A Survey of Fault Diagnosis and Maintenance Strategies in the Process Industry

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Abstract

This survey paper provides a comprehensive analysis of fault diagnosis, fault propagation, process monitoring, anomaly detection, and condition-based maintenance within the process industry. It highlights the critical role these strategies play in enhancing system reliability and operational efficiency. The integration of advanced technologies, such as deep learning and AI-based frameworks, has transformed maintenance strategies, offering unprecedented predictive accuracy and system reliability. Key findings indicate that while traditional methods laid the groundwork for Intelligent Fault Diagnosis, machine learning techniques have significantly improved predictive capabilities. The study underscores the importance of systematic approaches, including specification-driven methods and explainable AI, in constructing reliable prediction models and enhancing maintenance strategies. Future research directions focus on improving the accuracy of remaining useful life predictions and exploring machine learning techniques for various machinery types. The survey emphasizes the transformative potential of advanced technologies in achieving greater operational excellence, reducing maintenance costs, and ensuring long-term system reliability. By leveraging these technologies, the process industry can develop more intelligent, adaptive, and efficient maintenance strategies, contributing to sustainability and resilience across various domains.

1 Introduction

1.1 Importance of Fault Diagnosis and Maintenance

Fault diagnosis and maintenance are crucial in the process industry, significantly impacting system reliability and performance. In Laser Additive Manufacturing (LAM), these processes are vital for ensuring consistent part quality and operational success [1]. The complexity and nonlinearity of industrial systems necessitate advanced fault diagnosis techniques to maintain reliability [2].

Real-time monitoring and conformance checking enhance system performance by swiftly identifying and addressing potential issues [3]. This is particularly pertinent in data-scarce environments, such as defect detection in industrial monitoring [4]. Robust fault diagnosis and maintenance strategies are essential for optimizing performance and ensuring reliability, especially amid internal degradation and sudden shocks [5].

These processes also optimize business operations by recommending interventions based on execution data, thus improving operational efficiency [6]. The challenges of data leakage and biases in predictive monitoring further emphasize the importance of fault diagnosis and maintenance in sustaining system reliability [7]. The ongoing focus on these areas underscores their critical role in achieving operational excellence and longevity in various sectors.

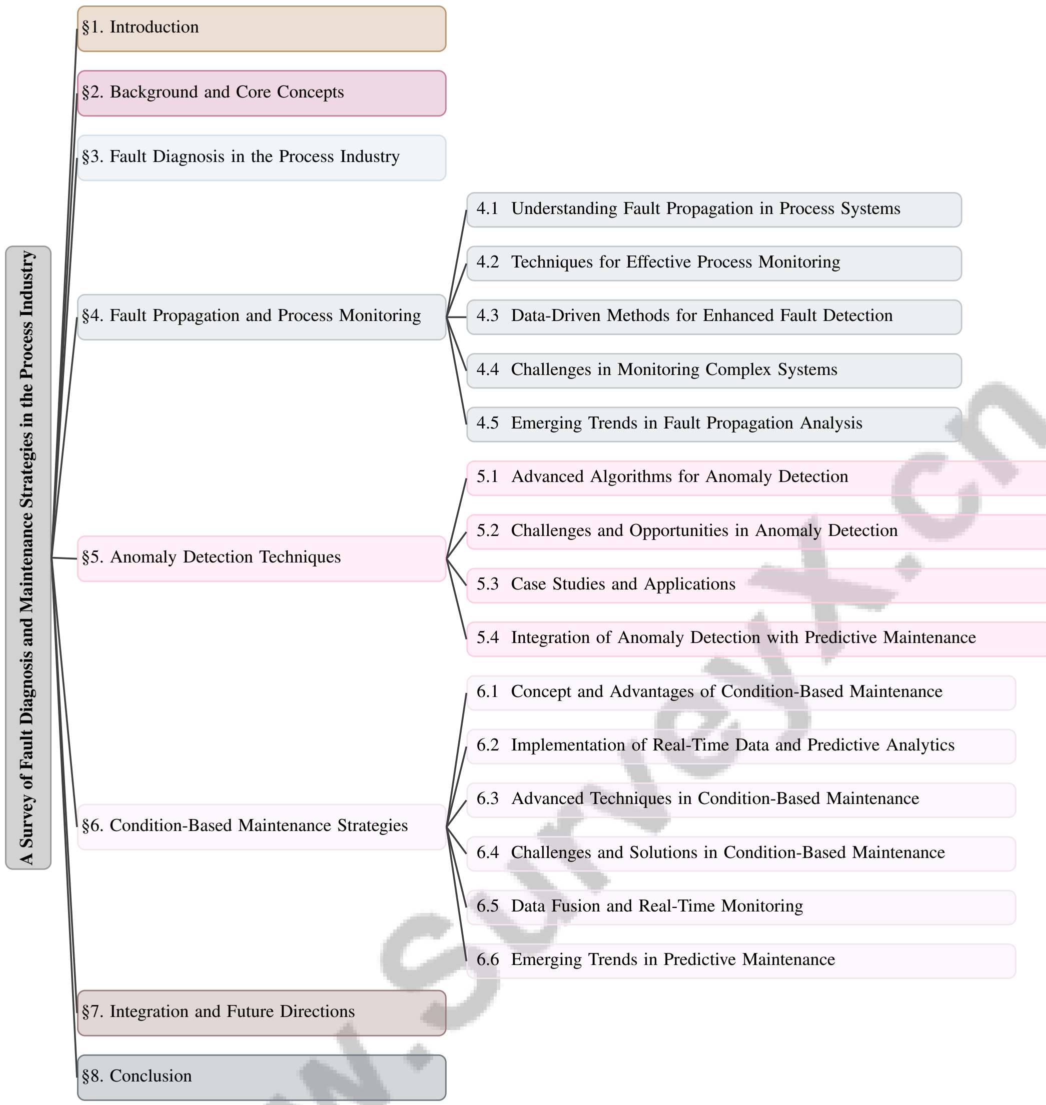

Figure 1: chapter structure

1.2 Challenges in Ensuring Optimal Performance and Reliability

The process industry faces numerous challenges that hinder optimal performance and reliability. A primary concern is the interdependence between degradation processes and sudden shocks, complicating maintenance strategy analysis [5]. This complexity is intensified by distribution shifts across different units, which obstruct effective anomaly detection and the integration of training data [8].

In LAM, defects such as porosity and cracks arise from intricate thermal dynamics and unstable printing speeds, posing significant challenges [1]. Additionally, validating prescriptive monitoring methods in real-world applications and the need for diverse interventions remain substantial hurdles [6]. Existing methods often struggle to predict failures and optimize maintenance actions based on the condition of multiple machines and the availability of spare parts [9].

Inherent limitations in online conformance checking methods, which may overestimate deviations, further affect the reliability of process monitoring [3]. Addressing these multifaceted challenges requires innovative solutions to enhance algorithmic development, improve data handling, and foster better system integration, crucial for sustained operational excellence.

1.3 Objectives and Significance of Keywords

This survey aims to systematically classify and synthesize advancements in fault diagnosis, process monitoring, anomaly detection, and condition-based maintenance within the process industry. A key focus is the assessment of maintenance costs and performance measures under finite life cycle conditions, essential for developing robust condition-based maintenance strategies [5]. The survey also reviews in-situ process monitoring techniques and adaptive quality enhancement methods, particularly in LAM [1].

Additionally, it seeks to establish a standardized benchmark for constructing unbiased datasets, facilitating fair comparisons and reproducibility in predictive process monitoring research [7]. The examination of existing prescriptive process monitoring methods provides a structured overview of their objectives, interventions, and data requirements [6].

Keywords such as fault diagnosis, process monitoring, anomaly detection, and condition-based maintenance are significant for optimizing system performance. Fault diagnosis identifies and rectifies malfunctions using advanced techniques like clustering and statistical hypothesis testing, crucial for predictive maintenance aimed at minimizing downtime and production costs. Process monitoring offers continuous oversight, employing predictive and prescriptive approaches to analyze event data for timely interventions. Integrating alarm systems and cost-benefit analyses empowers workers to mitigate risks and enhance operational outcomes [10, 11, 12]. Anomaly detection identifies deviations from normal patterns, while condition-based maintenance implements strategies based on equipment conditions, collectively advancing the understanding of intelligent systems in the process industry.

