemannian algorithm for the fault detection of valve stiction in steam turbines [78]. The effectiveness of the proposed method was compared to traditional FDD methods through experiments and simulations. Figure 6 depicts the proposed FDD approach.

Martınez et al. [45] proposed a fault tolerant control (FTC) for the turbine in a TPP, which was evaluated in a practical case study and dynamic simulator with various scenarios, such as initial stage pressure, superheated pressurized steam, and drum pressure. The proposed approach was shown to be applicable to a broad range of situations with strong nonlinear dynamics [50]. The FTC scheme was also integrated with a data-driven approach, using ANFIS and SVM classifiers for FDD. The FTC scheme demonstrated effective fault accommodation and improved steam turbine availability [79]. Zhang et al. presented a graph model approach to categorize healthy and faulty conditions in the dead zone of the control valve, with high diagnostic accuracy that can be applied in the real industrial environment [80]. Another study used a Modified Locality-Preserving Projection (MLPP) based on the Riemannian approach to overcome limitations in intrinsic feature space for effective fault diagnosis. A framework for process monitoring was established, and kernel density estimation was used to approximate confidence bounds. The proposed approach was tested under various noisy scenarios, with results showing its accuracy [81].

Table 1. Comparison of Model-Based Approaches for Turbine Fault Detection in Power Plant Systems.

Fault Detection Approach	Fault/Consequence	Outcome
Integrated SVM with ANFIS [74]	List of different faults, such as, fouling, TS, boiler pressure.	The proposed FDD system is primarily appealing due to the potential advantages of lowering maintenance costs, increased productivity, and enhanced steam turbine accessibility.
ANFIS technique [75]	Various faults: Boiler pressure, fouling, TS, etc.	The proposed FDD model showed the generalization capabilities for variable operating conditions, such as alteration in the fault behavior over time.
MEDSS model using Kalman filter [76]	Rotor-to-stator rubbing fault.	The MEDSS filter has demonstrated promise in detecting distinctive uncontrollable fault attributes in rotating machines, particularly in low SNR scenarios.
Kalman filter [82]	Turbine blade fault due to fatigue.	By assessing deterioration severity and replacement scheduling, overall performance and reliability prediction can be used to enhance accessibility and implement maintenance until failure happens.
ILPP scheme using Riemannian metric [77]	Fouling fault.	The performance of the proposed approached is effective, as compared to the other conventional techniques.
Riemannian algorithm [78]	Valve stiction fault of the steam turbine.	Applicability of the approach in both single control loop and cascaded control loop.
FTC approach [45]	Actuator fault.	Applicable to use in broader range of situations with strong nonlinear dynamics.
FTC approach based on ANFIS [79]	Various faults: actuator fault, TS fault, fouling, etc.	Applicability of the proposed FTC approach under various types of steam turbine fault circumstances.
Graph model approach [80]	Control valve fault	Effectively applicable in the real industrial environment, enhancing economic advantages and execution safety.
MLPP based on Riemannian [81]	Blades fouled fault	Applicable under variable operating conditions (validated using various noisy conditions).
Unsupervised fuzzy C-means (FCM) algorithm [83]	Misaligned and amplified data	Generalization and capable of working on unseen data.

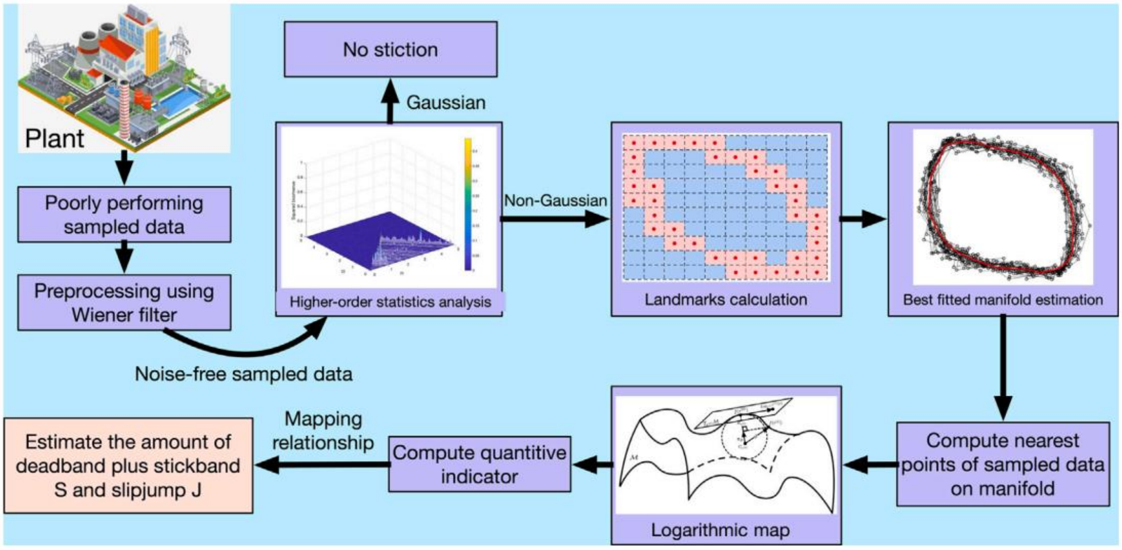

Figure 6. Diagram of the Proposed Riemannian-based Fault Detection Method for Power Plant Systems [78].

