

MACHINE LEARNING APPROACHES FOR FAULT DETECTION AND
DIAGNOSIS IN POWER SYSTEMS

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Article Information	ABSTRACT
Received: 10 th January, 2024	<i>Power systems' dependability and effectiveness are crucial for an uninterrupted and safe supply of energy. Conventional techniques for power system problem diagnosis and detection often depend on expert knowledge and rule-based systems, which may not be sufficient to handle complex and dynamic circumstances. The use of machine learning (ML) techniques to improve problem identification and diagnosis in power systems is examined in this research. The article analyses numerous ML approaches, including supervised learning, unsupervised learning, and ensemble methods, applied to distinct datasets from power systems. These databases include data from sensors positioned strategically across the electrical grid, including voltage levels, current readings, and frequency fluctuations. A potential approach to improving the dependability and efficiency of vital infrastructure is the use of machine learning in power systems for issue identification and diagnosis. As the sector develops, it will be more important to take into account issues of interpretability, explainability, and ethical implications to guarantee the appropriate use of these technologies in the field of power system operations and maintenance.</i>
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Introduction

In the world of modern power systems, ensuring the reliable and efficient operation of electrical networks is paramount. As the demand for electricity continues to rise and the complexity of power systems increases, the need for advanced fault detection and diagnosis mechanisms becomes imperative. This paper explores the intersection of power systems, fault detection and diagnosis, and the transformative role played by machine learning (ML) techniques in enhancing the robustness and reliability of power infrastructure.

In the web of modern civilization, power systems serve as the lifeline, ensuring a seamless flow of electricity to meet the ever-growing demands of industries, households, and critical infrastructures. According to Kundur (2019), power systems encompass an extensive network of generators, transformers, transmission lines, and distribution systems that work cohesively

to deliver reliable electricity. The efficiency and reliability of power systems are paramount for sustaining economic activities and maintaining the quality of life. A comprehensive understanding of the various components within power systems is fundamental to addressing the challenges and complexities inherent in their operation (Glover & Sarma, 2020). Key elements include generators that convert mechanical energy to electrical energy, transformers facilitating voltage transformation, transmission lines for efficient power transfer, and distribution systems ensuring electricity reaches end-users (Wood & Wollenberg, 2016). These components collectively form a dynamic and interdependent network, susceptible to faults that can disrupt the continuous and stable supply of electricity.

The uninterrupted functioning of power systems is of paramount importance for the vitality of society. Faults within the power grid, such as short circuits, equipment failures, and transmission line faults, can lead to disruptions, causing economic losses, and compromising the stability and reliability of the entire network (Haque & Islam, 2018). Rapid and accurate fault detection and diagnosis are crucial to minimize downtime, prevent cascading failures, and maintain the resilience of power systems. As noted by Tleis in 2016 that faults not only pose operational challenges but also have far-reaching implications on the safety of equipment, personnel, and the environment. Understanding the root causes of faults and swiftly identifying their presence is essential for timely intervention and effective maintenance, ensuring the longevity and efficiency of power system components. Moreover, fault information serves as an important input for decision-making processes, allowing operators to implement appropriate corrective measures promptly (Liu et al., 2019). According to Gao et al. (2021), there are three primary processes in the intelligent fault diagnostic process: (1) employing field sensors to acquire data; (2) preprocessing signals to extract features; and (3) applying machine-learning algorithms to categorise defects. This procedure is often known as a pattern recognition issue. Several signals, including vibration, sound emission, current, and infrared heat from the field, may be measured as part of the signal collection approach (Márquez et al., 2012). In particular, condition monitoring and diagnosis by vibration signal analysis has been deemed beneficial for rotating machinery since vibration signals include the most inherent properties associated with health issues (Zarei et al., 2014). During the feature extraction process, it is necessary to comprehend the properties of signals received from different field sensors and develop the appropriate sensitive features to solve particular diagnostic difficulties (Gao et al., 2021).

