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Cutting-Edge AI Approaches with MAS for PdM in Industry 4.0: Challenges and Future Directions

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Abstract

Integrating Artificial Intelligence (AI) within Industry 4.0 has propelled the evolution of fault diagnosis and predictive maintenance (PdM) strategies, marking a significant shift towards smarter maintenance paradigms in the mechatronics sector. With the advent of Industry 4.0, mechatronic systems have become increasingly sophisticated, highlighting the critical need for advanced maintenance methodologies that are both efficient and effective. This paper delves into the confluence of cutting-edge AI techniques, including machine learning (ML) and deep learning (DL), with multi-agent systems (MAS) to enhance fault diagnosis precision and facilitate PdM in the context of Industry 4.0. Specifically, we explore the use of various ML models, including Support Vector Machines (SVMs) and Random Forests (RFs), and DL architectures like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which have been effectively oriented to analyses complex industrial data. Initially, the study examines the progress in AI algorithms that accelerate fault identification by leveraging data from system operations, sensors, and historical trends. AI-enabled fault diagnosis rapidly detects irregularities and discerns the fundamental causes, thereby minimizing downtime and enhancing system reliability and efficiency. Furthermore, this paper underscores the adoption of AI-driven PdM approaches, emphasizing prognostics that predict the Remaining Useful Life (RUL) of machinery. This predictive capability allows for the strategic scheduling of maintenance activities, optimizing resource use, prolonging the lifespan of expensive assets, and refining the management of spare parts inventory. The tangible advantages of employing AI for fault diagnosis and PdM are showcased through a case study from authentic mechatronics implementations. This case study highlights successful implementations, documenting real-world challenges such as data integration issues and system interoperability, and elaborates on the strategies deployed to navigate these obstacles. The results demonstrate improved operational reliability and cost savings and shed light on the pragmatic considerations and solutions that facilitate the adoption of AI and MAS in industrial applications. The paper also navigates the challenges and prospective research avenues in applying AI within the mechatronics domain of Industry 4.0, setting the stage for ongoing innovation and exploration in this transformative domain.

Keywords: Artificial Intelligence (AI), multi-agent systems (MAS), machine learning (ML), predictive maintenance (PdM), Industry 4.0

1. Introduction

At the forefront of Industry 4.0, the mechatronics industry (MI) is at a pivotal juncture, facing the dual challenges of ensuring equipment reliability and optimizing maintenance operations. PdM stands as a cornerstone in this advanced manufacturing revolution, offering a strategic approach to reduce operational interruptions and extend the lifespan of machinery [1]. This study explores the transformative impact of AI on fault diagnosis and PdM within the mechatronics field, marking a transition towards more intelligent maintenance solutions.

The advent of sophisticated mechatronic systems across various sectors underscores the need for maintenance strategies that are not only efficient but also proactive and adaptable. AI technologies, including ML and DL, are at the heart of this evolution, offering unprecedented accuracy in fault diagnosis and enabling effective PdM strategies [2]. This study will dissect the integration of AI and MAS in the MI, underscoring their pivotal roles in enhancing diagnostic precision and PdM capabilities.

The journey towards realizing Industry 4.0's full potential begins with the accumulation of intelligent data analysis. industrial internet of things (IIoT) is critical in this transformation, facilitating the interconnectivity of machines and computing systems. This interrelation provides a holistic, real-time view of manufacturing operations, laying the

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groundwork for smart factories [3]. By leveraging the synergy between AI, MAS, and IIoT, this study aims to emphasize the innovative approaches to fault diagnosis and PdM, paving the way for more resilient and efficient manufacturing environments.

The integration of AI in fault diagnosis and PdM is revolutionizing mechatronics, a field that stands at the confluence of electronics, mechanics, and computing. AI, particularly through ML and DL, brings a new level of precision in identifying and predicting potential system failures before they manifest [4]. In the area of MI, this is not just theoretical but is applied in various forms; such as, vibration analysis using DL for early detection of anomalies in rotating machinery or AI-enabled visual inspection systems that improve quality control on production lines [5].

To ground this discussion in real-world practice, our study will discuss case studies such as the implementation of SVM model in monitoring and maintaining robotic assembly lines, which showcase increased uptime and reduced maintenance costs [6]. Another example will include the deployment of AI in sensor-rich environments, which allows for advanced diagnostics and efficiency in complex automated systems using long short term memory (LSTM) [7]. These industry examples illustrate the tangible impacts of AI in MI. The paper explores them throughout to demonstrate the practical implications of AI integration in enhancing fault diagnosis and PdM strategies.

1.1. Industry 4.0: A Digital Revolution

The last decade has seen a profound transformation in the manufacturing sector, heralded by the advent of Industry 4.0. This shift is characterized by the seamless integration of various cutting-edge technologies such as Cloud and Edge computing, AI, ML, DL, big data analytics (BDA), cyber-physical systems (CPS), advanced connectivity solutions like 5G and Wi-Fi 6, the internet of things (IoT), sensor technologies, robotics, and digital twins (DT) [8], as illustrated in Figure 1. These pillars include advanced automation and robotics, where cobots (collaborative robots) work alongside human operators, improving efficiency while introducing challenges in human-machine interface design. The IoT is another pillar, enabling devices to communicate seamlessly; however, it raises issues regarding data security and integration of disparate systems. BDA provides insights into massive volumes of production data, driving decisions in real time, but it presents hurdles in data processing and management. Cloud Computing offers scalable resources for storage and computation, though it necessitates robust network infrastructure to prevent latency. Cybersecurity becomes increasingly vital as interconnected systems become potential targets for cyber threats and attacks, necessitating sophisticated protection strategies. Extended reality (XR) is also crucial, offering immersive training and simulation, which must overcome user adoption and hardware limitations. Additive manufacturing, or 3D printing, opens new avenues for on-demand production, confronting material and process reliability concerns [9], [10]. Edge computing enhances PdM by processing data directly at the collection source, significantly reducing latency and bandwidth, which is critical for real-time operational adjustments [11]. Real-time analytics further complements this by providing instant data analysis, enabling timely decisions that prevent equipment failures and optimize manufacturing processes [12]. These technological advancements are at the core of the digitalization of manufacturing processes, significantly altering conventional manufacturing paradigms to enhance operational efficiency, flexibility, and responsiveness. This evolution fosters the emergence of more connected and intelligent factories, underlining the necessity to examine the strategies adopted by manufacturers, the integration challenges they face, and the emerging trends shaping the future of manufacturing [13], [14], [15].