1.4 Structure of the Survey

The survey is structured to comprehensively explore fault diagnosis and maintenance strategies within the process industry. It begins with an **Introduction** that highlights the importance of these strategies, the challenges in maintaining optimal performance and reliability, the survey's objectives, and the significance of key terms, culminating in a roadmap of the paper's structure.

Following the introduction, **Background and Core Concepts** are presented, defining essential concepts such as the process industry, fault diagnosis, fault propagation, process monitoring, anomaly detection, and condition-based maintenance, while examining their interrelationships and relevance.

The survey then delves into , discussing various methodologies, including traditional techniques, statistical methods, and modern approaches like machine learning and artificial intelligence (AI). The significance of intelligent fault diagnosis (IFD) is emphasized, showcasing its role in automating machine health state identification and reducing human intervention. The evolution of these methodologies, from early statistical analyses and clustering techniques to deep learning and transfer learning, is also explored [12, 13]. The integration of domain knowledge with data-driven approaches is highlighted.

Next, the discussion transitions to , evaluating fault propagation mechanisms, advanced monitoring techniques, and data-driven methodologies for improved fault detection. This includes a novel process decomposition algorithm and the application of principal component analysis (PCA) for fault occurrence identification. A value-driven framework for predictive process monitoring categorizes existing methods to help organizations select suitable techniques based on data availability. The importance of explainable machine learning models in predictive monitoring is also addressed, along with challenges in monitoring complex systems and emerging trends in fault propagation analysis [14, 11, 15].

The section on reviews various techniques employed in the industry, the challenges of anomaly detection, and the role of advanced algorithms in enhancing detection accuracy, supplemented by case studies and real-world applications.

are explored next, discussing the advantages of condition-based maintenance over traditional methods. The implementation of real-time and predictive analytics is examined, focusing on advanced techniques for process optimization and associated challenges. The research underscores the significance of prescriptive process monitoring methods that recommend real-time interventions to improve business performance, while also addressing the need for validation in real-world applications. The role of process analytics in identifying inefficiencies and enhancing decision-making is emphasized,

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aiming to support continuous improvement in operations [16, 6, 17]. The discussion also includes data fusion and real-time monitoring's role in optimizing maintenance strategies and emerging trends in predictive maintenance.

The survey concludes with the section, which synthesizes fault diagnosis, process monitoring, anomaly detection, and condition-based maintenance into a unified strategy for the process industry. This section highlights the importance of developing a cohesive framework to leverage predictive monitoring methods effectively, enhancing organizations' ability to anticipate issues and optimize performance through comprehensive analysis of event data and execution traces [18, 15]. Emerging technologies and future research directions are identified to improve existing systems.

Each section builds upon the previous one, creating a logical flow that guides the reader through the complexities of fault diagnosis and maintenance strategies in the process industry, with particular emphasis on defect detection, process monitoring, and adaptive quality enhancement [1].The following sections are organized as shown in Figure 1.

2 Background and Core Concepts

2.1 Process Industry Overview

The process industry, comprising sectors such as pharmaceuticals, chemicals, oil and gas, and food and beverage, transforms raw materials into finished products via chemical, physical, or biological processes. This industry relies heavily on continuous and batch processing operations, necessitating stringent monitoring and maintenance to ensure optimal performance [4]. Advanced technologies like digital twins (DTs), utilizing methodologies such as Convolutional Neural Networks (CNNs) and Hidden Markov Models (HMMs), enhance operational efficiency and predictive capabilities [19]. Predictive business process monitoring, while crucial for forecasting and decision-making, often lacks integration with key performance indicators, highlighting an area for improvement [20]. The incorporation of eXplainable Artificial Intelligence (XAI) in Predictive Process Monitoring (PPM) enhances model transparency and trust. Effective monitoring is essential in applications like carbon fiber defect inspection and semiconductor laser maintenance, underscoring the industry's reliance on robust strategies to prevent degradation and ensure performance [4, 21]. By leveraging process execution data, organizations can uncover insights, identify bottlenecks, and make data-driven decisions, while alarm-based interventions in prescriptive monitoring facilitate proactive measures [16, 10, 15].

2.2 Fault Diagnosis and Fault Propagation

Fault diagnosis is essential for detecting and classifying faults in complex industrial systems, crucial for maintaining system integrity and safety [2]. Techniques such as thermal imaging for motor faults and vibrational analysis for bearing conditions exemplify innovative diagnostic approaches [22, 23]. Fault propagation involves the spread of faults within a system, potentially impacting multiple components. This is concerning when faults in non-critical parts affect critical ones, as seen in CNC machine tools and gearbox systems, necessitating robust methodologies to manage fault propagation [24, 25]. Addressing intermittent fault detection in weakly stationary processes is crucial, as traditional methods often struggle with data non-independence [26]. Control-aware Process Monitoring (CAPM) enhances detection by integrating control information, while the lack of labeled data in rotating machinery highlights the need for explainable AI models [11, 27].

2.3 Process Monitoring and Anomaly Detection

Process monitoring and anomaly detection ensure operational efficiency by identifying deviations from expected patterns. Modern systems, characterized by high-dimensional data, require advanced techniques beyond traditional methods like PCA, which often falter due to data sparsity [8]. Dynamic statistical methods and auxiliary information-based techniques enhance monitoring accuracy, though they face limitations due to underlying assumptions [28, 29]. Unsupervised transfer learning is pivotal when traditional methods lack representative data from healthy operations [8]. Conformance checking, crucial for early fault detection, involves comparing observed behaviors against models to identify deviations [3]. By integrating real-time analytics, industries can enhance monitoring robustness, extract actionable insights, and improve decision-making, supporting continuous improvement and operational excellence [16, 30, 14, 31].

2.4 Condition-Based Maintenance (CBM)

Condition-Based Maintenance (CBM) shifts maintenance strategies from time-based to adaptive, data-driven frameworks, aligning activities with real-time equipment assessments to optimize resources and minimize downtime [5]. CBM employs continuous monitoring and advanced analytics to predict failures, integrating technologies like Structural Health Monitoring (SHM) and Digital Twins to enhance predictive capabilities [32]. Data fusion strengthens fault diagnosis by combining data sources for a comprehensive equipment health understanding [6]. CBM addresses the limitations of Time-Based Maintenance (TBM) by offering a cost-effective solution that maximizes equipment lifetime and reduces costs, aligning maintenance with operational conditions [33, 34]. Real-time monitoring with advanced sensors enables proactive interventions, preventing failures and optimizing spare parts usage, contributing to sustainable manufacturing environments.

2.5 Interrelationships and Relevance

The interconnections between fault diagnosis, fault propagation, process monitoring, anomaly detection, and condition-based maintenance form an integrated framework enhancing operational efficiency in the process industry. Fault diagnosis initiates timely maintenance actions and is linked with fault propagation, crucial for developing effective monitoring strategies [24]. Process monitoring ensures continuous oversight, integrating multiple sensing technologies and machine learning, as seen in LAM, to enhance quality and control [1]. Anomaly detection benefits from methodologies improving operational deviation identification, underscoring the necessity of robust frameworks [35]. CBM aligns maintenance with real-time equipment assessments, optimizing resource allocation and minimizing downtime by employing insights from diagnosis and monitoring. This integration improves maintenance reliability and efficiency, enabling proactive actions that prevent downtime and reduce costs. The framework supports operational excellence, integrating real-time data analysis for production planning, spare parts management, and reliability improvement across complex systems [33, 34]. Leveraging advancements in automated fault diagnosis, particularly through intelligent systems utilizing machine learning and natural language processing, industries can enhance maintenance efficiency and safety. Interpretable deep learning methods provide clearer fault classification insights, fostering trust among non-technical personnel. The integration of predictive maintenance and condition-based monitoring facilitates early fault detection and accurate diagnosis, ensuring sustained operational success [12, 36, 35].