However, the introduction of machine learning (ML) has transformed problem identification and diagnosis in power systems, providing new analytical tools for processing massive volumes of data created by linked components. ML algorithms may reveal complicated patterns, identify abnormalities, and anticipate probable errors with more accuracy than conventional approaches (Chowdhury & Rahman, 2018). This revolutionary capacity places machine learning (ML) as a critical tool for improving power system reliability and resilience. Kim and Lee (2020) emphasised that the use of machine learning in power systems is multidimensional, including predictive maintenance, real-time monitoring, and decision support systems. ML models may train and adapt to the dynamic behaviour of power systems using historical data and real-time observations, allowing for the early detection of defects and probable breakdowns. This proactive strategy not only reduces downtime but also optimises maintenance schedules, lowering operating costs while improving overall system performance.

There have been numerous studies looking into the potential of ML techniques in fault detection and diagnosis in power systems, such as Vaish et al. (2021), who found that adaptive and intelligent protection methodology, based on advanced measurement techniques and intelligent fault diagnosis such as machine learning (ML), is useful in meeting the

challenges of newer generation sources and loads on traditional power system protection schemes. ML-based power system problem diagnosis has been the subject of several research studies. However, ML approaches are rapidly changing, necessitating a comprehensive and up-to-date evaluation of ML-based power system failure diagnostics. Additionally, Peykarporsan et al.'s (2023) investigation into the machine learning technique for four-legged inverter fault identification and diagnosis shown that, in the absence of transformers, four-legged inverters are a good option for imbalanced loads. Inverters with open and short circuit switches are susceptible to malfunctions. Therefore, in order to guarantee the system's prompt restoration in the event of a malfunction, machine learning-based fault detection and diagnostic techniques are crucial. However, for a system to operate safely and dependably, precise and effective problem detection and diagnostics are essential. Deep learning-based methods have advanced quickly in recent years, enabling the automated and effective learning of high-level feature representations from the raw input data (LeCun et al., 2015). A variety of deep learning techniques have also demonstrated exceptional feature learning capacity and noteworthy diagnosis outcomes in mechanical fault diagnosis. These techniques include deep belief networks (DBN), sparse autoencoders (SAE) (Sun et al., 2016), denoising autoencoders (DAE), sparse filtering, convolutional neural networks (CNN), and recurrent neural networks (RNN) (de Bruin et al., 2017).

Overview of ML

A subset of artificial intelligence (AI), machine learning (ML) focuses on creating models and algorithms that let computers learn from data and provide precise judgements or predictions. Machine learning's main objective is to free computers from the need for explicit programming for each job by allowing them to learn from experience and become more intelligent machines. Without explicit programming, computers can function autonomously thanks to machine learning methods. Machine learning systems has the ability to learn on their own, advance, improve, and adjust to new data. Massive datasets are used in machine learning, an algorithmic technique, to find patterns and gain insightful knowledge. Machine learning methods do not depend on a predetermined equation or existing model; instead, they employ computer techniques to extract knowledge directly from data. Throughout the learning process, machine learning algorithms get more and more adaptable as the number of samples provided increases. A subset of machine learning called deep learning enables computers to simulate real-world human behaviours like learning from examples. Performance-wise, it outperforms traditional machine learning techniques.

Key Concepts of Machine Learning in Detection Diagnoses

Features and Labels: In supervised learning, the input variables are referred to as features, and the output variable to be predicted is called the label. The goal is to learn the mapping from features to labels.

Training and Testing Data: A typical machine learning workflow involves splitting the dataset into training and testing sets. The model is trained on the training set and evaluated on the testing set to assess its generalization performance.

Model Evaluation: Various metrics, such as accuracy, precision, recall, and F1 score, are used to evaluate the performance of machine learning models. The choice of evaluation metric depends on the specific task and goals.

Overfitting and Underfitting: When a model learns the training set too well, it overfits and starts to identify noise and unimportant patterns. Conversely, underfitting occurs when the model is too simplistic to identify the underlying patterns in the data.

Hyperparameters and Model Tuning: Machine learning models often have hyperparameters that need to be set before training. Model tuning involves finding the optimal values for these hyperparameters to improve performance.

