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***Harnessing Artificial Intelligence for Optimum Performance in Industrial Automation***

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**Abstract:** This study examines the extensive domain of artificial intelligence (AI) applications in industrial automation, including historical background, fundamental principles, and advanced techniques such as Machine and Deep Learning. This text examines practical applications, highlighting the crucial role of AI in improving industrial efficiency, precision, and flexibility. The study focuses on the successful integration of artificial intelligence (AI) in predictive maintenance, production optimization, and quality control domains. It also addresses issues such as integration complexities, data privacy, and ethical problems. The review provides valuable insights into forthcoming advancements, with the goal of providing guidance to researchers, practitioners, and policymakers in the ever-changing field of AI and industrial optimization. It emphasizes the crucial role of AI in shaping the future of industrial automation, leading to improved performance and operational excellence.

**Keywords:** Deep learning, Neural Networks, Machine Learning, Optimization, Artificial Intelligence

1. Introduction

The integration of Artificial Intelligence (AI) with industrial automation represents a significant shift in the manufacturing industry. AI fundamentally revolutionizes operations by implementing sophisticated algorithms and machine learning capabilities to enhance and streamline procedures. The optimization leads to increased productivity, as AI-driven systems have the ability to evaluate large datasets to detect trends, make well-informed judgments, and adjust to changing production conditions. One significant benefit is found in predictive maintenance, where AI algorithms use previous data to forecast equipment breakdowns. It signifies a profound transformation of manufacturing ecosystems, introducing a future where intelligence, flexibility, and efficiency come together to reimagine the potential of industrial processes. Nevertheless, despite the progress made in automation, there are always ongoing obstacles. The challenges of integration present a big obstacle, as the process of combining various systems and technologies can be intricate and necessitate significant financial commitments. The growing interconnectivity of industrial systems has heightened worries about data security, as it exposes them to potential cyber threats and vulnerabilities. Moreover, the resistance of certain sectors to embrace automation is mostly attributed to the significant upfront expenses and the requirement for specialized workforce education, which continues to pose a hurdle. The contemporary conversation also includes ethical questions around job displacement and the socio-economic impact of widespread automation. Hence, it is imperative to give priority to addressing these challenges in order to fully harness the potential of industrial automation and accomplish a seamless fusion of technology and industry. The utilization of Artificial Intelligence (AI) in industrial settings plays a crucial role in enhancing performance, marking a significant change in the way enterprises strive for efficiency and production. Artificial Intelligence (AI), encompassing the fields of deep learning, machine learning, and cognitive technology, expedites the process of making intelligent decisions and finding adaptable solutions to problems. AI algorithms utilize real-time analysis of large datasets to uncover patterns, trends, and correlations that may not be detected by traditional analytical methods. AI's cognitive ability allows it to utilize data to make predictions, hence improving the accuracy of forecasting and resource allocation. Furthermore, in the realm of manufacturing, AI enables predictive maintenance, allowing for the anticipation of equipment malfunctions before to their actual occurrence, thereby reducing the amount of time that production is halted. The AI's adaptive learning skills provide continuing enhancement, as the systems grow and maximize their performance through continuous data feedback. In addition to automation, artificial intelligence (AI) enables a high degree of agility and responsiveness, enabling industrial processes to quickly adjust to changing conditions. The integration of AI into industrial optimization represents a significant period of change, where smart algorithms not only make operations more efficient but also actively contribute to the improvement and advancement of performance standards in a dynamic and data-focused industrial environment. The historical progression of Artificial Intelligence (AI) in industrial applications can be traced through several periods that highlight the transition from fundamental notions to the complex, data-driven systems observed in the present day. During the 1950s and 1960s, the primary emphasis was on developing rule-based AI systems and expert systems that sought to imitate the cognitive processes involved in human decision-making. Despite their computer limitations, these systems established the foundation for incorporating intelligence into industrial automation. In the following years, there was a significant increase in both interest and investigation into machine learning, as artificial intelligence applications started to include algorithms with the ability to acquire knowledge from data. During the 1980s and 1990s, there was significant advancement in control technologies and the application of artificial intelligence techniques in industrial settings, although the extent of deployment was restricted. Nevertheless, the broad implementation of these early AI systems was hindered by the constraints in computer capacity and the intricate nature of real-world industrial settings. The onset of the 21st century witnessed a notable transformation, as a result of the convergence of enhanced processing capacities, extensive datasets, and more advanced algorithms. Machine learning techniques, especially those related to neural networks, became well recognized, and the use of AI in industrial automation increased. During this period, artificial intelligence (AI) was incorporated into various domains, including predictive maintenance, quality control, and the optimization of manufacturing processes. The latest stage, in line with the industry 4.0 concept, experienced a significant transformation in industrial automation. Smart factories have emerged, employing AI-powered technologies such as robotics, Internet of Things (IoT), and advanced analytics. The integration of these components facilitated the advancement of intricate, interconnected systems capable of real-time data analysis and intelligent decision-making. Neural networks have enabled deep learning models to achieve remarkable proficiency in pattern recognition and sophisticated prediction, thereby significantly improving the efficiency and adaptability of industrial processes. The Objective of this article is to thoroughly investigate the various uses and progressions of artificial intelligence (AI) in industrial automation. The aim is to clarify the historical context, core ideas, and practical applications of AI, highlighting its role in improving efficiency and adaptability. The study emphasizes the concrete advantages and valuable insights obtained from the incorporation of AI, using successful case studies. It also tackles issues such as the complexities of integration and ethical considerations. In essence, it offers direction for researchers, practitioners, and policymakers to effectively navigate the ever-changing field of AI in industrial optimization and promote future progress.