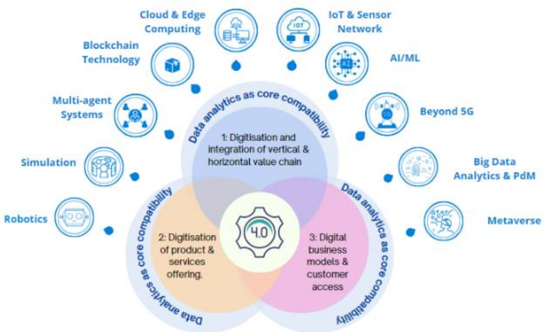

Figure 1. The essential pillars of Industry 4.0 (adopted from [9])

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The power of Industry 4.0 to propel the industrial sector towards a future of enhanced machine control, autonomous information sharing, and interoperable production systems is what makes it so fundamental [16]. Attaining unmatched connectivity and integration in manufacturing environments is a crucial objective of this revolutionary era, as it permits the creation of enormous data landscapes via machine monitoring and sensor deployment [17]. However, there are various challenges in the way of the shift to Industry 4.0. Because different manufacturers produce different products, current manufacturing frameworks frequently struggle with challenges related to centralized control systems and data heterogeneity [18], [19]. Such centralized structures may instigate compatibility problems with current legacy systems and hinder the easy incorporation of Industry 4.0 technology [20]. Moreover, the heterogeneity of data generated by various vendors makes it more difficult to standardize communication and accomplish interoperability within the digital ecosystem, which causes serious obstacles to the smooth implementation of Industry 4.0 activities [21]. To address these challenges, strategies such as implementing middleware that standardizes data formats and adopting data virtualization techniques can be effective [22]. These solutions facilitate data integration, enabling AI models to perform optimally across diverse systems and enhancing overall system interoperability. Moreover, these approaches ensure AI applications can access and analyses necessary data without direct system integration, promoting better decision-making and operational efficiency [23].

1.2. PdM

Predictive maintenance (PdM) has emerged as a key tactic in industries such as power plants, transportation networks, public utilities, and emergency services where operational reliability is crucial [24]. The long-term planning of many operational tasks, including production, maintenance, and inventory management, depends on this technique [25]. Nevertheless, its wide range of applications, PdM implementation may be constrained by logistical and technological issues [26], [27]. Since equipment failures can cause major disruptions such as schedule delays, delivery setbacks, and the requirement for unscheduled staff overtime, PdM is especially important in production contexts [1], [27]. Figure 2 demonstrates the effectiveness of ML/DL in PdM for industrial infrastructure. It outlines two main categories of ML/DL-based PdM solutions: supervised, which uses datasets containing information on past failures, and unsupervised, which relies on datasets with logistics and process information but lacks specific maintenance data.

PdM is distinguished by the variety of technologies it employs to facilitate prompt maintenance actions that are predicated on ongoing system monitoring [28]. Together with visual cues of equipment degradation, this monitoring makes early fault diagnosis possible by utilizing previous data and ML/DL techniques [29], [30]. In line with Industry 4.0’s tenets, PdM aims to lower maintenance expenses, accomplish zero-waste production, and reduce the likelihood of significant failures [31]. The contrast between data-driven and experience-driven maintenance methodologies emphasizes how maintenance tactics have changed in the context of Industry 4.0 [32], [33].

Figure 2. ML/DL-based industrial infrastructure for PdM (adopted from [24])

Data is the foundation of the PdM methodology. An enormous amount of operational data is produced by the deployment of sensors and IIoT integration. These data, which frequently include alerts and cautions suggestive of anomalous equipment circumstances, play a crucial role in evaluating the state and health of machinery under observation [6]. The PdM area has made extensive use of ML and DL techniques because of their capacity to handle multivariate and high-dimensional datasets [34]. ML techniques are adept at detecting and classifying equipment’s faulty behaviors, as well as predicting time to failure using intelligent predictive algorithms.

A significant aspect of PdM is the prediction of the RUL of a component. By estimating RUL, the anticipated time of failure can be deduced, allowing Maintenance & Repair Operations (MRO) to be scheduled optimally. The use of historical data is crucial in generating accurate predictions from a PdM strategy. Therefore, Run-to-failure (R2F) and preventative maintenance (PvM) strategies must be previously implemented to accumulate data for PdM modelling [6], [35], [36], [37].

1.3. MAS

Multi-agent system (MAS) in smart manufacturing is an emerging technology, which has not been widely used by manufacturers but has a high potential to develop a more autonomous and efficient system, especially in complex manufacturing processes is agent-based computation [38]. Agent-based technologies have attracted considerable interest in the research community due to their ability to tackle highly distributed and reconfigurable control systems [39]. These can help in developing a more dynamic and flexible manufacturing solution.