3 Fault Diagnosis in the Process Industry

Fault diagnosis in the process industry necessitates an exploration of foundational methodologies that have informed current practices. Traditional and statistical methods have historically underpinned diagnostic efforts, yet they reveal critical limitations that drive the evolution toward more advanced techniques. As illustrated in Figure 2, the hierarchical structure of fault diagnosis methodologies highlights this evolution, showcasing the transition from traditional and statistical methods to advanced machine learning and AI-based techniques. This figure categorizes key challenges, techniques, and innovations, demonstrating the integration of domain knowledge with data-driven approaches, as well as the current trends aimed at enhancing diagnostic accuracy and efficiency. The following subsection discusses these traditional and statistical methods, their applications, challenges, and the necessity for innovation in this domain.

3.1 Traditional and Statistical Methods

Traditional and statistical methods have long been essential in fault diagnosis, providing tools for identifying and mitigating faults within complex systems by relying on historical data and statistical models. However, these methods face challenges due to the high cost and difficulty of acquiring sufficient labeled data for diverse operational conditions, making retraining from scratch impractical [37]. They often assume linear and stationary vibration signals, which is not valid due to their inherent nonlinear and non-stationary nature [38]. This limitation is particularly evident in supervised bearing

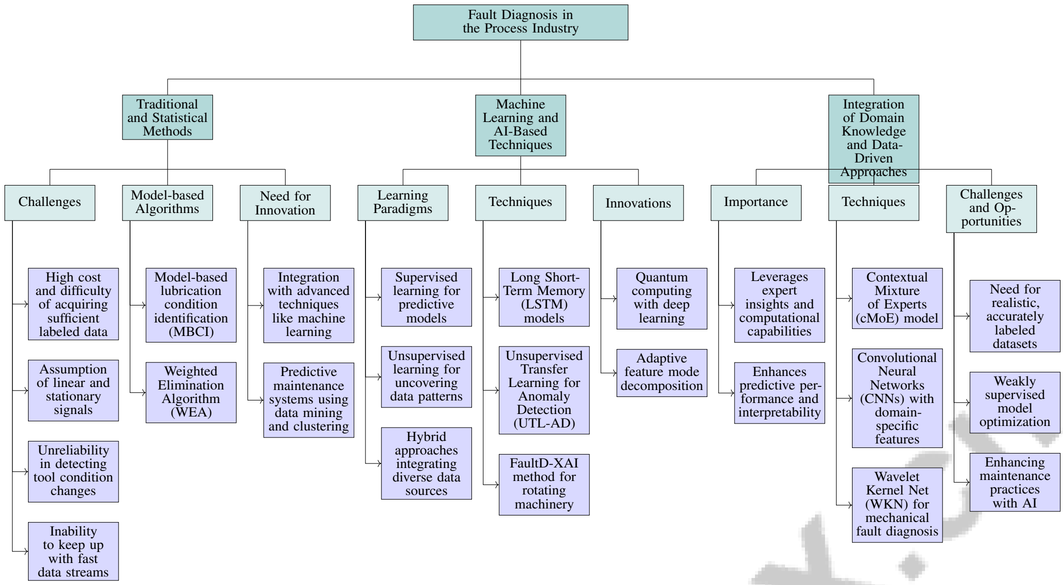


Figure 2: This figure illustrates the hierarchical structure of fault diagnosis methodologies in the process industry, highlighting the evolution from traditional and statistical methods to advanced machine learning and AI-based techniques, and the integration of domain knowledge with data-driven approaches. Key challenges, techniques, and innovations are categorized to demonstrate the progression and current trends in enhancing diagnostic accuracy and efficiency.

fault diagnosis, heavily reliant on extensive labeled datasets, which can be both time-consuming and infeasible [39].

Traditional Tool Condition Monitoring (TCM) methods in machining processes have been criticized for their unreliability in detecting tool condition changes during complex operations [39]. This necessitates the development of more adaptable techniques for dynamic manufacturing environments. Existing analytics systems' inability to keep up with fast data streams, resulting in delayed insights and control actions, exacerbates these challenges [17].

Model-based algorithms within traditional frameworks show promise in enhancing fault diagnosis. For instance, the model-based lubrication condition identification (MBCI) method utilizes rotor vibration data to identify lubrication conditions, addressing some limitations of traditional methods [23]. The Weighted Elimination Algorithm (WEA) seeks a maximal, calculable matching of minimum cost in a weighted bipartite graph representing relationships between model constraints and variables [40].

Despite advancements, traditional methods still face obstacles in data collection and detailed diagnostics, hindering effective monitoring in the process industry [11]. Innovative approaches are critical, as traditional methods alone are insufficient for modern industrial environments. The evolution of predictive process monitoring methods, categorized by prediction types, input data, and algorithm families, exemplifies the shift toward more adaptable diagnostic frameworks [41].

While traditional statistical methods have laid a robust foundation, their limitations—such as reliance on specific data assumptions and hypothesis testing challenges—highlight the need for integrating advanced techniques like machine learning. Modern methodologies, including predictive maintenance systems leveraging data mining and clustering techniques, enhance fault detection by managing contemporary industrial complexities. Intelligent fault diagnosis frameworks, supported by natural language processing and transfer learning, significantly improve system adaptability and efficacy, leading to more reliable maintenance practices and reduced downtime [13, 11, 42, 12, 35].

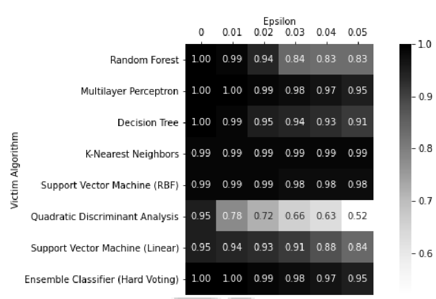
3.2 Machine Learning and AI-Based Techniques

Machine learning (ML) and AI-based techniques have transformed fault diagnosis in the process industry, offering sophisticated solutions that improve diagnostic accuracy and efficiency. Techniques employed in Digital Twins (DTs) development include supervised, unsupervised, and hybrid learning paradigms. Each paradigm offers unique advantages in addressing complex industrial challenges such as process monitoring and predictive control. Supervised learning is crucial for creating predictive models, while unsupervised learning uncovers hidden data patterns. Hybrid approaches enrich modeling capabilities by integrating diverse data sources and contextual knowledge, essential for navigating the rapidly evolving industrial landscape [43, 19, 35].

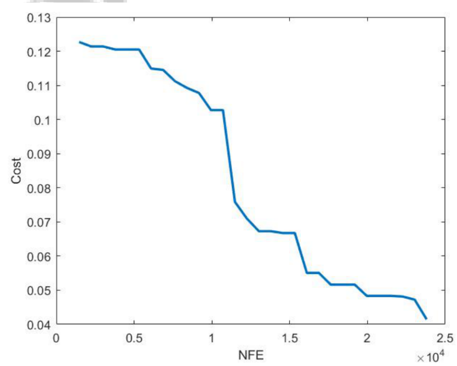
Supervised learning methods, like Long Short-Term Memory (LSTM) models, provide robust frameworks for KPI prediction and fault diagnosis, particularly effective in adapting to time-varying data [44]. Unsupervised approaches, such as the Unsupervised Transfer Learning for Anomaly Detection (UTL-AD) method, enhance detection capabilities by aligning healthy data distributions from different units [8]. The FaultD-XAI method integrates synthetic data generation and explainable AI techniques, enhancing fault diagnosis in rotating machinery [27].

Hybrid approaches, like quantum computing with deep learning, advance fault diagnosis by efficiently extracting features from normal and faulty operations [2]. Adaptive feature mode decomposition techniques, optimized using algorithms like the artificial hummingbird algorithm (AHA), offer improved diagnostic performance through enhanced feature extraction [38].