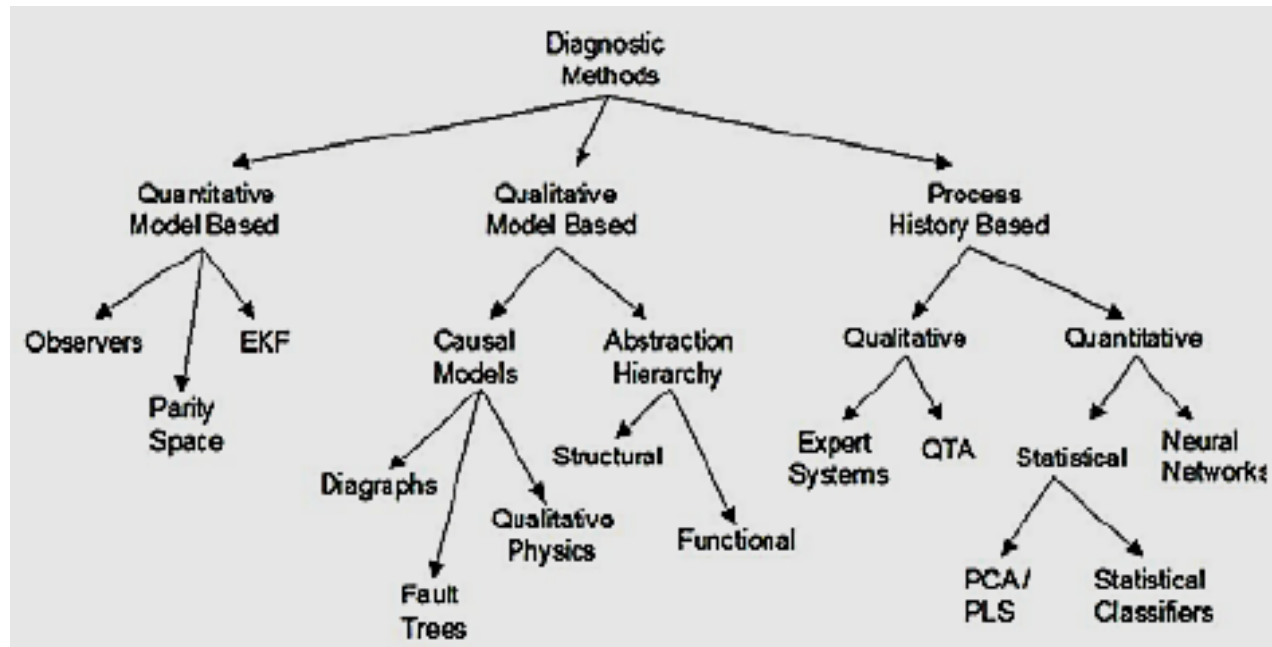
Machine Learning Algorithms

- **Linear Regression:** Employed to forecast a continuous output by leveraging linear associations among input characteristics.
- **Decision Trees:** Hierarchical structures that create choices by evaluating input attributes, often used for tasks involving classification and regression.
- **Support Vector Machines (SVM):** SVM are a powerful tool for both classification and regression tasks. The main objective of SVM is to identify a hyperplane that optimally divides various classes.
- **Neural Networks:** Modelled after the human brain, neural networks are composed of linked nodes arranged in layers. Deep learning is a specific branch of machine learning that emphasises the use of deep neural networks, which consist of numerous layers.
- **K-Nearest Neighbors (KNN):** The KNN technique is a straightforward method that assigns a data point to a class based on the majority class of its k-nearest neighbours.
- **K-Means Clustering:** An unsupervised learning approach used to divide data into separate groups.