3.1.2. Data-Driven Based Fault Detection

The field of FDD in steam turbines of TPPs has recently seen a shift toward data-driven approaches. These approaches, known as "knowledge-based FDD", utilize artificial intelligence and machine learning algorithms to analyze large amounts of data and detect potential faults in real-time. Unlike model-based and signal-based FDD, data-driven approaches do not rely on prior information, and, instead, learn from historical data. Advances in artificial intelligence and machine learning have made data-driven approaches a popular research topic in recent years [84]. The use of these techniques results in improved efficiency, reduced downtime, and increased plant reliability. The data-driven methods make use of a range of techniques, such as signal processing, machine learning, and data analytics, to identify deviations from normal behavior that may indicate a fault. One popular approach is to use machine learning algorithms, such as ANNs and SVMs, to build a model of the normal behavior of the steam turbine. The model is then used to compare actual data with expected data, and determine if deviations are significant enough to indicate a fault. In summary, the use of data-driven techniques in steam turbine FDD has the potential to greatly improve the reliability and efficiency of TPPs by enabling the early detection and correction of faults. The continued development and implementation of these techniques will play a crucial role in the future of the thermal power industry.

There have been several advancements in data-driven techniques for FDD in the steam turbines of TPPs. In recent years, data-driven approaches have gained popularity due to the advancements in AI and machine learning. These techniques make use of data analysis, signal processing, and machine learning algorithms to identify faults in real-time. By analyzing large amounts of data generated by the plant, data-driven methods can detect faults early, which can reduce downtime, improve efficiency, and increase plant reliability.

Studies have shown the effectiveness of using data-driven techniques, such as deep learning, machine learning, supervised and unsupervised learning, and hybrid approaches for FDD. For example, Salahshoor et al. [75] used adaptive neuro-fuzzy inference classifiers to identify 12 major faults in a steam turbine. Another study proposed a neural network-based approach for fault detection in a steam turbine, which involved data collection in both laboratory and real-world conditions [42]. Figure 7 highlights the application of deep learning for FDD in steam turbines. The data used in this study were collected in both laboratory and real-world environments, and underwent a preprocessing stage, which included segmentation. The model was then trained, followed by the fault diagnosis process. This approach is an example of the use of data-driven methods in the field of FDD in steam turbines [85].

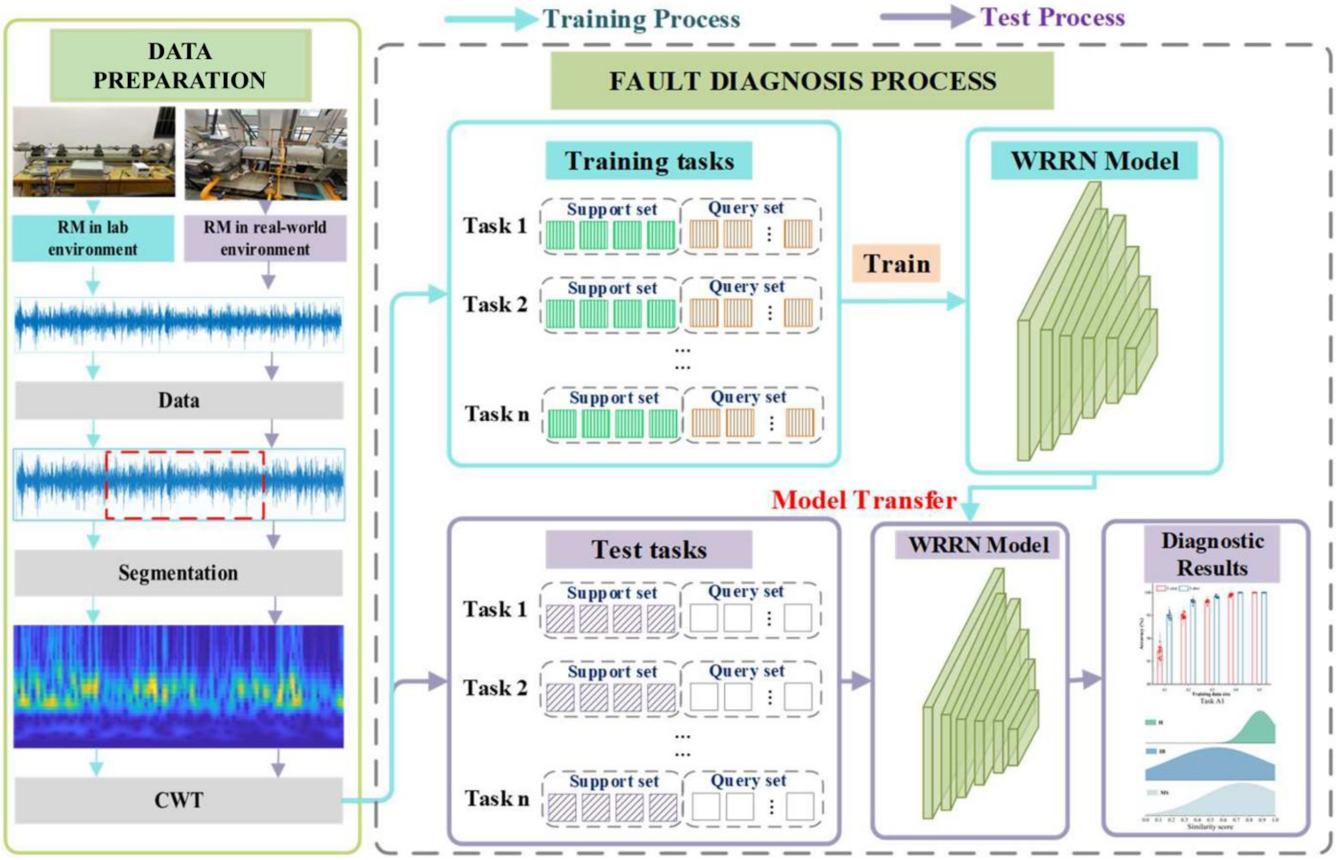

Figure 7. Illustration of Data-Driven Deep Learning Based FDD Approach for Power Plant Systems [85].