The agents' technology represents one of the main information and communication technologies in the industry [40]. The concept "agent" represents an autonomous intelligent entity which perceives through sensors, acts upon an environment using actuators and directs its activity towards achieving goals. The multi-agent notion allows different physical or abstract entities (ex. manufacturing units, resources, subcontractors, etc.) to be modelled as autonomous intelligent agents with particular objectives. A MAS is composed of different kinds of agents that can perform specific tasks [41]. The distributed nature of such a system is also conforming to the distributed nature of recent industrial systems [42]. Figure 3 shows the MAS architecture. According to Chen et al. [43], the MAS's primary characteristics are as follows:

1) Every agent in the MAS can control their behavior and engage in independent competition or cooperation.
2) Agents also can work together to create a cooperative system with fault tolerance to accomplish separate or shared objectives. So, if some agents malfunction, more other agents will independently adjust to the new setting and carry on with their tasks, preventing the entire system from entering a failure status.
3) The MAS system itself has a distributed design, and for this reason, the agent exhibits traits of low coupling and high cohesion, the system has a large capacity for expansion, and that's called "flexibility and scalability".
4) Ability to cooperate with a distributed system, a multiagent system. Through the use of the proper tactics, agents can work together to accomplish the overall objective.

This paper introduces a forward-thinking multi-agent-based framework that represents the zenith of innovation in integrating ML models for adaptive decision-making. The proposed framework, crafted with a keen focus on PdM, is engineered to enhance synergy among diverse ML models, thereby propelling efficiency to new heights and surmounting the limitations of conventional maintenance methodologies.

A detailed case study, which we will delve into Section 4, is a testament to the framework's viability. Deployed within a bustling manufacturing facility, the framework brought to life an ecosystem of ML models, each tuned to anticipate and pre-empt equipment failures. The agents, designed to operate in concert, dissected and synthesized multifaceted data from the manufacturing milieu, paving the way for a predictive prowess previously unattainable [38]. This collaborative intelligence not only catalyzed an enhancement in predictive capabilities but also ushered in significant cost efficiencies and a marked reduction in unscheduled equipment downtime [44].

Figure 3. MAS architecture overview depicting dynamic interactions and collaboration among autonomous agents in a distributed environment

Table 1 provides a detailed look at how MAS is employed across various sectors within mechatronics, specifically focusing on their use in fault diagnosis and PdM. These studies illustrate the practical applications of MAS and highlight specific approaches and architectures, such as decentralized systems and integrating MAS with advanced technologies like ML/DL and DT, to improve operational efficiency and predictive capabilities in industrial sceneries.

Table 1. Recent studies in the area of agent-based manufacturing in mechatronics

Study	Technology Used	Method
	Planning and scheduling	
Cadavid et al. [45]	Machine Learning for Production Planning and Control (PPC)	Implemented ML to enhance PPC in Industry 4.0, proposing a mapping for higher system efficiency.
Lujak et al. [46]	Decentralized MAS	Proposed a decentralized approach for capacitated production planning problems.
Dittrich and Fohlmeister [47]	MAS with RL	Presented a cooperative MAS approach for production control using reinforcement learning (RL).
Jost et al. [48]	Decentralized MAS	Implemented cost-benefit functions and market economy aspects in a transport system.
	Quality control and diagnosis	
Rokhforoz et al. [49]	Multi-agent Decision Support System	Proposed a MAS for PdM in power grids to minimize costs and maximize reliability.
	Reconfiguration	
Kim et al. [50]	Modular Factory Testbed with Distributed Control	Developed a testbed emphasizing modularity under a distributed shop-floor control architecture.
Mueller et al. [51]	MAS for Cyber-Physical Production Systems (CPPS)	Discussed the potential of CPPS for reconfiguration issues in industrial automation.
Atmojo et al. [52]	MAS with OPC-UA and IEC 61499	Presented flexibility and interoperability in an assembly line with a plug-and-produce approach.
	Service, cloud AI-based	
Huang et al. [53]	MAS with Recursive Bayesian Estimation (RBE) and GNNs	Demonstrated a control framework for optimizing production yield using a multi-agent approach.
Yong et al. [54]	Bayesian Neural Networks (BNNs) and MAS	Proposed real-time condition monitoring using probabilistic ML in a CPS.
	Others	
Seitz et al. [55]	MAS with OPC-UA for CPPS	Proposed a MAS concept using OPC-UA for adaptable industrial automation circumstances.
Haben et al. [56]	MAS with Open Software Protocols (OSPs) and IoT	Developed a MAS using open protocols and standard hardware for customized product manufacturing.

1.4. Research Questions

As we delve into the integration of AI and MAS within the PdM framework of Industry 4.0, we are guided by several critical questions that aim to dissect the complexities, challenges, and opportunities of these technologies in the MI:

1) How can AI algorithms be optimized to enhance fault diagnosis capabilities within mechatronic systems under Industry 4.0 sceneries, and what are their current limitations?
2) In what ways does the integration of MAS specifically enhance PdM strategies in MIs?
3) What specific integration issues and challenges arise when combining AI and MAS for PdM in Industry 4.0 environments, and what solutions exist to mitigate these challenges?
4) Considering the developing landscape of Industry 4.0, what are the emerging challenges and potential research directions for AI and MAS in enhancing PdM in MI?

1.5. Structure of the Paper

Next in Section 2, we delve into the advancements of AI algorithms that have been pivotal in enhancing fault diagnosis processes through the analysis of system behavior, sensor data, and past maintenance records. The introduction of AI-enabled tools has been instrumental in the swift detection of irregularities and pinpointing their origins, thereby considerably reducing downtime while boosting both system dependability and efficiency [57]–[59].