Fault Detection and Diagnosis in Power System

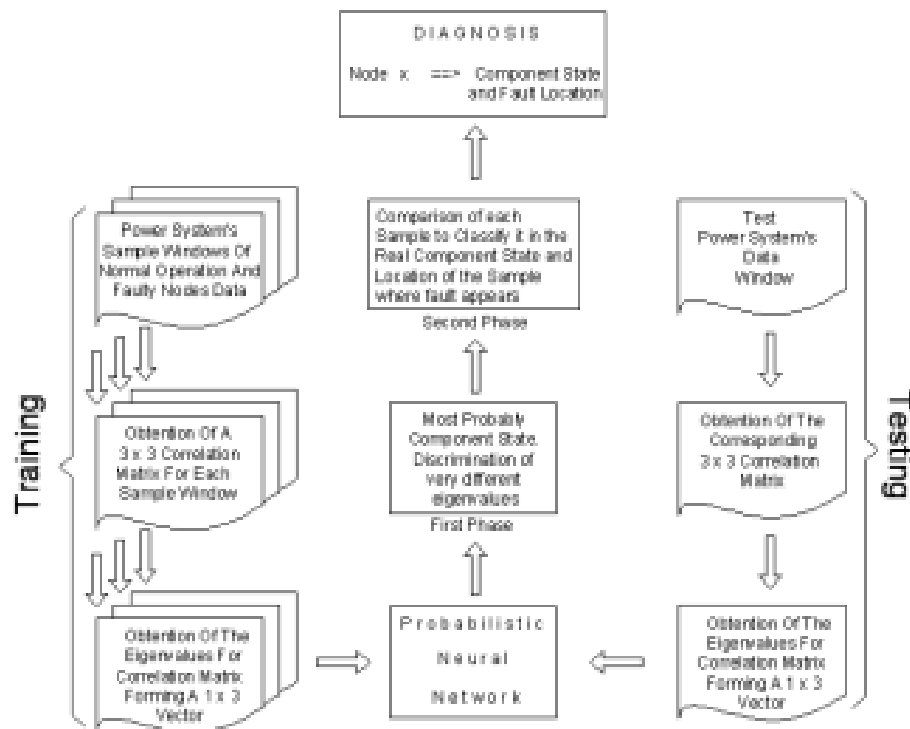
Power systems are critical infrastructures that play a pivotal role in the modern world, providing the necessary energy for various applications ranging from residential use to industrial operations. Ensuring the reliability and stability of power systems is paramount for the seamless functioning of societies and economies. However, power systems are susceptible to faults and disturbances that can lead to disruptions, outages, and even catastrophic failures.

Classification of Diagnostics Method



Power system fault detection and diagnosis (FDD) is an essential element of real-time monitoring and preventative maintenance programmes. Conventional methods rely on rule-based systems and expert knowledge, whereas contemporary power systems are complex and always changing, necessitating more sophisticated and flexible approaches. Machine learning (ML) methods have become effective instruments for identifying and diagnosing issues, enhancing the precision and effectiveness of operations.

The effectiveness of modern societies and economies depends on the essential nature of dependable and consistent power networks. Power systems, being the fundamental infrastructure for delivering energy, are intricate networks that are susceptible to many faults and interruptions. Early and accurate detection and diagnosis of issues in power systems are essential to avoid disruptions, save downtime, and provide a consistent and reliable energy supply. Conventional methods for identifying and analysing issues often prove inadequate in efficiently handling the increasing intricacy and ever-changing characteristics of modern power systems. As a result of these issues, there is a growing inclination to use machine learning (ML) methods in order to enhance the precision and effectiveness of diagnostic and fault detection systems.