Table 2 highlights the various knowledge-based data-driven approaches for steam turbine FDD. Dhini et al. [42] compared the performance of a neural network (NN) classifier across three different scenarios, with the last two scenarios (with and without PCA) outperforming the first scenario, which only used selected process parameters. Chen et al. [86] evaluated the fault detection performance of a support vector machine (SVM)-based framework, and compared it to linear discriminant analysis (LDA) and backpropagation neural network (BPN). The study found that the SVM performed better than the other two methods. In another study [32], a novel extreme learning machine-radial basis function network (ELMRBF) was proposed for steam turbine FDD, and its efficiency was compared to backpropagation neural networks (BPNN). Ashraf et al. [87] proposed ANN and SVM models based on relative vibration modeling for steam turbine shaft bearing FDD, and found that the ANN model performed better than the SVM model. Que et al. [88] presented a semi-supervised framework based on GAN and particle filter (PF) for FDD and remaining useful life (RUL) prediction of steam turbine, and verified its efficiency through real-world examples. Fang et al. [89] proposed a data-driven approach based on ANNs for the vibration FDD of the steam turbine, and found that the features extracted using ANN outperformed those extracted using empirical mode decomposition (EMD). Wang et al. [90] used a residual network to diagnose misalignment and imbalance faults in the steam turbine, which eliminated the limitations of conventional signal processing techniques, and improved precision and reliability. Helin et al. [91] proposed a compressive approach for steam turbine FDD, consisting of unsupervised PCA and an NN-based autoencoder.

Table 2. Comparison of Data-Driven Based FDD Approaches for Steam TPP Systems.

Approach	Fault	Outcomes
Neural network with PCA [42]	Various faults, such as misalignment, robot bowing, blade erosion.	Good classification performance under real industrial applications.
SVM based fault classification [86]	Various faults such as flow, erosion of blade, failure of bearing, etc.	The presented work is capable of real application.
Extreme learning machine-radial basis function networks (ELMRBF) approach [32]	Various faults in the turbine, such as case cracking, blade cracking, rotor bowing, misalignment.	This study identifies characteristics that have a significant impact on the given specification.
ANN and SVM based FDD [87]	Bearing fault of the steam turbine	Vibration reduction of the bearing of the steam turbine's high-speed shaft can inhibit downtimes and costly maintenance, contributing to the machinery's safe and constant execution.
Semi-supervised model based on GAN and PF [88]	Anomaly detection: generator power is used as a health indicator (HI)	Applicable in the real application, and can be used to determine the HI and RUL.
Feature extraction based on ANN [89]	Imbalance and rubbing	The extracted feature outperforms the conventional feature based on EMD.
Residual network [90]	Misalignment and imbalance	This solves the limitations of traditional techniques, and reduces the computational cost.
Various approaches, such as unsupervised, PCA, and NN based autoencoder [91]	Anomaly detection of steam turbine	Long-term data are utilized; hence, the problem evaluation on big data (two years) is considered, which effectively detects anomalies in the steam turbine.
ANN approach [92]	Steam turbine bearing fault	Computationally less expensive model, as compared to previous models.
Deep learning based wide residual relation network (WRRN) [85]	Imbalance, misalignment	It is demonstrated that the WRRN can reliably detect rotating machine fault types using small, or even single, samples.

3.1.3. Statistical Method-Based Fault Detection

An effective and efficient way to detect and diagnose faults in steam turbines is through the implementation of statistical methods. This approach involves the collection of data from various sources within the turbine, such as vibration sensors, temperature sensors, and pressure gauges. The data are then processed using statistical techniques, such as regression analysis, principal component analysis, and clustering algorithms, to identify patterns and anomalies in the system [93,94]. For example, a sudden increase in vibration readings from a certain part of the turbine may indicate a problem with a bearing, or a misaligned rotor. Similarly, elevated temperature readings may indicate a problem with the cooling system, while changes in pressure readings can indicate a leak in a pipe. By detecting these faults early on, plant operators can take prompt corrective action to avoid costly downtime and repairs. Additionally, statistical-based fault detection and diagnosis can help to identify the root cause of a problem, allowing for targeted repairs and improved maintenance strategies.

Table 3 shows statistical-based approaches that have recently been used for the FDD of the steam turbine. Zhao et al. [95] proposed CWT for different fault evaluation of the steam turbine. The power distribution of the signal in the time and frequency domain can be easily depicted using a time–frequency contour map. In summary, it provides an effective method for identifying steam turbine faults involving a breakdown change. Ajami et al. [96] presented statistical approach based on independent component analysis (ICA) for a real turbine (model V94.2). As a preliminary step in ICA, the input data undergo whitening and centering. This process involves transforming the original signals into variables with a mean value of zero, and then linearly transforming these centered signals so that they are uncorrelated, and have unity variance. Figure 8 illustrates the mixing and separation process of the ICA algorithm.