Furthermore, this study will highlight the application of AI-driven PdM methods. The ability to precisely forecast the RUL of crucial mechatronic components has transformed PdM, enabling maintenance to be planned more efficiently and resource utilization to be optimized all in Section 3. Through a case study, this discussion aims to underscore the significant role of AI in improving the durability and operational effectiveness of PdM in monitoring the condition of hydraulic systems, while also addressing the impediments and prospective research pathways in the rapidly developing arena of AI in Section 4. Section 5 outlines the main obstacles in applying AI for PdM and potential directions for forthcoming research and development within MI.

2. Literature Review

Manufacturing procedures have undergone a tremendous transition as a result of Industry 4.0, with a particular emphasis on PdM enabled by AI and ML/DL [60]. PdM has become well-known for its capacity to foresee equipment malfunctions before they happen. To find patterns suggestive of possible equipment breakdowns, this procedure involves gathering and evaluating data from several sensors [61]. Adopting PdM improves system control, reduces downtime for systems or machines, enhances production quality, and is cost-effective [62].

The application of AI in mechatronics has entirely changed how problem diagnostics is done [63]. PdM has entered a new phase as ML and DL algorithms can now predict equipment failures with a speed and precision never before possible, contributing to increased operational uptime and productivity [59].

ML models like RF and Gradient Boosting Machines (GBM) are particularly effective for these data types due to their ability to implement feature selection and reduce dimensionality [64]. This makes them ideal for PdM, where several variables must be considered simultaneously. These models can isolate significant features from extensive datasets, boosting computational efficiency and prediction accuracy [65].

DL techniques, especially Autoencoders, are utilized for their proficiency in data compression and feature extraction from high-dimensional data [66], [67]. Autoencoders can transform complex datasets into manageable forms without losing critical information, facilitating more accurate fault diagnosis and system health assessments [68]. Moreover, SVM with kernel tricks are used to handle the nonlinear relationships often present in multivariate data [69], [70]. This capability allows SVM to classify complex datasets effectively, providing robust fault detection mechanisms in PdM systems [71]. By integrating these sophisticated AI algorithms, we can leverage their unique capabilities to enhance the PdM framework, ensuring more accurate predictions and efficient data handling.

This section investigates how AI, specifically ML and DL, enhances fault diagnosis in manufacturing. It explains the role of PdM in using sensor data to predict equipment failures, thereby enhancing system control and quality, minimizing downtime, improving production, and cutting costs. Moreover, it underlines AI adoption challenges such as data integration and quality, suggesting solutions to enhance efficiency and cost-effectiveness.

2.1. Advancements in Machine Learning

ML algorithms, which are well-known for their ability to identify early indications of malfunctions and failures before they become system-wide problems, are at the forefront of these technical advancements [72]. ML models have been thoroughly trained on large datasets, especially those that are based on supervised learning, such as RF and SVMs [73]. These models are quite good at seeing little irregularities in the way machinery operates, which may be signs of imminent problems. Concurrently, unsupervised learning methods such as NNs and clustering are being used more and more to identify unknown defect kinds without requiring pre-labelled data. This method greatly broadens the reach of diagnostic procedures to include problems that were not previously identified [74]. Figure 4 presents a detailed taxonomy of ML categories, techniques, and models that are pivotal in maintenance-related activities [75].

The precision of ML algorithms in fault diagnosis has seen considerable enhancement in recent times. For instance, to predict downtime in stamping presses more effectively, a novel methodology was introduced [76]. This method integrates time segmentation and feature dimension reduction with anomaly detection, alongside ML classification strategies. Utilizing Randomized Decision Trees (the most effective among the twelve classifiers evaluated) this approach achieved a 96% ROC AUC index and notably increased the macro F1-score by 22.971%, compared to using only the classification techniques. The analysis was based on a dataset comprising 13,568 real instances across seven different parameters, which were categorized into two groups: operational condition and failure state.

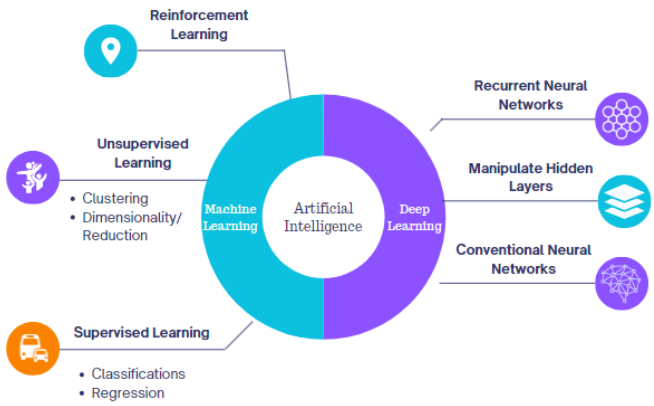

Figure 4. ML and DL algorithms (adopted from [25])

2.2. Deep Learning Innovations

DL, a specialized branch of ML focusing on NNs with several layers, has propelled fault diagnosis to new heights. CNNs and RNNs have been pivotal in processing and analyzing complex sensor data, converting it into actionable intelligence [24]. These models are particularly proficient in feature extraction, independently recognizing complex patterns within high-dimensional data that might elude human analysts or traditional computational approaches [60].