Overall, ML and AI-based techniques provide robust, adaptive solutions addressing modern industrial operations' dynamic nature. These advancements significantly enhance fault detection accuracy, improving maintenance efficiency, process sustainability, and workplace safety. Innovations leverage machine learning and natural language processing to optimize diagnostic systems using digitized fault descriptions and domain-specific knowledge, increasing operations' reliability and efficiency. In mining conveyor belt operations, novel pattern recognition approaches demonstrate superior performance in identifying mechanical failures and optimizing production cycles, supporting targeted preventive maintenance strategies [31, 35].



(a) The image shows a heat map of the accuracy of various machine learning algorithms on a dataset with different values of epsilon.[45]



(b) The graph depicts the relationship between the cost and the number of function evaluations (NFE) for a given dataset.[46]

Figure 3: Examples of Machine Learning and AI-Based Techniques

As shown in Figure 3, in fault diagnosis within the process industry, integrating machine learning and AI-based techniques offers enhanced accuracy and efficiency in identifying and addressing anomalies. The example highlights two visualizations underscoring these techniques' capabilities. The first is a heat map illustrating various machine learning algorithms' accuracy—such as Random Forest, Multilayer Perceptron, Decision Tree, K-Nearest Neighbors, and Support Vector Machines—across different epsilon values, crucial in adversarial machine learning contexts. This aids in understanding how algorithm performance varies with epsilon changes, providing insights into robustness and reliability. The second visualization shows the relationship between cost and the number of function evaluations (NFE), showcasing how cost diminishes as NFE increases. This demonstrates the optimization potential of machine learning algorithms in reducing operational costs while maintaining or improving diagnostic accuracy. These examples encapsulate AI and machine learning's transformative impact in refining fault diagnosis processes, ensuring more resilient and cost-effective industrial operations [45, 46].

3.3 Integration of Domain Knowledge and Data-Driven Approaches

Integrating domain knowledge with data-driven approaches is crucial for effective fault diagnosis in the process industry, facilitating advanced models that harness expert insights and computational capabilities. By leveraging digitized fault descriptions and work orders from domain experts, alongside advancements in natural language processing, these models achieve improved accuracy and adaptability in diverse operational environments. For example, the Contextual Mixture of Experts (cMoE) model incorporates process knowledge during learning, enhancing predictive performance and interpretability in real-world applications like quality prediction in sulfur recovery and polymerization processes [43, 35]. This synergy is crucial for addressing industrial systems' complexities and nonlinearities, enhancing fault detection processes' accuracy and interpretability.

Domain knowledge provides a deep understanding of system behavior, facilitating models that accurately reflect underlying processes and fault scenarios. This knowledge is essential for constructing digital twins and simulation models replicating normal and failure conditions, generating valuable training data for fault diagnosis [47]. Data-driven approaches complement this by employing advanced machine learning techniques to analyze vast operational data, identifying patterns and anomalies indicative of faults. AI techniques, renowned for high classification accuracy, automate feature extraction processes, improving fault diagnosis efficiency [48].

Integrating Convolutional Neural Networks (CNNs) with domain-specific features exemplifies this approach, where CNN-based feature extractors pair with domain critics utilizing Wasserstein distance to learn invariant features across domains [49]. This enhances diagnostic models' robustness by ensuring extracted features remain consistent across operational conditions. Adaptive feature mode decomposition techniques, optimized through algorithms like the artificial hummingbird algorithm, further improve feature extraction and fault identification in noisy environments [38].

The combination of CNNs and Long Short-Term Memory (LSTM) networks provides a powerful framework for capturing local features and long-term dependencies in time-series data, enhancing diagnostic accuracy [50]. Interpretable models like the Wavelet Kernel Net (WKN) offer significant advantages in mechanical fault diagnosis, providing enhanced classification accuracy and interpretability compared to traditional methods [51].

Integrating domain knowledge and data-driven methodologies creates a robust framework for fault diagnosis, enhancing condition monitoring systems' effectiveness. These systems leverage automated fault diagnosis techniques, supported by machine learning models, to assist human experts in improving maintenance efficiency, process sustainability, and workplace safety. However, applying intelligent fault diagnosis (IFD) faces challenges such as needing realistic, accurately labeled datasets for model training and validation and transferring models to diverse industrial environments. Recent advancements in natural language processing and digitizing fault descriptions by domain experts provide opportunities to utilize technical language annotations in industrial datasets, facilitating weakly supervised model optimization. The shift towards predictive maintenance (PDM) in Industry 4.0 emphasizes diagnosing multiple faults in rotating machinery, where data-driven approaches and AI can enhance maintenance practices significantly. A systematic literature review highlights multi-fault diagnosis research's current state, identifying key challenges and gaps while proposing AI-grounded solutions for future exploration in this vital field [42, 35]. By leveraging expert insights alongside advanced machine learning techniques, industries can refine diagnostic capabilities, ensuring more reliable and efficient operations.

4 Fault Propagation and Process Monitoring

In order to effectively address the complexities of fault propagation within process systems, it is essential to understand the underlying mechanisms that facilitate the spread of faults across interconnected components. This understanding serves as a foundation for developing robust monitoring strategies that can mitigate the impact of faults and enhance operational reliability. The following subsection delves into the intricacies of fault propagation in process systems, exploring key concepts and methodologies that inform effective diagnostic and monitoring approaches.

4.1 Understanding Fault Propagation in Process Systems

Analyzing the mechanisms of fault propagation within process systems is pivotal for enhancing operational reliability and efficiency. Fault propagation involves the spread of faults through interconnected components and processes, significantly impacting system performance and longevity [5]. In complex systems such as CNC machine tools, the identification of key fault propagation paths is crucial, as these can lead to cascading failures, thereby necessitating robust diagnostic strategies [24]. Similarly, in hydrodynamic bearings, understanding fault propagation mechanisms like oil starvation is essential, as it can lead to significant system failures [23].

The variability in operational conditions and external influences further complicates fault propagation analysis, as seen in applications such as wind turbines, where data-driven online monitoring must account for these factors to effectively manage fault propagation [52]. Advanced methodologies like the Generalized Probabilistic Monitoring Model (GPMM) address the inadequacies of existing deterministic multivariate statistical methods by accounting for additive noise and providing confidence levels in process monitoring, thus enhancing the understanding of fault propagation dynamics [53].

Furthermore, the integration of adaptive feature mode decomposition techniques in vibration signal analysis, as demonstrated in bearing health assessments, facilitates a deeper understanding of fault propagation by comparing proposed methods against baseline techniques such as EEMD and VMD [38]. The effectiveness of specification-driven predictive business process monitoring methods, which translate high-level task specifications into actionable prediction models, underscores the importance of adaptable strategies in managing diverse fault propagation scenarios [54].

Understanding fault propagation mechanisms is crucial for developing effective diagnostic and monitoring strategies that not only mitigate the impact of faults but also enhance the reliability and longevity of complex process systems. Research indicates that faults can propagate through both inherent and induced dependencies among critical components, significantly affecting system performance and lifetime. For instance, in multi-component systems like CNC machine tools, the key fault propagation paths can shift over time, necessitating adaptive maintenance strategies. By employing advanced modeling techniques, such as multi-layered Markov chains, we can better capture these dynamics and inform proactive measures that ensure sustained operational success across various industrial applications. [55, 24]. By leveraging advanced models and integrating expert insights, industries can enhance their ability to predict and manage fault propagation, thereby optimizing system performance and longevity.

4.2 Techniques for Effective Process Monitoring

"Effective process monitoring is essential for enhancing the reliability and efficiency of industrial systems, as it enables early fault detection through advanced predictive and prescriptive techniques, facilitates timely interventions to mitigate risks, and ensures optimal operational performance by analyzing real-time data and historical event logs." [10, 11, 18, 6, 15]. Various advanced techniques have been developed to enhance monitoring capabilities, each addressing specific challenges and offering distinct advantages in complex industrial environments.