Mubaraali et al. [97] proposed a statistical approach for the turbine FDD by using the CWT to remove noise from the signal. The features are extracted using statistic filter (SF) and Hilbert transform (HT) integrated with moving-peak-hold method (M-PH). Zhang et al. presented a kernel generalized discriminant analysis (KGDA), where the data are transformed from the original set to high-dimensional feature space. The statistic length among normal and test data are then calculated to determine the presence or absence of a malfunction. If a fault happens, a comparable analysis is used to identify the type of fault. The results show that the proposed technique can prevent systematic errors and fault misdiagnosis caused by changes in the operating environment and model insecurity. Lin et al. [98] proposed grey clustering analysis (GCA) using (FFT) analysis. In summary, the highest and lowest values of the power spectrum imply a vibration fault at a specific frequency, and frequency trends are used to diagnose mechanical vibration faults.

Table 3. Comparison of Statistical-based Fault Detection Techniques for steam turbine Power Plant Systems.

FDD Approach	Fault/Signal Type	Advantages
CWT approach [95]	Vibration signal with various kinds of faults, such as rubbing, oil whip, looseness, loss of component, unbalance.	The proposed model is effective, and can potentially be used in real-world application.
CWT based SF and HT combined with M-PH [97]	Vibration data, bearing fault.	The proposed method outperforms other approaches in terms of fault signal extraction and fault diagnosis of low-speed bearings.
Kernel generalized discriminant analysis (KGDA) [99]	Vibration data/various kind of fault; unbalance, misalignment, oil whip, radial rubbing.	This approach captures the nonlinear correlation, and proficiently synthesizes changing information in multiple process factors.
ICA based statistical approach [96]	Different thermal parameters related to the flow.	The model can compensate for environmental and model uncertainty.
GCA analysis based on FFT [98]	Vibration signal.	Ease of implementation, practical application with high accuracy.
Wavelet spectrum based FDD of turbine generator [100]	Thermal signal measurement.	The early fault can be detected using the energy profile based on wavelet spectrum.

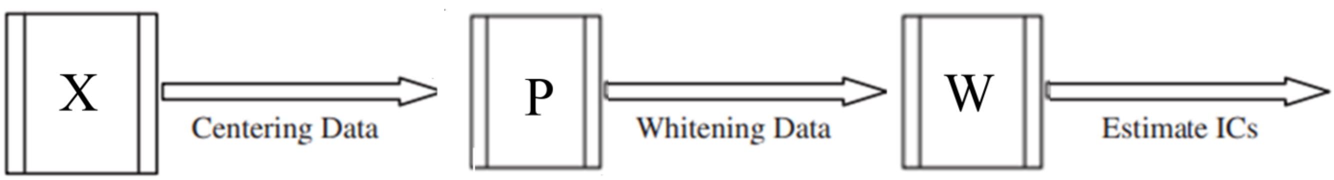

Figure 8. Illustration of the Mixing and Separation Process using ICA Algorithm [96].

3.2. Application of FDD Approaches in Boiler Tube Leakage Detection

In this section, we examine the use of FDD techniques, including both model-based and model-free approaches, in the context of the boiler in a TPP.

3.2.1. Model-Based Methods

In the area of boiler tube leak detection, various mathematical models have been widely used [69]. This conventional approach takes into account both the steady and dynamic aspects of process variables, making it a suitable solution for various fault diagnosis applications. However, in some cases, this method may not provide precise results, as it can be difficult to establish a valid mathematical model of the process for specific industrial scenarios. Panday et al. [101] designed a straightforward monitoring tool to detect leaks in the boiler section of a 300 MW power plant. They compared the amount of feedwater needed to produce steam under normal and faulty conditions, and established the ratio of feedwater flow rate to steam flow rate as the key parameter for anomaly detection, since the available data did not include other indicators used in previous studies, such as water level, blowdown, or make-up water. To minimize false alarms, they set a threshold for the difference in slope between the normal and leaky data sets. They also applied an EMA filter to reduce noise in the raw signals. The results showed that a decrease in economizer outlet temperature represents a leak, as shown in Figure 9. This tool was created as a simple and effective solution for real-time leak detection when other critical measurements are not available.

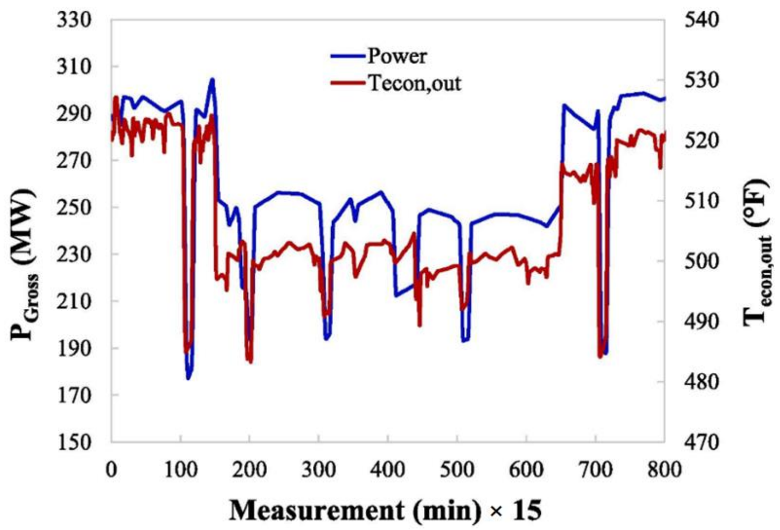

Figure 9. Consequence of a Leak: A Graph Showing the Decrease in Economizer Outlet Temperature [101].