Authors in [77] investigate enhancing fault classification for PdM in the IIoT through Automated Machine Learning (AutoML) strategies. It introduces two innovative models: AutoML, utilizing PyCaret, and AutoDNN, employing AutoKeras. These models are designed to pinpoint faults in ball bearings, and tested against the Case Western Reserve University bearing faults dataset, where they showcased high levels of accuracy, recall, precision, and F1 score. This paper highlights the revolutionary potential of AutoML in IIoT scenarios, providing insightful information for industries like energy and manufacturing. It illustrates how effective AutoML is at expediting PdM procedures and cutting down on maintenance expenses and time.

2.3. Real-World Applications in Industry 4.0

The incorporation of AI-driven models into mechatronic systems has been greatly improved by developments in sensor technology and data-processing capabilities [78]. High-resolution sensors deliver the detailed data required, while the advancement in computational resources facilitates real-time processing and analysis, embodying CPS. This combination enables a comprehensive and nuanced understanding of system health and behavior, resulting in more precise and prompt fault diagnosis. Figure 5 shows a schematic diagram of the manufacturing structure of CPS.

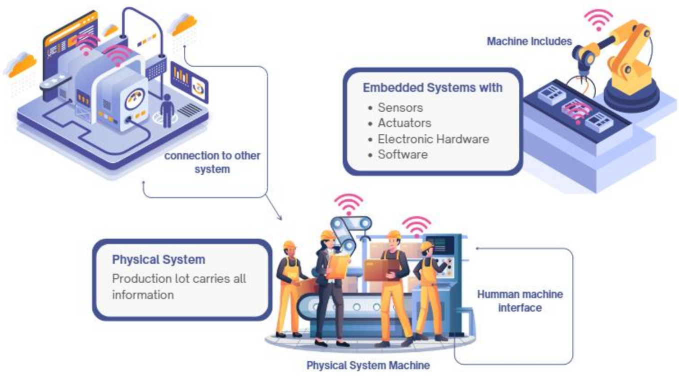

Figure 5. Structure of a manufacturing CPS (adopted from [79])

In [80], they delve into the application of AI and ML for PdM in spacecraft fault detection, isolation, and recovery (FDIR). This study reviews existing FDIR techniques, proposes a novel predictive model leveraging ML and explainable AI, and assesses various ML methods for telemetry analysis and anomaly detection. It underscores the potential of predictive FDIR to improve spacecraft efficiency and autonomy, stresses the necessity for AI explainability, and tackles challenges such as data accessibility and the intricacies of DL. It advocates for a hybrid approach that merges data-driven with expert knowledge-based methods to advance FDIR strategies.

Another study [81] presents a predictive analysis method designed for industrial systems, with a particular emphasis on anticipating supplier delays. This methodology involves the collection and analysis of high-quality industrial data to progress predictive models that support decision-making and improve operational performance. Revealing the broad applicability of predictive analysis beyond traditional mechatronic systems, this work leverages ML techniques to propose a framework for increasing industrial adaptability and efficiency. It emphasizes the extensive relevance and versatility of predictive analysis within the industrial sector.

2.4. Advancements in Sensor Technology and Data Analysis

The progression in sensor technology and data analysis capabilities has been a cornerstone for enabling AI-powered fault diagnosis systems [82]. A notable investigation [7] proposed a predictive model for estimating the RUL of machinery by employing a unique feature known as mean peak frequency, extracted from vibration signal spectrograms. By applying LSTM, the study projected mean peak frequency values to estimate RUL against a predetermined threshold. Conducted across three different experimental setups differing in throttle adjustments and blade conditions, this approach resulted in RUL forecasts of 4 seconds, 10 seconds, and 10 seconds, alongside respective root mean square error (RMSE) figures of 3.7142 Hz, 1.4831 Hz, and 1.3455 Hz. The authors outlined the study's shortcomings, pointing out that it only examined one component of flight operation and that it only used one feature; mean peak frequency. They suggested that to expand the prediction horizon, future studies could investigate other features or modelling methodologies and include a wider range of operational scenarios, such as handling false alarms or maneuvers.

A new level of complexity is added to mechatronic systems through the incorporation of sensor interfaces. The difficulties of developing and putting into practice adaptable sensor interfaces fit for industrial use were examined in research [83]. Creating circuits that can handle high voltages, guaranteeing dependable data acquisition and processing, and preserving system scalability and compatibility are major challenges. To overcome these challenges, a multidisciplinary strategy combining knowledge from AI, industrial design, software engineering, and electronics is required. This emphasizes the need for all-encompassing approaches to address the complexities of sensor technology integration in industrial settings.

2.5. Challenges in AI Adoption for Fault Diagnosis

There are still challenges in integrating AI into fault diagnostics, despite advancements [84]. Since AI models require large, high-quality datasets to train effectively, challenges like data availability and quality continue to be tough [85].

Moreover, there is cause for concern over the openness of AI decision-making processes, which forces stakeholders to depend on the findings of AI “black boxes” without having a thorough understanding of the choices made [16].

As noted in a study on autonomous vehicles [86], the path towards integrating AI in defect diagnosis has significant obstacles, such as the requirement for enormous data quantities, data quality, and the clarity of AI choices. With the use of a residual explanation to provide context for the findings and an Adversarial Learned Denoising Shrinkage Autoencoder (ALDSAE) for anomaly identification, this work presents an interpretable defect diagnosis system for autonomous cars. It places a strong emphasis on evaluating how the environment affects sensor data and explaining anomaly detection outcomes. The explanation provides quick, efficient feature importance analysis, and the ALDSAE model outperforms conventional detectors in accuracy.

Encouraging efficient human-robot interaction in industrial settings is a major challenge for mechatronics [87]. The difficulty is in designing environments where workers may safely engage with autonomous robots. A thorough grasp of the dynamics of human-robot interaction and the creation of systems that can instantly adjust to human actions and behaviors are necessary for designing collaborative systems that are safe and effective.