One prominent approach involves the use of teacher-student network structures, which are designed to predict both process and quality-relevant variables. This method underscores the importance of effective monitoring in maintaining system integrity by enabling accurate prediction of process outcomes and timely interventions [56]. Additionally, clustering-based predictive process monitoring frameworks offer early warnings for potential compliance violations, highlighting the necessity of continuous oversight to detect faults before they escalate [57].

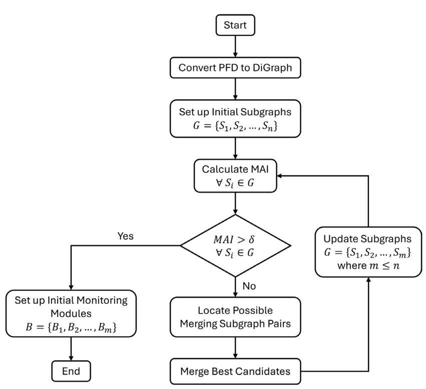
Real-time data analytics platforms, such as RT-DAP, are integral to effective process monitoring. These platforms integrate real-time data streaming, storage, and analytics to support immediate decision-making in industrial processes, thereby enabling the rapid identification and resolution of process deviations [17]. The use of such platforms ensures sustained operational performance by providing timely insights into process anomalies.

The computation of generalized Jensen-Shannon Divergence is another robust technique used to assess deviations in dynamic systems, offering a method for detecting anomalies and maintaining process stability [58]. This approach is complemented by mixed EWMA-CUSUM charts and other memory-based process monitoring techniques, which are evaluated based on their statistical performance in steady-state conditions [59].

Moreover, the integration of probabilistic calculations, such as those used in fatigue reliability and life cycle cost evaluations, can be incorporated into process monitoring techniques to enhance predictive accuracy and reliability [60]. The Control-aware Process Monitoring (CAPM) method exemplifies effective monitoring by decomposing complex processes into modules based on material flows and control pairs, facilitating precise fault detection and identification [11].

The strengths of existing research include the development of more sensitive monitoring techniques that can leverage auxiliary information to improve control chart performance [29]. Furthermore, the PPFA approach employs a state-space model to represent the dynamics of latent variables influenced by measurement noise, enhancing the robustness of process monitoring systems [28].

Overall, effective process monitoring relies on a combination of advanced techniques, including predictive modeling, real-time data analytics, probabilistic assessments, and modular decomposition. By integrating advanced methods such as intelligent fault diagnosis (IFD), predictive and prescriptive process monitoring, and on-device anomaly detection, industries can significantly enhance their monitoring capabilities. These approaches facilitate early fault detection through automated analysis and interventions, leveraging data-driven insights and natural language processing for improved model accuracy. Consequently, organizations can achieve sustained operational excellence by optimizing maintenance efficiency, ensuring workplace safety, and effectively managing production cycles. [10, 6, 31, 15, 35]



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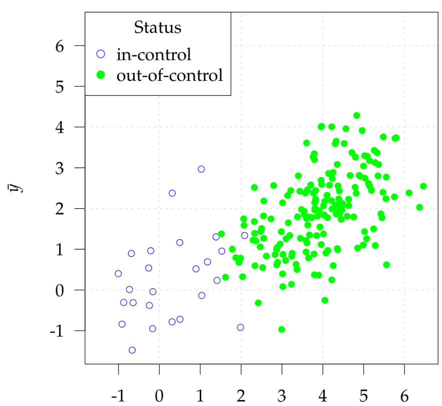

(b) The image shows a scatter plot with two different groups of data points, labeled "in-control" and "out-of-control," plotted against a variable labeled "y."[29]

Figure 4: Examples of Techniques for Effective Process Monitoring

As shown in Figure 4, In the realm of process monitoring, understanding and managing fault propagation is crucial for maintaining system efficiency and safety. The example provided illustrates techniques for effective process monitoring through the lens of data visualization. The scatter plot serves as a key tool in this context, showcasing two distinct groups of data points labeled "in-control" and "out-of-control." This visual representation helps in differentiating between normal operational states and potential anomalies. The plot is structured on a grid, with both axes ranging from -1 to 6, providing a clear 2D space for analysis. The "in-control" data points are depicted as green circles, while the "out-of-control" data points are shown as blue circles. Such visual techniques are instrumental in quickly identifying deviations from expected behavior, thereby facilitating timely interventions and enhancing the overall process monitoring strategy. [**?**]villagomez2024faultdetectionidentificationusing,saleh2021reviewcritiqueauxiliaryinformationbased)

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4.3 Data-Driven Methods for Enhanced Fault Detection

Data-driven methods have become integral to enhancing fault detection accuracy and efficiency in the process industry, leveraging advanced machine learning techniques and comprehensive datasets. These methods address the complexities and dynamic nature of modern industrial systems, providing robust frameworks for identifying faults. A notable approach is the integration of quantum-assisted generative and discriminative training, which enhances feature extraction and classification performance, thereby addressing the limitations of traditional statistical methods [2].

The Unsupervised Transfer Learning for Anomaly Detection (UTL-AD) method exemplifies the potential of data-driven techniques by aligning diverse data distributions while preserving sample relationships, thus improving the generalization of anomaly detection across different operational contexts [8]. Similarly, the FaultD-XAI methodology leverages synthetic data to represent various fault conditions, enhancing model learning and interpretability, which is crucial for effective fault diagnosis in complex systems [27].

Incorporating data-driven approaches like the IPAC algorithm, which maintains an updated state-space for conformance checking, further enhances fault detection by leveraging previously computed results. This method exemplifies the continuous adaptation of models to evolving process conditions, thereby improving detection accuracy and efficiency [3]. Additionally, the use of alternative data augmentation techniques enhances model training and performance, as demonstrated in specialized production environments where traditional data collection may be limited [4].

Overall, data-driven methods provide a comprehensive framework for improving fault detection in the process industry. By leveraging advanced machine learning techniques alongside domain-specific insights, intelligent fault diagnosis (IFD) systems enhance operational excellence and reliability across various industries. These systems utilize automated fault diagnosis methods to improve maintenance efficiency, process sustainability, and workplace safety. Recent advancements in natural language processing and weakly supervised learning enable the integration of digitized fault descriptions from domain experts, facilitating the development of realistic datasets for training models. Furthermore, interpretable deep learning methods, such as convolutional neural networks with Grad-CAM visualizations, enhance trust in model predictions by providing clear insights into feature importance. The implementation of real-time anomaly detection approaches in critical operations, such as mining conveyor belts, further exemplifies how these methodologies can effectively identify and mitigate potential faults, ultimately supporting targeted preventive maintenance and optimizing production processes. [31, 13, 36, 35]

4.4 Challenges in Monitoring Complex Systems

Monitoring complex systems within the process industry presents numerous challenges, primarily due to the intricate nature of these systems and the dynamic environments in which they operate. One significant challenge is the computational complexity associated with larger systems, which can hinder the practical implementation of monitoring algorithms despite advancements in computational techniques [61]. This complexity often necessitates the development of more efficient algorithms capable of processing vast amounts of data in real-time, ensuring timely fault detection and system reliability.

Another challenge lies in the validation of predictive process monitoring methods, which are frequently not tested across a broad spectrum of real-world scenarios. This lack of comprehensive validation limits the applicability and generalizability of these methods in diverse industrial contexts, potentially reducing their effectiveness in practice [15]. To address this issue, there is a need for more robust validation frameworks that encompass a wide range of operational conditions and system configurations.

Furthermore, current studies often rely on flawed performance metrics, which fail to provide a clear justification for the adoption of complex monitoring techniques over simpler, traditional methods [59]. This reliance on inadequate metrics can lead to the unnecessary complexity of monitoring systems, resulting in increased computational demands without a corresponding improvement in performance. Therefore, it is essential to develop more accurate and relevant performance metrics that can effectively evaluate the benefits of advanced monitoring techniques.