General fault detection framework

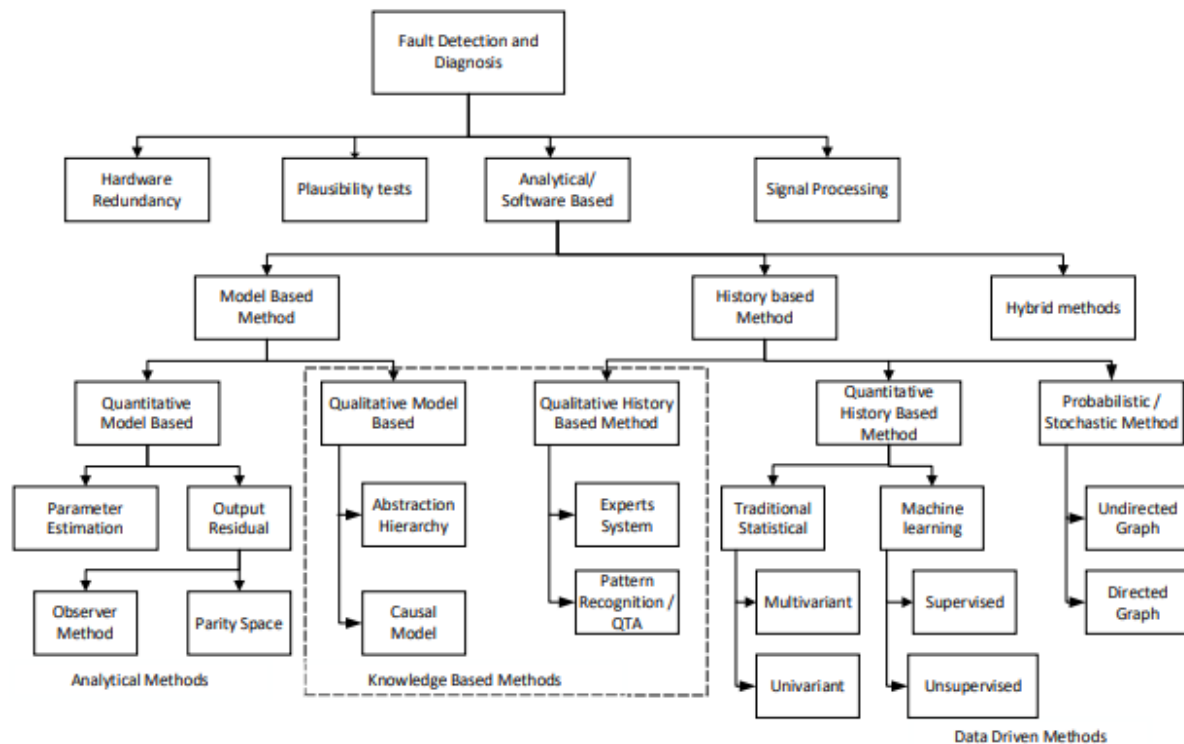
A power system has several components such as generators, transformers, transmission lines, and distribution networks. The interplay of these components creates a dynamic and intricate environment, which may lead to mistakes caused by equipment breakdowns, environmental circumstances, or unforeseen occurrences, among other potential factors. Conventional approaches to identifying defects often depend on rule-based systems and expert judgement, which may be insufficient in reflecting the complexities and unpredictability inherent in interconnected, extensive power networks.

Traditional Fault Detection and Diagnosis Methods

Traditional fault detection and diagnosis methods play a pivotal role in ensuring the reliability and performance of complex systems across various industries. These approaches, rooted in classical engineering principles, leverage signal processing, statistical analysis, and expert knowledge to identify abnormal conditions and diagnose faults. Techniques such as model-based methods, rule-based systems, and statistical process control have been extensively applied in diverse domains, including manufacturing, energy, and transportation. Model-based methods employ mathematical models to characterize system behavior and detect deviations from expected performance. Rule-based systems rely on predefined rules and expert knowledge to identify abnormal patterns in data. Statistical process control techniques monitor process variables to detect deviations indicative of faults. Researchers have extensively explored these methods, and their applications have been documented in seminal works by authors like R. Isermann, P. Frank, and others. While newer technologies are emerging, understanding the foundations of traditional fault detection and diagnosis remains crucial for addressing challenges in system reliability and maintaining operational excellence.

The advancement of many methodologies, such as mathematical, analytical, data-driven, statistical, computational, and hybrid methods, has greatly aided in the identification and

diagnosis of fault situations in recent years. The following enhanced classification of contemporary Fault Detection and Diagnosis (FDD) procedures is derived from the categorization of FDD methodologies presented in the studies conducted by Chiang et al. (2001), Venkatasubramanian (2003), Zhang and Jiang (2008), Mouzakis (2013), and Alzghoul et al. (2014).