All things considered, the industry’s capacity for problem identification has significantly improved thanks to the advancements in AI technology. The shift in manufacturing approaches towards more intelligent and data-driven maintenance techniques is a noteworthy development that aligns with the goals of Industry 4.0 [88], [89]. To fully reap the rewards of intelligent maintenance solutions, research must continue to progress and industry use of these advancements in AI must rise.

The significance of these technical breakthroughs is highlighted in research [90], which highlights how they reduce costs, streamline design and prototyping processes, and increase manufacturing efficiency in a variety of industries. Innovations like the creation of autonomous, unmanned aircraft have cut down on environmental effects, minimized human mistakes, and saved a significant amount of money and time. Furthermore, defense capabilities have been greatly enhanced by the use of AI in security activities, such as threat detection and perimeter defense [91]. These developments highlight how important mechatronics is to current warfare and aerospace technology, where efficiency, creativity, and precision are crucial.

3. Method

The adoption of AI in PdM within Industry 4.0 indicates a departure from conventional maintenance approaches [92]. This section explores into the transformation of maintenance strategies through AI-powered predictive analytics and prognostics, highlighting the enhancement of resource efficiency and the prolongation of equipment life [93].

3.1. Prognostics Powered by AI for PdM

AI plays a significant role in prognostics by estimating the RUL of machinery [94], which is fundamental to executing effective PdM. Research [93] focusses on applying AI methodologies for PdM in the industrial sector, utilizing computational analyses and simulations with real-world industrial datasets. Findings underscore the efficacy of preventive maintenance powered by comprehensive, accurate sensor data and sophisticated ML algorithms. The work points out that even straightforward AI solutions can significantly boost efficiency while keeping implementation costs low, thereby enhancing the sustainability of energy, materials, and water usage. Such strategies are becoming increasingly critical across various industries, promising enhanced maintenance efficiency and cost savings. A significant illustration of this is in [95], which investigates ML applications for PdM in hydroelectric power plants, with a specific focus on turbine load cycle optimization. The study developed a predictive model using load cycle-related variables and evaluated four ML algorithms, achieving an impressive accuracy rate of approximately 98% for maintenance forecasting, thus highlighting ML’s potential in PdM for industrial applications, especially in hydroelectric power generation.

3.2. Optimizing Maintenance Schedules with AI

AI’s capability extends to the optimization of maintenance schedules, facilitating the transition from fixed interval to condition-based maintenance planning. This shift not only conserves resources but also reduces operational disruptions.

Article [96] illustrates how ML algorithms can streamline maintenance activities, ensuring workload balance and minimizing unnecessary maintenance actions through “Flow-Shop” Scheduling optimization.

3.3. Extending Equipment Lifecycles through AI

A key benefit of integrating AI into PdM is the extension of equipment lifecycles. By pre-empting excessive wear and facilitating timely maintenance interventions, AI contributes to the longevity of machinery The study of [6] proposes a novel method, combining digital twins and PdM with ML, to enhance robotic cell reliability. Their case study on a spot-welding robotic cell demonstrates optimized reliability through real-time detection and classification of faulty stepper motor bearings, estimating their RUL.

3.4. Challenges in AI Implementation for PdM

Despite AI's substantial benefits in PdM, its integration faces hurdles, including data quality concerns, compatibility with existing systems, and the demand for skilled personnel to analyze AI findings. As highlighted [97], navigating these challenges is essential for the successful application of AI in PdM strategies.

AI-driven PdM techniques are crucial for propelling the MI towards more sustainable, cost-efficient, and reliable operations. Leveraging AI’s predictive analytics, industries can foresee potential failures and refine maintenance schedules, thus enhancing machinery’s overall lifecycle. Ongoing progress in AI technology is expected to further advance and refine these PdM approaches [98].

We note a notable gap in research regarding the application of MAS in this domain. Despite the potential benefits of integrating MAS with AI techniques for PdM, limited literature or studies are addressing this approach. Given the significance of MAS in Industry 4.0, further exploration and research are warranted to leverage its capabilities effectively in PdM and advance the domain. In brief, the exploration of challenges in AI implementation for PdM underscores the need for innovative solutions to enhance manufacturing processes. The upcoming section will explore our case study which demonstrates the potential of a MAS framework in advancing PdM practices within the Oil and Gas industry (OGI).

4. Result

This section explores a case study demonstrating the application of MAS in improving PdM within manufacturing. It discusses the implementation plan, expected outcomes, and improvements and provides concise insights into MAS’s practical deployment and benefits.

4.1. Case Study Background

The manufacturing industry faces ongoing challenges in reducing equipment downtime and preventing unexpected failures, which are essential for maintaining operational efficiency and reducing costs [99]. Traditional maintenance methods, largely based on periodic inspections, often prove inadequate, leading to increased inefficiencies and downtime [35], [100]. Addressing these issues, we examine the effectiveness of our newly developed MAS framework designed to significantly improve PdM in this sector.

This case study focuses on the application of MAS oriented for PdM in monitoring the condition of hydraulic systems, a critical component in the OGI. Given OGI’s reliance on the hydraulic system’s efficiency and reliability, implementing our MAS-based framework showcases its potential to enhance maintenance strategies, ensuring robustness and continuity in OGI’s demanding operations.

4.2. Implementation Plan

The framework is planned for deployment in a cutting-edge manufacturing facility, highlighting the incorporation of sophisticated ML models. These models are engineered to predict equipment malfunctions accurately by analysing data, including sensor outputs, historical performance, and maintenance records, to identify patterns indicative of potential equipment failures. Our intelligently designed agents play a necessary role in coordinating these predictive models and facilitating efficient information exchange. Figure 6 shows this integrated approach visually.