Sun et al. [102] proposed a model-based algorithm that incorporates a time-varying forgetting factor to identify leaks in boiler steam–water systems [94]. They used system identification methods to analyze the steam drum, taking into account the material balance relationship and measuring feedwater flow rate, steam flow rate, pressure change rate, and drum level. Chen et al. [69] developed a steam boiler leak detection system that uses a model-based least squares algorithm. The model includes heat and mass balance equations, and was tested in real-world conditions at Syncrude Canada, demonstrating its ability to provide early leak warnings. Li et al. [103] put forward the use of the group method of data handling (GMDH) technique to detect water leakage from interior tubing into steam space in high-pressure feedwater heaters. However, they pointed out that the GMDH model's complexity increases with the number of layers, making the evaluation of all possible nodes computationally intensive, which could be challenging for practical applications. Lang et al. [26] developed a leak detection system for generator tubes and heat exchangers that utilized an input/loss model based on heat and mass balance governing equations to calculate fuel flow, heating values, and fuel chemistry. The model was implemented at the Boardman coal plant, and was shown to effectively predict tube leaks. David et al. [104] introduced a simple model-based algorithm that was developed by creating a mathematical model of various boiler sub-systems, such as the furnace, boiler tubes, drums, and heat exchangers. The model's outputs were obtained by using real-time plant measurement data during the boiler operation. The fault detection in the model utilized a Kalman filter algorithm, which estimated all process variables at the input and output side of the boiler.

The residuals, generated by measuring the difference between the estimated and measured values, were used to determine if there was a fault in the boiler. If the residual value exceeded the threshold, it indicated a fault in the boiler. Table 4 compares the model-based fault detection techniques for boiler water wall tube leakage detection.

Table 4. Comparison of Model-based Fault Detection Techniques for Boiler water wall tube leakage detection.

FDD Approach	Fault	Advantages
Exponential Moving average filter and Kalman Filter [101]	Economizer tube leakage detection.	The proposed technique was simple, and can be extended to other sections of the boiler.
Least square algorithm [69,102,103]	Complete boiler.	Provided a simple and effective solution based on heat and mass balance relationships.
GMDH Model [103]	High-pressure feed water heater.	Simple and effective methods based on heat mass balance relationships.
Input/loss method [26]	Generator tubes and heat ex-changers.	Ease of implementation in real power plant, and effective in predicting tube leaks.
Kalman filter algorithm [104]	Complete Subsystems of the boiler.	Practical application with high accuracy.

3.2.2. Data-Driven-Based Methods

Recently, data-driven-based methods [86] are increasingly being used to detect and diagnose faults in TPPs, including boiler tube leakage. This approach incorporates the expertise and experience of operators in the industrial process, and can be used to support the analytical method. For example, techniques such as expert systems [105], wavelet analysis [106], pattern recognition, and ANNs (ANNs) have been used in the development of knowledge-based methods for fault detection. Data-driven FDD systems use machine learning algorithms to analyze data from sensors and other sources to identify patterns and anomalies that indicate a fault. These systems can be trained to recognize specific faults, such as boiler tube leakage, by learning from historical data, and can also be updated over time to improve accuracy. One example of a data-driven-based FDD system for boiler tube leakage is the use of predictive maintenance. This involves using AI-based algorithms to analyze data from sensors, such as temperature and pressure sensors, to predict when a fault is likely to occur [86]. This allows maintenance crews to proactively address the fault before it causes a significant problem, reducing downtime and costs. The process control data can provide sufficient information for effective tube leakage detection [107]. Rostek et al. [108] proposed a method for detecting and predicting tube leaks in fluidized bed boilers using an ANN. However, the use of ANNs requires a large amount of data for accurate predictions during the training phase, and obtaining comprehensive data sets, particularly from commercial units, can be difficult due to proprietary restrictions. These limitations may negatively impact the prediction capabilities of the ANN model. In their study, the team trained their neural networks on a five-year data set, and found promising results in early leak detection, leak prediction, and coarse fault isolation through the use of an ANN model. Figure 10 shows the design of the developed multilayer perceptron ANN.

Sohaib et al. [20] used wavelet packet analysis and deep neural networks to detect leaks in boiler tubes. The proposed method extracted salient features from acoustic signals, resulting in a high classification accuracy of 99.2%. Afgan et al. [105] applied an expert system to detect boiler tube leaks, using radiation heat flux measurements and a three-dimensional mathematical model of the furnace. The results of the case studies showed that the system was effective in detecting small leaks. Khalid et al. [15] proposed a machine learning-based waterwall tube leak detection algorithm. The approach consisted of two steps. Firstly, the most effective sensors were selected through correlation analysis. Secondly, various machine learning algorithms were applied to determine the accuracy of the proposed algorithm. The results showed that optimal sensor selection improved the accuracy of the machine learning classification. Ramezani et al. [109] developed a bidirectional long short-term memory recurrent neural network to detect tube leaks in power plant boilers. The system identifies abnormal acoustic signals that deviate from the reference or normal data it was trained on. The network was trained using data from a sample boiler, and was tested on the same boiler to determine its ability to detect leak presence. The results of the test indicate that this novel approach can accurately detect anomalies in signal levels, which indicate tube defects, with an acceptable level of accuracy. Table 5 compares various data-driven fault detection algorithms for detecting boiler tube leaks.