Methodological classification of fault detection and diagnosis (Adapted from Alzghoul et al., 2014)

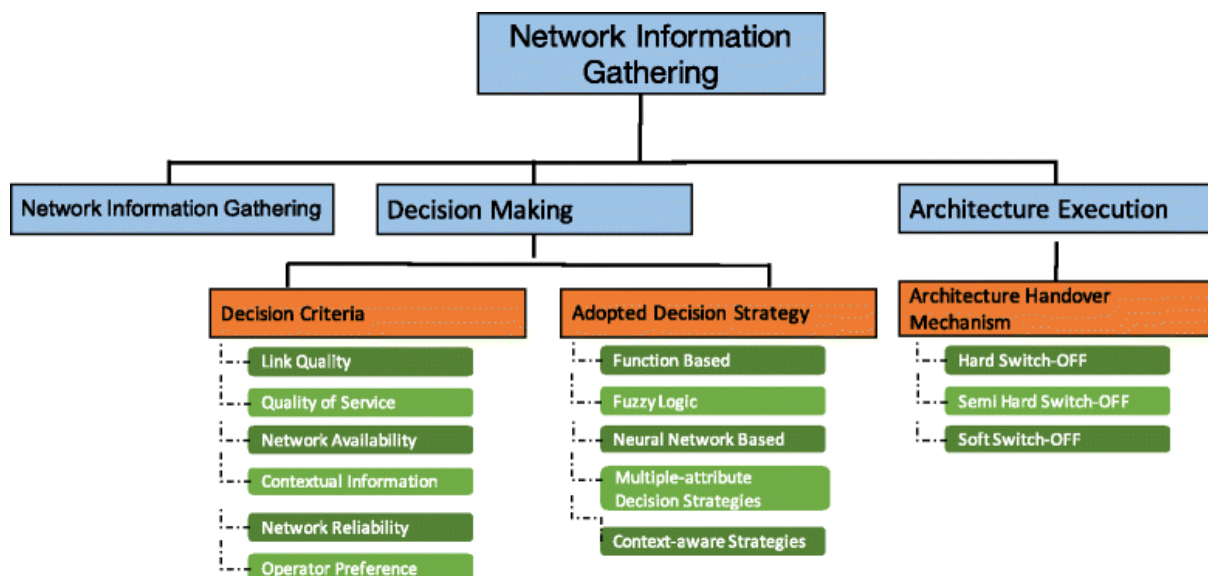
The categorization of fault detection and diagnosis in the process sector has been divided into four separate areas since the early 1970s: signal processing techniques, hardware redundancy, plausibility tests, and analytical models (Chiang et al., 2001). The FDD method was first devised utilising the hardware redundancy concept, obviating the need for identical hardware components in the operating system. An inherent limitation of this technique is its potential inability to precisely detect a malfunction scenario when a similar component system fails to provide the anticipated result. The plausibility test in the system process component relies heavily on the examination of physical laws. As process systems increase in complexity, plausibility tests become insufficient in identifying failure situations owing to the assumptions made by physics laws and the need for real-time system accuracy. Following the deployment of Industry 3.0, computer-based analytical or data-driven models replaced hardware redundancy and plausibility tests in response to the cited problems. Furthermore, signal processing approaches include the assessment of steady-state conditions in process signals to determine fault situations. However, this strategy is inadequate for complex process systems that include a large number of process parameters (Arunthavanathan, 2022).

Rule-Based Systems: Rule-based systems have been widely used for fault detection and diagnosis. These systems rely on predefined rules that capture the knowledge and expertise of domain experts. When certain conditions are met, these rules trigger an alarm or suggest a diagnosis. Early fault detection systems often employed simple if-then rules to identify deviations from normal operating conditions.

Signal Processing Techniques: Signal processing methods, such as Fourier analysis, wavelet analysis, and time-domain analysis, have been applied for fault detection. These techniques focus on analyzing signals from sensors to identify patterns indicative of faults. Frequency analysis, for instance, can be used to identify abnormal vibrations or oscillations in a mechanical system.

Statistical Methods: Statistical methods play a crucial role in fault detection and diagnosis. Techniques like statistical process control (SPC), principal component analysis (PCA), and multivariate statistical analysis have been applied to detect anomalies and deviations from normal behavior. Anomalies in sensor readings or process parameters are identified by comparing them to statistical models of normal behavior.