Agent Coordination Mechanism:

1) DPA (Data Processing Agent): The DPA collects, aggregates, and pre-processing numerous data types essential for PdM. This includes historical sensor data, performance statistics, and maintenance records. The DPA ensures that the data is cleaned, normalized, and transformed into a consistent format suitable for analysis. By establishing a solid data foundation, the DPA improves the accuracy and reliability of subsequent analyses performed by other agents. This pre-processing stage is vital for removing noise and handling missing values, which can significantly impact the quality of the predictive models.
2) MTA (Model Training Agent): The MTA plays a crucial role in developing ML models using the pre-processed data provided by the DPA. The MTA employs various ML algorithms to create models that can detect patterns indicative of equipment failures. This involves selecting appropriate features, tuning hyperparameters, and validating the models to ensure their robustness. Furthermore, the MTA continuously updates and retrains the models to adapt to new data trends, ensuring they remain accurate and effective. This agent's ability to refine models based on fresh data inputs is crucial for maintaining the system's predictive power.
3) DMA (Decision-Making Agent): The DMA is central to the MAS framework, acting as the coordinator for all other agents. The DMA facilitates real-time communication and collaboration among agents, ensuring that insights and recommendations derived from data analysis are promptly shared and acted upon. It integrates inputs from the DPA and MTA, synthesizing this information to make informed maintenance decisions. By orchestrating the collective efforts of the agents, the DMA ensures a cohesive and efficient approach to PdM. This agent's role is critical for implementing timely and proactive maintenance actions, ultimately reducing downtime and optimizing resource utilization.

The interaction among the DPA, MTA, and DMA is crucial for achieving a unified data analysis and interpretation approach. The DPA provides the necessary data foundation, the MTA develops and refines predictive models, and the DMA coordinates their efforts to facilitate effective decision-making. This collaborative framework enhances the overall predictive accuracy of the system, enabling proactive maintenance strategies that can significantly enhance operational efficiency and reduce costs.

To conclude, the agent coordination mechanism within the MAS framework involves the seamless collaboration of specialized agents, each performing distinct yet interdependent roles. The DPA ensures high-quality data preparation, the MTA develops adaptive predictive models, and the DMA orchestrates their collective efforts to implement effective maintenance strategies. This integrated approach is expected to enhance the accuracy and efficiency of PdM in smart manufacturing environments.

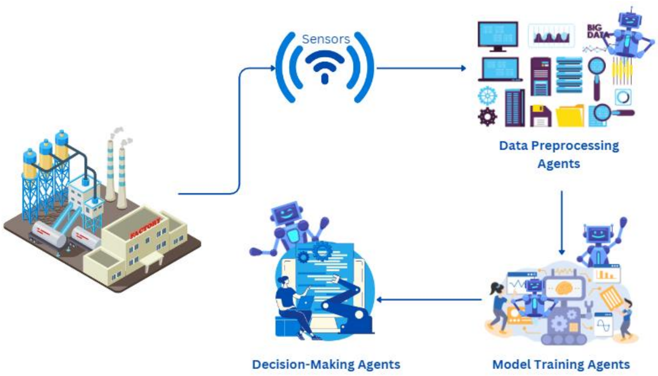

Figure 6. A visual representation of the proposed framework

Expected Outcomes and Improvements:

1) Enhanced predictive accuracy: Integrating the proposed MAS framework is anticipated to significantly enhance predictive accuracy, thereby bolstering decision-making processes within the manufacturing environment. By leveraging the collaborative capabilities of multiple agents, the framework enables a comprehensive analysis of various factors influencing equipment performance. This holistic approach encompasses aggregating and pre-processing diverse datasets, including historical performance metrics, sensor readings, and maintenance records. Through iterative interactions and knowledge sharing among agents, the MAS proposed framework facilitates the

identification of subtle patterns and anomalies indicative of potential equipment failures. As a result, the predictive models derived from this collaborative effort are expected to yield more precise and timely predictions, empowering maintenance teams to adopt proactive strategies to mitigate downtime and optimize asset performance.

2) Cost savings and reduced downtime: Implementing the MAS framework is poised to deliver substantial cost savings by preemptively detecting and addressing underlying issues before they escalate into critical failures. By harnessing the collective intelligence of distributed agents, the framework enables real-time monitoring and analysis of equipment health (e.g. PHM, RUL), allowing for early intervention and preventive maintenance measures. This proactive approach minimizes the need for costly emergency repairs and curtails unplanned downtime, enhancing overall operational efficiency and productivity. Moreover, organizations can achieve tangible maintenance cost reductions and higher asset utilization rates by optimizing resource allocation and scheduling maintenance activities based on predictive insights.

4.3. Case Study Conclusion

This case study validates the practical application of the proposed MAS-based framework in improving PdM within a real-world manufacturing context. The strategic coordination of ML models for PdM, driven by intelligent agents, signifies a shift towards more proactive and economically efficient equipment management strategies. The successful implementation of this framework not only serves as "proof of concept" for industrial applications but also emphasizes its real benefits, including significant cost reductions and minimized downtime. The cooperative efforts of the intelligent agents in this framework are expected to advance predictive capabilities that support decision-making and convert these advancements into tangible operational enhancements.

4.4. Challenges and Future Research Trends

As the MI advances under the influence of AI and Industry 4.0, it encounters several challenges alongside opportunities for future growth and innovation [101], [102]. This section outlines the main obstacles in applying AI for PdM and potential directions for forthcoming research and development within MI.