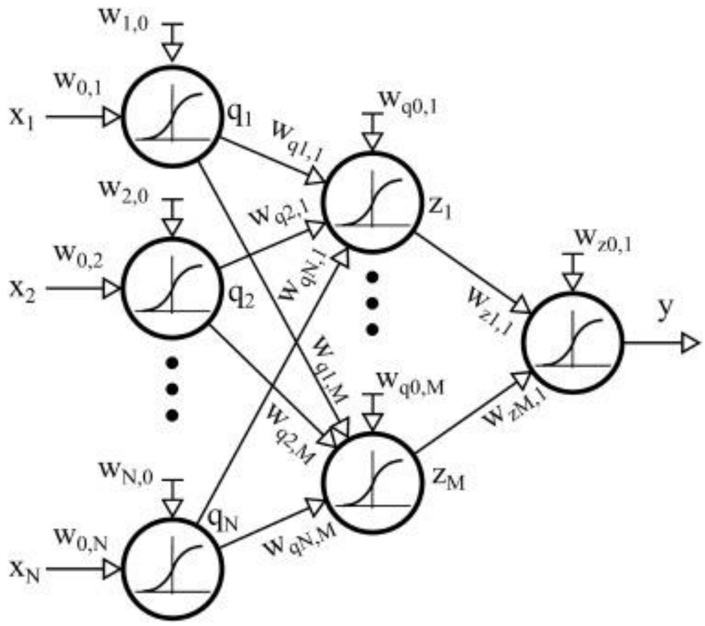

Figure 10. Representation of a developed Multilayer Perceptron Structure [108].

Table 5. Comparison of Different Data-Driven Algorithms for Boiler Tube Leak Detection.

Approach	Fault	Outcomes
ANN [42]	Various faults, including 12 faults of fluidized bed boiler.	Real world industrial applicability.
Expert system [105]	Waterwall tube leakage.	High accuracy using radiation heat flux measurements and three-dimensional model of furnace.
LSTM-based Model [109]	Various subsystems of the boiler.	High performance of the proposed model utilizing acoustic emission signals.
Machine learning-based optimal sensor selection algorithm [15]	Waterwall tube leakage detection.	Developed algorithm showed higher performance and ease of implementation in real power plant.
Deep neural network [20]	For all boiler tubes components.	High classification accuracy and applicable for practical implementation.
Multiplayer back propagation neural network [110]	Boiler burner system.	Used data mining technology to develop intelligent alarm.

3.2.3. Statistical Analysis Method

For many years, statistical methods have proven to be an effective tool in fault diagnosis applications. These methods include limit checking, frequency analysis, and data characteristic analysis, among others. Currently, one of the most popular signal processing-based algorithms for process monitoring is PCA [111]. PCA is widely used in process monitoring, as it reduces the dimension of the process variables. Yu et al. [112] proposed a novel method for detecting and identifying plugged tubes in the final superheater (FSH) tube banks. The method uses PCA for plugging detection and identification, and was applied to temperature data collected from an FSH tube bank in an 870 MW power plant. The results showed that the method was successful in detecting and identifying tube plugging and prevented severe failures by avoiding overheating. Figure 11 shows K-type thermocouples installed by banding on the FSH outlet header section to measure tube temperatures. These thermocouples are commonly used for temperature measurement due to their simplicity, cost-effectiveness, fast response time, and reasonable accuracy. They are also reliable in extreme environments such as boilers, ovens, and aircraft engines. K-type thermocouples are widely used in various industrial fields due to their accuracy and affordability. The temperature range they can measure depends on their diameters.

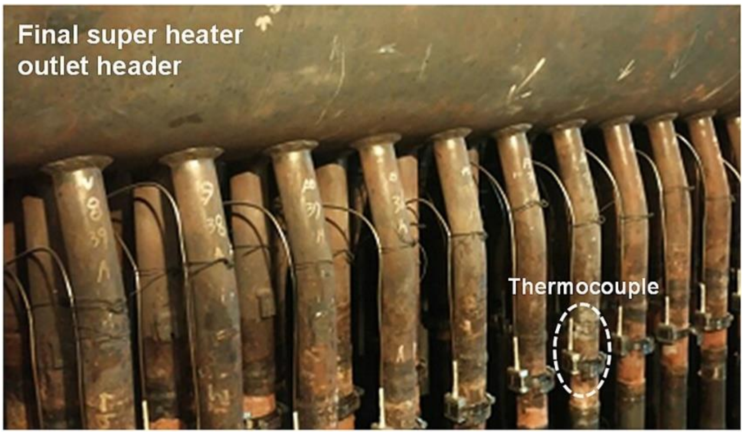

Figure 11. K-type thermocouples affixed to each tube in the outlet header section using banding [112].

Swiercz et al. [107] employed the Multiway PCA (MPCA) method for the early detection of leakages in the pipeline system of a steam boiler in a thermal-electrical power plant. The process variables were long segmented, so they were divided into smaller batches to represent the behavior of the power plant. MPCA was used to train the model for the healthy state of the boiler, and was periodically updated. The model was able to detect leakage when leak data were inputted. Several case studies confirmed the effectiveness of the model in the early prediction of boiler tube leakages. Xi Sun et al. [113] improved the PCA method for leak detection by effectively extracting fault information, and reducing the impact of noise and disturbances. The improved method was successfully used to detect a leak in a Syncrude Canada utility plant. Table 6 compares different statistical analysis-based algorithms for boiler tube leak detection.