To overcome these challenges, several potential solutions can be proposed. The integration of advanced data-driven approaches, such as machine learning (ML) and artificial intelligence (AI), significantly enhances the efficiency and accuracy of monitoring systems by utilizing large datasets to detect patterns and anomalies. This is particularly crucial in fields like predictive process mining, where the interpretability of ML models is essential for understanding complex business process data. Recent studies highlight the importance of developing interpretable models and employing post-hoc explanation techniques to navigate the "black-box" nature of these technologies. Furthermore, in the context of Industrial Internet of Things (IoT) data, effective anomaly detection and explanation methods are urgently needed, as they help identify and clarify anomalies within multivariate time series data. By leveraging domain knowledge and employing innovative algorithms, researchers have demonstrated that it is possible to achieve high-quality explanations for detected anomalies, thereby improving the reliability and transparency of intelligent monitoring systems. [14, 62]. Second, the development of scalable algorithms that can adapt to the size and complexity of industrial systems is crucial for ensuring real-time monitoring capabilities. Finally, fostering collaboration between academia and industry can facilitate the creation of more comprehensive validation frameworks, ensuring that monitoring methods are rigorously tested and applicable across various real-world scenarios.

By effectively addressing the challenges associated with predictive and prescriptive process monitoring and implementing tailored solutions, the process industry can markedly improve its monitoring capabilities. This enhancement will lead to increased reliability and efficiency of complex systems operating in dynamic environments, as organizations will be better equipped to leverage process execution data for identifying performance bottlenecks, optimizing resource utilization, and making informed operational decisions. Additionally, the adoption of advanced intervention policies will allow for timely responses to potential issues, thereby mitigating negative outcomes and fostering continuous improvement. [10, 63, 6, 16, 15]

4.5 Emerging Trends in Fault Propagation Analysis

Emerging trends in fault propagation analysis are increasingly focusing on the integration of advanced technologies and methodologies to enhance the accuracy and efficiency of fault detection and management in industrial systems. One prominent trend is the use of digital twins, which serve as virtual replicas of physical systems, enabling real-time monitoring and predictive analysis of fault propagation. Digital twins facilitate a deeper understanding of system dynamics and fault interactions, allowing for more precise identification of fault pathways and potential failure points [47].

The application of transfer learning methods is also gaining traction as a means to improve the performance of fault propagation models on real-world data. By leveraging knowledge gained from similar systems or conditions, transfer learning can enhance the adaptability and robustness of fault analysis models, reducing the need for extensive retraining and enabling quicker deployment in diverse industrial settings [47].

Furthermore, the integration of machine learning and AI techniques continues to revolutionize fault propagation analysis. These advanced technologies are essential for effectively managing and analyzing the vast amounts of data generated by the Industrial Internet of Things (IIoT). They enable the detection of intricate patterns within multivariate time-series data, facilitating real-time condition monitoring and predictive analysis of potential fault scenarios, such as estimating remaining useful life (RUL). Furthermore, they address the critical need for anomaly detection and explanation in IoT data, employing innovative methods that leverage domain knowledge and constraint violations to provide comprehensive insights into identified anomalies. This capability not only enhances fault diagnosis but also improves the overall quality of data management in industrial applications. [64, 62]. The use of explainable AI models is particularly noteworthy, as they offer transparency in decision-making processes, thereby increasing trust and facilitating the adoption of AI-driven fault analysis solutions in industry.

Overall, the convergence of digital twins, transfer learning, and advanced AI methodologies represents a significant advancement in fault propagation analysis. These trends not only enhance the predictive capabilities of fault management systems but also contribute to the development of more resilient and efficient industrial operations. As research in process optimization and predictive modeling advances, significant enhancements in model accuracy and applicability are expected, particularly through the integration of process knowledge and generative artificial intelligence (GenAI). These developments are likely to transform fault propagation analysis in the process industry by enabling organizations to leverage comprehensive process-related data for improved decision-making, better understanding of operational inefficiencies, and enhanced predictive performance. Specifically, methodologies such as the Contextual Mixture of Experts (cMoE) will facilitate the incorporation of operators' contextual insights, while GenAI models will provide versatile tools for optimizing processes and monitoring performance, ultimately driving continuous improvement and innovation in fault propagation analysis. [16, 43, 65]

5 Anomaly Detection Techniques

5.1 Advanced Algorithms for Anomaly Detection

Advanced algorithms significantly enhance anomaly detection in the process industry by improving predictive accuracy and diagnostic efficiency. Machine learning techniques, including Generative Adversarial Networks (GANs), generate synthetic training data to bolster model robustness against anomalies [4]. Nonparametric data depth-based control charts provide adaptable solutions across various industrial settings, enhancing detection capabilities [44]. Integrating explainability techniques with unsupervised anomaly detection improves fault interpretability, crucial for understanding root causes in complex systems [32]. Complementary data integration from multiple units enhances detection accuracy under varying operational conditions [8]. The Iterative Refinement Process (IRP) systematically improves training data quality, refining model accuracy in dynamic environments [66]. Real-time quantification of non-conformance through online monitoring algorithms provides timely insights into process deviations [3]. Quantum computing-assisted models, such as the QC-DL-FD, exhibit superior fault detection rates, showcasing quantum algorithms' potential in feature extraction [2]. Online-adaptive methods demonstrate high accuracy in identifying assembly defects, emphasizing adaptive algorithms' effectiveness in dynamic manufacturing contexts [67]. The Dynamic Probabilistic Predictable Feature Analysis (PPFA) method enhances anomaly detection by providing probabilistic interpretations of dynamic characteristics, addressing variability and uncertainty in industrial processes [28]. Collectively, these advanced algorithms integrate machine learning and AI techniques to facilitate rapid anomaly detection and resolution, particularly in mining conveyor belt systems, enhancing operational reliability and supporting preventive maintenance [14, 68, 31].

5.2 Challenges and Opportunities in Anomaly Detection

The process industry faces several challenges in anomaly detection due to industrial systems' complexity and variability. Computational intensity limits existing methods' applicability in dynamic environments, requiring substantial resources and training time, especially in sectors like mining [31]. The black-box nature of many models can hinder trust without clear explanations [69]. Misleading data points in training sets can lead to overfitting or false negatives, complicating robust model development [66]. Model-free detectors are susceptible to spoofing attacks, compromising detection accuracy [70]. High noise levels and lack of sensor data standardization further impede detection systems' effectiveness [71]. Delays in detection due to windowing approaches and reliance on user intervention add complexity to monitoring systems [72]. Despite these challenges, opportunities exist to enhance methodologies. Stream-based active learning techniques manage labeling costs while improving classification accuracy [73]. Correlation information through methods like OWMA-TCC effectively detects intermittent faults, improving sensitivity and reducing false alarms [26]. Data fusion techniques present further avenues for improving capabilities [71]. Systems leveraging expert knowledge for interpretability enhance reliability and trust in detection frameworks [74]. Addressing challenges such as low-frequency classes and misclassification due to language detection errors is crucial for improving accuracy [75]. Models like FaultD-XAI, utilizing synthetic data for training, reduce dependency on real labeled samples while maintaining high diagnostic performance [27]. Heuristic approaches' scalability for larger networks represents a significant opportunity for enhancing real-time condition monitoring [9]. Integrating advanced algorithms and innovative techniques offers substantial opportunities to enhance accuracy and operational efficiency. Predictive process monitoring advancements empower organizations to analyze execution data effectively, uncover insights, and identify performance bottlenecks. Interpretable machine learning methods facilitate understanding complex models, promoting trust and transparency. Real-time anomaly detection in mining conveyor belt operations identifies mechanical failures, supporting proactive maintenance and optimizing production cycles. These advancements underscore data-driven strategies' potential to transform operational practices within the industry [16, 14, 15, 31]. Addressing challenges and leveraging emerging technologies can significantly enhance capabilities, ensuring more reliable and efficient operations.