4.4.1. Obstacles in Implementing AI

1) Data management (quality, volume, and accessibility): A fundamental hurdle in utilizing AI for fault diagnosis and PdM is the necessity for substantial, high-quality data sets [101]. The success of AI models heavily depends on having access to accurate, comprehensive data collection. Data that is inconsistent or lacking can lead to flawed predictions, compromising the dependability of AI-powered maintenance strategies.
2) System Integration: Integrating AI technologies with existing legacy systems poses a substantial challenge. Many current mechatronic systems weren't initially designed to support AI integration, making the adaptation process intricate, lengthy, and expensive [72].
3) Workforce Expertise: The deployment of AI in PdM demands a workforce proficient in AI model development, implementation, and analysis. There's a pressing demand for educational programs to furnish maintenance engineers and technicians with AI skills [103].
4) Interpretability and Trust of the Model: The opaque nature of some AI models challenges their interpretability [5]. Building trust with users and stakeholders often necessitates the development of AI solutions that are transparent and whose decision-making processes can be easily understood and rationalized [104].
5) Cybersecurity and Data Privacy: The increased use of sensors and actuators amplifies the need for stringent cybersecurity measures to protect operational integrity and safety. Concerns about integrating open-source platforms and external data processing systems stem from potential security vulnerabilities. These platforms must implement sophisticated security measures to ensure data protection, requiring tight integration with the company's existing systems [105].

4.4.2. Directions for Future Research

1) Innovative Developments: Trends in AI for PdM include leveraging edge computing and real-time analytics for superior performance in isolated locations, utilizing explainable AI (XAI) to enhance model transparency, and amalgamating AI with cutting-edge robotics for more effective maintenance processes [106], [107].

2) Enhancement in AI Algorithms: Continuous AI research is set to yield more advanced, efficient algorithms. Future improvements might feature sophisticated DL models, real-time adaptive learning capabilities, and algorithms that demand less data for precise predictions.
3) Cross-Sector Applications: Investigating AI's application in PdM across different MI sectors could uncover universal best practices and innovative strategies. Collaborations across industries might provide valuable insights that propel the field forward.
4) System Integration and Interoperability: The seamless functioning of systems is crucial for minimizing the risk of operational failures. In this paper, we proposed a MAS framework that embodies a strategic and intelligent approach to PdM, markedly diminishing the chances of equipment failures in manufacturing settings [108].
5) Ethics and Responsible AI Use: With AI's expanding role in manufacturing, ethical considerations and the responsible application of AI have gained prominence. Future research will aim to ensure AI applications are equitable, transparent, and congruent with societal norms.

5. Conclusion

As the MI continues to navigate the complexities of Industry 4.0, the integration of AI and PdM strategies stands at the forefront of transformative manufacturing practices. This paper has critically examined the burgeoning role of AI in enhancing fault diagnosis and maintenance protocols, underpinned by the cutting-edge capabilities of ML and DL algorithms, alongside the strategic implementation of MAS. Through comprehensive analysis, case studies, and discussions on current challenges and future directions, we have illuminated the pathway towards a more resilient, efficient, and intelligent manufacturing paradigm.

The exploration of AI-driven prognostics for PdM has revealed significant advancements in the predictive accuracy of equipment malfunctions, underscoring the potential for substantial reductions in downtime and operational costs. The case study on developing PdM in manufacturing through a MAS-based framework further validates the applicability and efficacy of AI in real-world industrial settings, showcasing the synergetic benefits of intelligent agent collaboration in optimizing maintenance schedules and extending equipment lifecycles.

However, the journey towards full AI integration in PdM is not devoid of challenges. Issues such as data availability and quality, integration with existing systems and new technologies, the skill gap in the workforce, and the need for interpretable and trustworthy AI models have been identified as critical hurdles. Moreover, the imperative for robust cybersecurity measures and ethical considerations in AI deployment emphasizes the complexity of transitioning to AI-driven maintenance strategies.

Looking forward, the continuous evolution of AI technologies promises to address these challenges, with emerging innovations such as edge computing, real-time analytics, and explainable AI poised to further refine PdM processes. The potential for cross-industry applications of AI in PdM suggests a broad horizon for innovation, offering insights into universal best practices and fostering a collaborative ecosystem for technological advancement.

In conclusion, the integration of AI in PdM within the MI represents a pivotal shift towards smarter, more efficient, and sustainable manufacturing operations. By embracing the opportunities and navigating the challenges presented by AI and MAS, the industry can leverage these technologies to achieve unparalleled improvements in maintenance strategies, operational efficiency, and competitive advantage. The continued research, development, and industry adoption of AI advancements are imperative for realizing the full potential of intelligent maintenance systems, setting a new standard for the future of manufacturing in the era of Industry 4.0. For our future work, we plan to further our research by implementing experimental studies that will test the practical applications of AI and MAS in PdM. This hands-on approach will allow us to detect the impacts directly, refine the technologies based on real-world data, and improve our understanding of the complex dynamics within smart maintenance systems.

6. Declarations

6.1. Author Contributions

Conceptualization: S.Y.B., N.A.Y.; Methodology: S.Y.B, N.A.Y.; Software: S.Y.B.; Validation: S.Y.B., N.A.Y., A.M.E.; Formal Analysis: S.Y.B., N.A.Y., A.M.E.; Investigation: S.Y.B.; Resources: S.Y.B, N.A.Y.; Data Curation:

S.Y.B; Writing Original Draft Preparation: S.Y.B.; Writing Review and Editing: N.A.Y., S.Y.B., A.M.E.; Visualization: S.Y.B.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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