Table 6. Comparison of Different Statistical analysis-based Algorithms for Boiler Tube Leak Detection.

Approach	Fault	Outcomes
PCA [112]	Final superheater tube leakage.	Successful in detecting and identifying tube plugging and prevented severe failures by avoiding overheating.
Improved PCA [113]	Boiler water/Steam leak.	The proposed method was tested on real data from a utility plant in Fort McMurray, Canada, for boiler water and steam leak detection.
Multiway PCA [107]	Riser and downcomer tube leakage.	High performance of the proposed Multiway PCA.
Clustering-based method [114]	Boiler tube leakage.	The proposed approach leverages unsupervised learning, and does not require labeled training samples.

3.2.4. Comparative Analysis of Intelligent Techniques for TPPs

This section provides a comparison of state-of-the-art intelligent techniques used in thermal power plants. Table 7 presents an overview of the different intelligent techniques employed, their corresponding applications, the performance metrics evaluated, and key findings and conclusions. The table provides a clear understanding of the effectiveness of various intelligent techniques in different applications. These techniques have been used for applications such as fault detection and diagnosis, predictive maintenance, and optimization. The evaluation of these techniques was based on metrics such as accuracy, efficiency, and cost savings. The key findings of this comparison highlight the effectiveness of intelligent techniques in improving the overall performance of thermal power plants.

Table 7. Comparison of Intelligent Techniques for Thermal Power Plant Applications.

Intelligent Technique	Key Findings and Conclusions	Performance Metrics	TPP Application
Deep neural network (DNN) [20]	Proposed classification mechanism using wavelet packet transform analysis of the acoustic emission signal	99.2% (classification accuracy)	Boiler tube leakage detection
Whole Process model [115]	Developed monitoring platform with the functions of online estimation of key state variables	1.1 % (mean relative deviation)	Boiler tube leak detection
SVM [116]	Prediction of the unburned carbon content of fly ash in the boiler and the exhaust steam enthalpy in turbine	0.068 % (mean relative error)	Online monitoring of 300 MW TPP
Deep learning flexible boundary regression [117]	Proposed impulse detection methodology that employs deep learning methodology	99.8% (classification accuracy)	Boiler tube leak detection
Hybrid intelligent system [118]	A Hybrid fault detection approach based on Decision fusion technique	99.99% (classification accuracy)	Steam generator unit transient condition
Residual network [90]	Proposed a fault diagnosis method based on Knowledge Graph and Bayesian Network	99.1% detection accuracy	Steam turbine rotor fault diagnosis
Graph neural network [119]	Fault representation through Graph neural network	86% inference accuracy	Steam turbine system
Vibration signal analysis [120]	Wavelet transform and statistical pattern recognition employed in the proposed approach	100% fault detection accuracy	Rolling element bearing in rotating machinery
Probability neural networks (PNNs) [121]	Proposed approach based on PNNs to fuse three information entropy	100% classification accuracy on training data and 80% accuracy on unseen data	Steam turbine rotor

4. Challenges, Limitations, and Future Research Directions

This section outlines the challenges and potential areas of future research for FDD techniques in the context of TPPs.

4.1. Current Challenges and Limitations of FDD Techniques in TPPs

FDD is an essential part of the maintenance and operation of TPPs, particularly for boilers and turbines. Despite its importance, FDD faces a number of challenges and limitations as mentioned below, which must be addressed to ensure its effectiveness.

- One of the main challenges of FDD in TPPs is the complexity of the systems involved. Boilers and turbines are highly complex systems that involve a large number of components and processes, which can make it difficult to identify faults and diagnose problems. Additionally, the variability in the performance of these systems can make it difficult to establish normal operating conditions, which is essential for effective FDD.

- Another challenge of FDD in TPPs is the limited availability of data. In many cases, the data used for FDD are based on sensor readings, and these readings are often limited by the frequency and accuracy of the sensors. This can make it difficult to accurately diagnose problems and identify faults, especially when the data are incomplete or noisy.
- A third challenge of FDD in TPPs is the complexity of the algorithms used for analysis. Many of the FDD algorithms used in TPPs are based on artificial intelligence and machine learning techniques, which can be complex and difficult to implement. Additionally, these algorithms require significant computational resources, which can limit their ability to be applied in real-time.
- The limitations of FDD in TPPs also include issues related to maintenance and repair. In some cases, FDD algorithms may identify faults that are difficult to repair, or the cost of repair may be high. Additionally, the time required to repair faults may be longer than the time required to detect the faults, which can reduce the effectiveness of FDD.
- Another limitation of FDD in TPPs is the potential for false alarms. FDD algorithms can sometimes generate false alarms, which can result in unnecessary maintenance and repair activities. This can lead to increased costs, decreased efficiency, and reduced reliability of the power plant.
- Finally, FDD algorithms may not always be effective in detecting faults in all components of a TPP. For example, some faults may not be detectable by current FDD algorithms, or the algorithms may not be effective in detecting faults in certain types of equipment or processes.