Fuzzy Logic Systems: Fuzzy logic has been used to model uncertainty and imprecision in fault detection and diagnosis. Fuzzy logic systems can handle vague and ambiguous information, making them suitable for complex systems where precise modeling is challenging. Fuzzy expert systems have been employed to represent the expertise of human operators in diagnosing faults.



Dynamic Network Management Concept

Neural Networks: Artificial neural networks, including feed forward and recurrent architectures, have been applied to fault detection and diagnosis. These systems learn from historical data and can adapt to changing conditions. Backpropagation algorithms and self-organizing maps are examples of neural network approaches used for fault diagnosis.

Model-Based Approaches: Model-based methods involve creating mathematical models of the system and comparing actual behavior with the expected behavior predicted by the model. Discrepancies indicate the presence of faults. Bond graph modeling, state-space modeling, and system identification are examples of model-based approaches.

Expert Systems: Expert systems integrate domain knowledge into a knowledge base and use an inference engine to reason about the system's state. These systems emulate human expertise in fault diagnosis. MYCIN and Dendral are early examples of expert systems applied to medical diagnosis and chemical analysis, respectively.

Hybrid Approaches: Hybrid approaches combine multiple techniques to enhance the accuracy and reliability of fault detection and diagnosis. For example, combining neural

networks with rule-based systems or integrating statistical methods with model-based approaches.

System Failure, Risk Assessment, and Risk Mitigation in Power Station

The identification of risks and the conduction of risk assessments mostly depend on the design of process systems or the deployment of plants (Arunthavanathan, 2022). Implementing efficient abnormal situation management, alarm management, and safety instrumented systems (SIS) might possibly reduce the probability of a hazardous incident taking place in a system or facility. However, if a malfunction occurs and leads to failure and an accident, the first action for the RA would be to examine the accident situation and ascertain the cause of the mishap. When evaluating the safety implications of system failure analysis, it is essential to scrutinise the system's flaw, the circumstances surrounding the failure, and the subsequent accident that occurred. Therefore, the first objectives of the risk analysis perspective on system failure include assessing and simulating the probability of faults resulting in failures by failure modelling. Furthermore, it involves doing research on the accident scenario by examining the initial events and their consequences using an accident model (Arunthavanathan, 2022).

Machine Learning Approaches and Fault Detection and Diagnoses in Power Station

Machine Learning (ML) has become a powerful instrument for fault diagnosis and detection, revolutionising conventional methods and enhancing the efficiency and accuracy of systems in several fields. The historical background, methods, and real-world uses of machine learning (ML) for fault detection and identification are examined in this overview of the literature. This study makes a distinction between machine learning, knowledge-based, and statistical approaches. Instead of adhering to clear rules, machine learning models extract knowledge from data by identifying patterns or making assumptions. While statistical models create correlations to produce information from incoming data, knowledge-based models employ rules applied to data to get knowledge. Research has been done by Liu et al. (2018) and Lei et al. (2020) on the use of machine learning techniques for defect diagnosis and detection. The learning process, which may be supervised or unsupervised, determines how machine learning techniques are classified. Supervised learning comprises the user supplying input to teach a computer model, whereas unsupervised learning allows the model to independently gain information.

Supervised Machine Learning

According to Lo, Flaus, and Adrot (2019), a comprehensive historical dataset that includes both accurate and inaccurate information is essential for supervised learning. In order to build the model, it is necessary to collect the defective condition data in a holistic manner. Since there is no erroneous data, this strategy is difficult for a freshly built system to employ. According to the research, supervised machine learning methods like Neural Networks (NN) and Support Vector Machines (SVM) are often used for problem scenario categorization. The first use of neural networks for the purpose of detecting process system failures occurred in the second part of the 1980s. Hoskins and Himmelblau (1988), Venkatasubramanian and Chan (1989), and Lit et al. (1990) were among the research that used neural network-based methodologies to detect and diagnose process system faults. Data from nonlinear dynamic systems may be analysed using FDD approaches that are based on neural networks. The early 1990s saw a dramatic increase in funding for scientific studies. Now more than ever, building models using neural networks is a complex process that calls for powerful computers and copious amounts of data collected under usual and non-typical settings (Arunthavanathan, 2022). Vapnik (1995) laid forth the foundational theories that formed the basis of the SVM-