5.3 Case Studies and Applications

Method Name	Performance Metrics	Application Contexts	Model Robustness
FADS[76]	Auc Roc	Additive Manufacturing	Diverse Datasets
CWHA[69]	Accuracy, F-score	Predictive Maintenance Systems	Diverse Datasets
ADIA[74]	Classification Accuracy	Aircraft Engine Monitoring	High Classification Accuracy
IRP[66]	Auroc Scores	Industrial Quality Control	Dynamic Threshold Adjustment
OAAD[67]	Accuracy, F1-score	Aircraft Manufacturing	Different Datasets

Table 1: Summary of various anomaly detection methods, their performance metrics, application contexts, and model robustness across different industrial domains. The table highlights the versatility and effectiveness of these methods in scenarios such as additive manufacturing, predictive maintenance systems, aircraft engine monitoring, industrial quality control, and aircraft manufacturing. Each method is evaluated based on specific performance indicators and its ability to handle diverse datasets or achieve high classification accuracy.

Anomaly detection techniques have been effectively implemented across various industrial contexts, demonstrating their effectiveness in identifying and mitigating faults. Table 1 provides a comprehensive overview of anomaly detection methods applied in diverse industrial contexts, detailing their performance metrics, application areas, and robustness. The Feature Anomaly Detection System (FADS), tested on the MVTec Anomaly Detection dataset and a custom dataset of additively manufactured lattices, achieved an average AUC ROC of 0.93, demonstrating robustness in detecting anomalies in complex industrial products [76]. In semi-supervised learning, the HELM model achieved benchmark performance with 99.5

5.4 Integration of Anomaly Detection with Predictive Maintenance

Integrating anomaly detection with predictive maintenance strategies marks a significant advancement in the process industry's ability to preemptively address potential system failures, optimizing operational efficiency and equipment longevity. Anomaly detection systems like FADS localize defects and provide insights into their locations, enabling targeted interventions that prevent minor issues from escalating into major failures [76]. The IRP enhances this integration by adaptively refining datasets, improving models' generalization and reducing sensitivity to noise, ensuring predictive maintenance strategies are based on accurate data, critical for managing complex systems effectively [66]. Furthermore, the online adaptive anomaly detection method demonstrates superior accuracy in identifying defects in dynamic manufacturing settings, underscoring its relevance for real-time predictive maintenance applications [67]. Future research should focus on validating methodologies with real-world labeled data and exploring multivariate techniques to address system complexities [74]. Enhancements in adaptability and robustness, coupled with real-world testing, could significantly bolster these integrated strategies' effectiveness [67]. By leveraging advanced techniques within predictive maintenance frameworks, industries can achieve proactive and efficient maintenance operations, ultimately enhancing system reliability and performance.

6 Condition-Based Maintenance Strategies

6.1 Concept and Advantages of Condition-Based Maintenance

Condition-Based Maintenance (CBM) represents a pivotal shift from traditional time-based approaches, focusing on real-time equipment data to inform maintenance decisions. This data-driven strategy enhances operational efficiency and asset longevity by enabling predictive analytics and continuous monitoring, which preemptively address potential failures and reduce downtime [5]. Unlike fixed schedules, CBM tailors interventions to actual equipment conditions, improving reliability and minimizing costs.

CBM integrates advanced diagnostic and real-time conformance checking techniques, such as Control-aware Process Monitoring (CAPM), which enhance fault detection and origin identification, aligning maintenance actions with equipment status [11]. These parameter-free methods seamlessly integrate into existing systems, supporting real-time decision-making [3]. Techniques like Dynamic Probabilistic Predictable Feature Analysis (PPFA) and synthetic data generation further refine fault detection and adapt to changing industrial conditions [28, 4].

Explainable AI in CBM enhances transparency and understanding of predictive outcomes, crucial for informed interventions and validating monitoring methods. Aligning model explanations with data characteristics fosters trust and precision in decision-making [77, 6]. CBM's proactive approach optimizes maintenance by leveraging real-time sensor and historical data, improving production planning, spare parts management, and system reliability across sectors [43, 33, 34, 15].

6.2 Implementation of Real-Time Data and Predictive Analytics

Implementing real-time data and predictive analytics revolutionizes Condition-Based Maintenance (CBM), enabling timely maintenance actions that reduce downtime and costs. IoT-based prognostics highlight real-time data's role in accurate condition monitoring and maintenance planning [78]. Historical data aids in developing predictive models for anticipating failures and optimizing schedules, as seen in railcar analyses [79]. LSTM frameworks enhance sensor data monitoring, improving anomaly detection and early issue identification [80].

Cost-benefit analysis methodologies, combined with modular dynamic fault tree analysis and Monte Carlo simulations, provide robust frameworks for evaluating the economic viability of real-time data in maintenance strategies [81]. Condition monitoring systems illustrate real-time data's critical role in predicting failures and optimizing schedules [34]. In wind turbine gearboxes, real-time analytics are essential for evaluating and optimizing maintenance strategies [82].

Real-time data integration in multi-component systems, exemplified by multi-stage stochastic maintenance models and Markov decision processes, allows for condition-based maintenance models that account for degradation and shocks. Optimization of maintenance policies under periodic inspections highlights economic and stochastic dependencies, using copula functions and Monte Carlo simulations for optimal intervals [83, 84, 85]. These models enhance planning by accommodating equipment degradation and system dynamics.

Real-time data and predictive analytics in CBM represent a major advancement, enabling proactive operations. Leveraging continuous data streams and advanced models enhances system reliability and efficiency, achieving cost reductions while promoting sustainability. Integrating process knowledge into modeling, as seen in the Contextual Mixture of Experts approach, improves predictive performance and interpretability. Prescriptive Business Process Monitoring techniques transform insights into actionable recommendations, optimizing KPIs and addressing inefficiencies. Statistical process monitoring methods, enhanced by stream-based active learning, facilitate dynamic classification, improving quality management and resource utilization [16, 43, 20, 73].

6.3 Advanced Techniques in Condition-Based Maintenance

Advanced Condition-Based Maintenance (CBM) techniques leverage innovative methodologies to optimize maintenance strategies, reducing costs and enhancing performance. Neural networks, such as the N-CBM approach, improve failure time estimation compared to traditional methods [86]. Piecewise deterministic Markov processes (PDMP) refine CBM by modeling deterministic and stochastic processes, capturing equipment degradation complexities [84].

Combined models assessing degradation processes ensure timely maintenance decisions and optimize resources through continuous monitoring [87]. Supervised learning algorithms predict propulsion system component conditions, enhancing maintenance planning [88]. Stochastic programming within CBM frameworks offers comprehensive analytical models for decision-making, optimizing schedules and reliability [61].

Optimal control-limit policies for CBM balance costs and benefits of maintenance actions, enhancing efficiency by reducing long-term expenses [89]. Real-time analytics and sensor technology reduce downtime and costs, enabling continuous monitoring and timely interventions [90]. The SDHT2 method monitors bearing degradation, providing insights for maintenance planning [91].

Combining fault tree analysis with Monte Carlo simulations assesses maintenance requirements and ROI for CBM strategies, ensuring efficient resource allocation [81]. These techniques enhance predictive accuracy through real-time monitoring, optimizing resources and improving reliability by preventing failures and minimizing downtime [45, 33, 92, 34].

6.4 Challenges and Solutions in Condition-Based Maintenance

Implementing Condition-Based Maintenance (CBM) in the process industry faces challenges due to system complexity and variability. Accurately detecting degradation is hindered by inadequate indicators and historical data integration, leading to suboptimal monitoring [91]. The stochastic nature of failures and operating conditions complicates Remaining Useful Life (RUL) estimation, affecting model selection and data availability [93].

High initial investments deter CBM adoption despite potential savings [81]. Multi-component system complexity and imperfect maintenance actions further complicate adoption [94]. Reliable predictions depend on high-quality sensor data, as inaccuracies affect decisions [34]. CAPM may struggle in dynamic processes with limited control information, reducing effectiveness [11]. CWHA method limitations with complex datasets highlight the need for robust frameworks [69]. Solving Markov Decision Process (MDP) complexities for larger networks may be infeasible with current methods [9].