In summary, while FDD is an essential part of the maintenance and operation of TPPs, it faces a number of challenges and limitations that must be addressed to ensure its effectiveness. These challenges and limitations include the complexity of the systems involved, the limited availability of data, the complexity of the algorithms used for analysis, and issues related to maintenance and repair. Additionally, FDD may not always be effective in detecting faults in all components of a TPP, and the potential for false alarms must also be considered. To address these challenges and limitations, it is necessary to continue to improve the FDD algorithms and methods used in TPPs, and to develop new approaches that can better detect and diagnose faults in these complex systems.

4.2. Future Research Directions for FDD Techniques in TPPs

FDD techniques play a crucial role in the maintenance and operation of TPPs, particularly for boilers and turbines. To continue to improve the effectiveness of FDD in this context, ongoing research and development are needed. The following are some of the potential areas of future research for FDD techniques in TPPs:

- Big Data and Advanced Analytics: With the increasing availability of data from sensors, SCADA systems, and other sources, advanced analytics techniques are needed to process these data and improve the accuracy of FDD algorithms. This could involve the use of machine learning and artificial intelligence algorithms, as well as the development of new approaches to data analysis that can better handle the complexity and variability of the data generated by TPPs.
- Real-Time Monitoring: To ensure the timely detection of faults and the effective diagnosis of problems, real-time monitoring techniques are required that can process data from sensors and other sources in near real-time. This will require the development of new algorithms and techniques that can process large amounts of data quickly and accurately, and the deployment of these algorithms in real-world TPPs.

- Integration of Multiple Sensors: To improve the accuracy of FDD algorithms, there is a need for the integration of multiple sensors and sources of data. This could involve the use of sensor fusion techniques, which can combine data from multiple sources to provide a more comprehensive view of the state of a system, as well as the development of new sensors and measurement techniques that can provide additional information about the operation of boilers and turbines.
- Predictive Maintenance: To improve the efficiency and reliability of TPPs, predictive maintenance techniques are required that can anticipate faults and problems before they occur. This could involve the use of machine learning and artificial intelligence algorithms to analyze data from sensors and other sources, as well as the development of new approaches to data analysis that can identify patterns and trends in the data.
- Energy Efficiency: To improve the energy efficiency of TPPs, FDD techniques are needed that can identify inefficiencies and opportunities for improvement. This could involve the use of advanced analytics techniques to analyze data from sensors and other sources, as well as the development of new algorithms and approaches that can better identify inefficiencies and improve the energy efficiency of boilers and turbines.
- Context-Aware FDD: To improve the accuracy of FDD algorithms, there is a need for context-aware techniques that can take into account the specific context of a TPP. This could involve the use of machine learning and artificial intelligence algorithms to analyze data from sensors and other sources, as well as the development of new algorithms that can better understand the context of a system and identify faults and problems more effectively.
- Cybersecurity: To ensure the security of TPPs, FDD techniques are needed that can detect and respond to cyber threats. These could involve the use of machine learning and artificial intelligence algorithms to detect and respond to cyberattacks, as well as the development of new techniques that can better protect TPPs from cyber threats.
- Cost-Effective Solutions: To ensure the widespread adoption of FDD techniques in TPPs, cost-effective solutions are necessary that can be implemented in real-world scenarios. These will require the development of new algorithms and techniques that can be implemented with limited computational resources, and the deployment of these algorithms in real-world TPPs.

In summary, the future of FDD techniques in TPPs is promising, and ongoing research and development are needed to continue to improve their accuracy and efficiency.

5. Conclusions

Advances in FDD for TPPs have greatly improved the efficiency, reliability, and safety of these systems. The use of model-based, data-driven, and statistical-based algorithms has enabled the development of sophisticated systems for the detection and diagnosis of faults in real-time.

- Model-based algorithms have become increasingly important in the operation of TPPs. These algorithms, which are based on mathematical models and simulations, allow power plants to analyze large amounts of data, and identify patterns and anomalies that may indicate faults. The use of model-based algorithms in conjunction with other digital technologies, such as artificial intelligence and machine learning, has enabled the development of sophisticated systems for continuous monitoring of the health of power plants and the detection of potential faults in real-time.
- Data-driven algorithms, such as statistical process control and condition monitoring, are also playing an important role in FDD. These algorithms allow power plants to collect and analyze vast amounts of data, providing insights into the performance and health of the system.
- Statistical methods, such as principal component analysis (PCA) and multivariate statistical analysis, are used to identify patterns and correlations in the data that can be used to detect faults. These methods can provide a quantitative measure of the relationship between different variables, and can be combined with other

techniques, such as pattern recognition or machine learning algorithms, to enhance their performance.

Overall, the use of these advanced algorithms is contributing to the development of predictive maintenance systems, which allow power plants to proactively address faults, and minimize downtime and costs. As these algorithms continue to evolve and become more sophisticated, they will play an increasingly important role in ensuring the long-term viability of thermal power generation. In conclusion, advances in FDD algorithms are a critical component of the future of thermal power generation. By improving the efficiency, reliability, and safety of these systems, these technologies are contributing to the sustainable development of the energy sector. As these algorithms continue to develop and evolve, they will enable the creation of even more advanced systems that will help ensure the long-term viability of thermal power generation.

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Abbreviations

ANN	Artificial neural network
EMA	Exponential moving average filter
FDD	Fault detection and diagnosis
MPCA	Multiway PCA
PCA	Principal component analysis
SVM	Support vector machine
TPP	Thermal Power Plant

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