based approach to FDD in nonlinear systems, which he attributed to statistical learning and pattern recognition. He wraps up the lesson by explaining how to construct nonlinear binary classifiers using the kernel approach. Support vector machines aim to classify data by addressing fundamental ML issues such as overfitting, nonlinearity, dimensionality, model selection, and local minimums (Corties & Vapnik 1995). Due to the success of the kernel method, SVM is now a leading topic in FDD studies. Recent work by Li et al. (2005) successfully adapted support vector machines (SVMs) from their original binary classification purpose to multiclass classification. Methods like support vector machines (SVMs) and neural networks (NNs) can tell the difference between normal and unusual situations. To pinpoint and assess the malfunction scenario, more algorithm improvements, physical system model inclusion, or probabilistic techniques are needed.

Unsupervised Machine Learning

In order to train the model, supervised learning requires labelled data, which is one of its primary drawbacks. However, it would be challenging to generate statistics from such data in the context of a process business. In recent years, the unsupervised learning approach has become increasingly prevalent in machine learning FDD. Unsupervised machine learning models are trained using historical data that lacks labelling. However, these models select categorization categories by utilising the algorithm to detect a concealed pattern in the data. Unsupervised model behaviours in FDD frequently involve the implementation of clustering and anomaly detection techniques (Dike et al., 2019; Arunthavanathan, 2022).

Probabilistic Methods

Fault detection and diagnosis (FDD) systems frequently employ Bayesian Networks (BN) and Hidden Markov Models (HMM), both of which are founded on stochastic probabilistic theories. Preserving the Markov property, a Hidden Markov Model (HMM) is a probabilistic model that describes a set of random variables and their relationships using an undirected network (Arunthavanathan, 2022). The Bayesian framework is a directed probabilistic graphical model that is acyclic in nature. It is frequently employed in numerous contexts, fault detection and diagnosis being one of them.

Deep Learning in Fault Detection

The utilisation of Deep Learning, specifically Neural Networks, in defect detection and diagnosis has increased in significance as a result of their inherent capability to generate hierarchical representations from data. Recurrent Neural Networks (RNNs) are superior at processing sequential data, whereas Convolutional Neural Networks (CNNs) are superior at evaluating and manipulating spatial data. It has been demonstrated that LSTM networks, which are a type of recurrent neural network (RNN), can capture temporal correlations in defect detection tasks.

Feature Selection and Dimensionality Reduction: ML methods often deal with high-dimensional datasets. Feature selection and dimensionality reduction techniques, such as Principal Component Analysis (PCA) and autoencoders, contribute to improving model efficiency and reducing the risk of overfitting. These techniques are critical for extracting relevant information from complex datasets, enhancing the performance of fault detection models.

Transfer Learning: Transfer learning involves leveraging knowledge gained from one domain to improve performance in another. In fault detection, pre-trained models on related tasks can be fine-tuned for specific applications, particularly in cases where labeled data is

limited. Transfer learning enhances the generalization capabilities of ML models, making them more adaptable to different environments.

Ensemble Learning: Ensemble learning combines multiple models to improve overall performance. Techniques like bagging and boosting have been applied in fault detection and diagnosis to enhance robustness and accuracy. Random Forests, an ensemble of decision trees, are particularly effective in handling noisy datasets and increasing the reliability of fault detection systems.

Conclusion

Machine Learning has brought about a paradigm shift in fault detection and diagnosis, providing innovative solutions that complement and, in some cases, surpass traditional methodologies. As the field continues to evolve, researchers and practitioners are poised to leverage the capabilities of ML to create more adaptive, efficient, and reliable fault detection systems across a wide array of industries. Understanding the current state of ML in fault detection and diagnosing its future prospects is essential for optimizing system performance and ensuring the resilience of complex engineering and industrial processes.

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