Solutions include enhancing data quality through robust sensor networks and real-time analytics, establishing data acquisition standards, and developing unified frameworks for diverse machinery [71]. Novel architectures for processing varied sensor data are essential [95]. Knowledge-driven neural network modulation enhances prediction accuracy by aligning training data with background knowledge [96]. Adaptive frameworks optimizing decision-dependent transitions improve reliability. Comprehensive cost-benefit analyses for scheduled and unscheduled maintenance enhance CBM economic viability [89]. Addressing challenges through advanced analytics, robust modeling, and adaptive frameworks optimizes maintenance, reduces costs, and ensures longevity and reliability.

6.5 Data Fusion and Real-Time Monitoring

Data fusion and real-time monitoring optimize maintenance strategies by providing comprehensive equipment health insights and enhancing decision-making. Integrating data from multiple sources, enabled by IoT and cloud computing, offers a holistic view of system conditions, facilitating accurate fault diagnosis and planning. This approach is vital in complex industrial environments, where data-driven decision-making analyzes real-time sensor data to predict failures and optimize strategies, improving performance and reducing downtime [43, 64, 94].

Real-time monitoring enhances data fusion by continuously overseeing equipment performance, enabling early anomaly detection and prompt maintenance. Advanced sensor technologies and analytics platforms like RT-DAP process vast data volumes, improving operational efficiency and supporting CBM strategies by addressing issues before escalation [90, 17]. Continuous monitoring captures transient faults and dynamic behaviors, allowing for dynamic schedule adjustments aligned with actual conditions.

Accurate sensor state estimation is critical, as degradation impacts costs. Precise monitoring and fusion techniques ensure cost-effective strategies [97]. Advanced models incorporating complex dependencies and real-time data enhance decision-making, improving strategy adaptability and effectiveness [83].

The integration of data fusion and real-time monitoring enhances predictive maintenance by improving fault diagnosis accuracy, facilitating timely interventions, and optimizing strategy effectiveness by adapting to data quality, reducing costs, and enhancing reliability and safety. Informed decisions become economically viable and operationally efficient [98, 71]. Leveraging these technologies enhances reliability and efficiency, improving performance and reducing costs.

6.6 Emerging Trends in Predictive Maintenance

Emerging trends in predictive maintenance focus on advanced technologies and methodologies to enhance strategy accuracy, efficiency, and applicability. IoT integration with predictive frameworks facilitates real-time data acquisition and analysis, enabling comprehensive and timely decisions. Cost-effective sensor technologies enable widespread deployment, reducing costs and improving efficiency [90].

Advancements in predictive analytics algorithms enhance maintenance by processing large data volumes to identify patterns and predict failures with greater accuracy, optimizing schedules, reducing downtime, and extending asset lifespans [90]. Scalability of solutions for larger networks is crucial for managing complex systems, ensuring strategies remain effective as demands grow [9]. Exploring degradation parameters' impact on strategies provides insights for optimization, enhancing adaptability and robustness [9].

These trends highlight predictive maintenance's potential to transform operations with accurate, efficient, and scalable solutions for managing equipment health. As research advances, improvements in sensor technologies, analytics, and scalability are anticipated. These advancements will enhance strategies, enabling real-time data use for condition-based maintenance, improving monitoring and control, increasing reliability, reducing costs, and optimizing resource utilization. Integrating process analytics and cloud-assisted IoT platforms empowers businesses to identify bottlenecks and make data-driven decisions, driving continuous improvement [16, 90, 99, 15].

7 Integration and Future Directions

7.1 Integration of Fault Diagnosis and Maintenance Strategies

Integrating fault diagnosis with maintenance strategies is essential for enhancing operational reliability and efficiency in industrial settings. This synthesis of methodologies addresses system complexities, forming a cohesive maintenance strategy. Quantum computing and deep learning significantly enhance fault diagnosis by efficiently extracting features from both normal and faulty operations, leveraging quantum algorithms to improve diagnostic accuracy and speed [2]. The integration of prescriptive process monitoring further enhances these strategies, allowing for better anticipation of failures and optimization of maintenance interventions in complex environments [6].

Incorporating the IPAC method into maintenance strategies strengthens system health management by improving fault detection and planning [3]. Data augmentation, when combined with traditional fault diagnosis, enhances operational reliability and efficiency. Future research should focus on multi-source alignment strategies to leverage fleet-wide operational experiences, improving anomaly detection adaptability [8]. Refining the Dynamic Probabilistic Predictable Feature Analysis (PPFA) model could extend its use to more complex processes, bolstering integrated maintenance strategies [28].

By employing integrated approaches such as predictive process monitoring and analytics, industries can achieve operational excellence through data-driven insights, effectively addressing performance bottlenecks, reducing maintenance costs, and ensuring long-term reliability [16, 15]. This strategic integration not only optimizes resource allocation but also enhances system resilience, fostering more intelligent and responsive maintenance frameworks.

7.2 Emerging Technologies and Future Directions

Emerging technologies in fault diagnosis and maintenance strategies promise significant improvements in operational reliability and efficiency. Self-supervised and federated learning methods are advancing model generalization and adaptability across diverse industrial settings, enhancing diagnostic robustness while preserving data privacy [100]. IoT and big data analytics are revolutionizing maintenance systems by offering real-time insights and predictive capabilities, facilitating continuous equipment health monitoring and timely maintenance interventions [94].

The exploration of explainable AI (XAI) within Predictive Process Monitoring (PPM) is crucial for improving decision-making, with future research focusing on standardized evaluation metrics and interactive explanation tools. Advancing models with richer statistical data and exploring additional industrial scenarios will enhance fault propagation understanding, leading to comprehensive models for fault management [55]. Enhancing TLS frameworks and developing improved TLP models can overcome traditional supervised learning limitations, boosting fault diagnosis efficacy [35].

AI-generated, for reference only.

Real-time data analytics should focus on extending database designs for heterogeneous data formats and incorporating resource-aware features into processing frameworks [17]. Addressing uncertainties in parameter estimation and exploring dependencies beyond economic factors are vital for refining condition-based maintenance models for multi-component systems [92].

Leveraging emerging trends in process analytics, predictive monitoring, and prescriptive interventions, industries can enhance operational excellence, significantly reduce maintenance costs, and ensure long-term reliability. These advancements enable actionable insights from process execution data, optimizing resource utilization and improving process performance through real-time decision-making and proactive interventions [16, 6, 10, 15]. Consequently, these technologies pave the way for more intelligent, adaptive, and efficient maintenance strategies, enhancing industrial operations' sustainability and resilience.

8 Conclusion

This survey elucidates the critical importance of fault diagnosis and maintenance strategies in the process industry, highlighting their significant impact on ensuring system reliability and enhancing operational efficiency. The integration of advanced technologies, particularly deep learning and AI-based frameworks, has markedly transformed maintenance strategies, offering new dimensions in fault detectability and system robustness. The systematic approach to these practices, as demonstrated by recent methodologies, underscores the potential of real-time applications to bolster system reliability.

Our findings reveal that while traditional methods laid the groundwork for Intelligent Fault Diagnosis (IFD), the infusion of machine learning techniques has significantly improved predictive accuracy. The emphasis on temporal stability in predictive process monitoring further illustrates the substantial advancements brought about by state-of-the-art technologies, enhancing both reliability and efficiency.

The necessity for systematic approaches is further underscored by the development of robust prediction models tailored to diverse business process monitoring tasks. The incorporation of explainable AI techniques into automated systems is paramount, fostering transparency and trust, which are crucial for effective maintenance strategies.

Future research endeavors should aim to refine methodologies across various machinery types and delve deeper into machine learning techniques to augment the precision of remaining useful life predictions. The potential for considerable cost savings through early fault detection accentuates the imperative to embrace cutting-edge technologies and drive organizational transformation.

In conclusion, the survey affirms the transformative potential of advanced technologies in the process industry, paving the way for more intelligent, adaptive, and efficient maintenance strategies. By leveraging these technologies, industries can achieve superior operational excellence, reduce maintenance costs, and maintain sustained system reliability.

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