2. Fundamental Concepts

The fundamental tenets of the field of artificial intelligence play a crucial role in shaping the domain of industrial automation, offering intelligent remedies to enhance efficiency and streamline processes. Machine learning (ML) is a fundamental idea that enables systems to acquire knowledge from data without the need for explicit programming. ML algorithms in industrial automation utilize historical data to discern patterns, trends, and correlations, facilitating predictive analytics, anomaly detection, and decision-making based on acquired insights. The process of deep learning, a specific branch of machine learning, is highly significant in industrial contexts. Deep networks of neurons are constructed of interconnected nodes stacked in layers, drawing inspiration from the anatomical organization of the human brain. In industrial automation, neural networks are employed for tasks ranging from fault detection to process optimization, leveraging their ability to capture intricate relationships within data. Reinforcement learning is a fundamental idea in which an artificial intelligence agent acquires knowledge by actively engaging with an environment and receiving feedback in the form of rewards or penalties, depending on its actions. In industrial automation, reinforcement learning finds application in autonomous systems and robotic control, enabling machines to adapt and optimize their behavior over time. Natural language processing (NLP) enables the exchange of information between humans and machines by interpreting and generating human language. In industrial settings, NLP can be employed for tasks such as voice commands, text analysis, and human-machine interfaces, enhancing the interaction and collaboration between operators and AI systems. The integration of these fundamental AI concepts in industrial automation holds the promise of creating adaptive, intelligent systems capable of learning, optimizing, and evolving in response to dynamic production environments. These notions jointly enhance the revolutionary capacity of AI, fundamentally changing how sectors approach automation and paving the path for a more efficient and smarter future.

3. **LITERATURE REVIEW**

In their work, Masani et al. [1] emphasize the growing recognition of the vital role that machine learning approaches play in tackling the issues associated with the lack of an accurate automation system for production equipment, particularly in the field of predictive maintenance and monitoring of industrial machines. The authors propose overcoming the shortcomings of existing automation systems by advocating for the adoption of supervised machine learning techniques, specifically the Binary Decision Tree with the CART (Classification and Regression Trees) method. Carvahlo et al. [2] highlight the growing volume of data produced by industrial processes, production systems, and equipment in the field of Predictive Maintenance (PdM). Machine Learning (ML) techniques have become highly effective tools for Predictive Maintenance (PdM) applications, providing a proactive strategy to anticipate and prevent equipment malfunctions in industrial settings. Kroll et al. [3] mentions a growing emphasis on the role of Cyber Physical Production Systems in addressing the challenges presented by rising energy carrier costs and the goal of enhanced industrial efficiency. The European Union's considerable electricity consumption, as emphasized in the IEA Report, emphasizes the need to improve energy utilization in industrial operations. To promote energy efficiency, it is crucial to integrate anomaly detection systems, specifically for wear-level detection, in order to improve maintenance cycles. The field of study on predictive maintenance [4] in the context of the fourth industrial revolution, often known as Industry 4.0, has undergone substantial growth and conceptual advancement. The emergence of this revolution has led to new ideas, such as predictive maintenance, which plays a vital role in the broader framework of intelligent industrial systems. This study enhances the comprehension of academic progress in failure prediction, with a specific focus on the creation of decision support systems for predictive maintenance and design support systems. The investigation focuses on frameworks that integrate machine learning and reasoning approaches designed specifically to meet the unique demands of Industry 4.0. The study does a thorough examination of 38 selected publications from a pool of 562, specifically addressing the challenges related to the application of machine learning and informatics in the field of predictive maintenance. The research [6] examines the present advancements of machine learning methods specifically employed for predictive maintenance within the framework of Industry 4.0. The focus encompasses the categorization of research according to machine learning algorithms, classifications, types of machinery and equipment, data gathering devices, as well as methodologies, size, and types of data classification. This study aims to provide a comprehensive analysis of the notable contributions made by scholars in the domain of intelligent manufacturing throughout the industry 4.0 era. In the ever-changing field of maintenance modeling, recent advancements [7] driven by data-driven methodologies, Machine learning (ML), in especially, has generated prospects for a diverse array of purposes. Predictive maintenance (PdM) has been extensively adopted by the automotive industry to address the challenge of ensuring functional safety over the course of the product's life while effectively managing maintenance expenses. Teoh et al. [8] propose a novel approach that integrates genetic algorithm (GA)-based resource management with machine learning to facilitate predictive maintenance in fog computing. The study evaluates the efficacy of the Genetic Algorithm (GA) related with time, cost, and energy by conducting simulations with FogWorkflowsim**.** The research [9] is examining the shift from traditional maintenance to the use of Industrial Internet of Things (IIoT) technology, particularly through the adoption of a condition monitoring system (CMS). The CMS comprises of an experimental arrangement, an IIoT-driven condition monitoring application (CMA), and machine learning (ML) models. The study evaluates the efficacy of popular machine learning methods, specifically support vector machine (SVM), linear discrimination analysis (LDA), random forest (RF), decision tree (DT), and k-nearest neighbor (kNN). The DT model is regarded as the optimal selection for CMS because of its capacity to quickly determine threshold values and get excellent classification rates.

The paper [10] explores the field of cloud manufacturing, presenting a machine learning method for enhancing awareness of reality and optimizing processes. More precisely, the emphasis is on anticipatory production planning, which includes scheduling operations and allocating resources, as well as anticipating maintenance needs. By developing a hybrid control system that blends Big Data methods and machine learning algorithms, this research contributes significantly. The study introduces a novel approach that utilizes LSTM neural networks alongside deep learning in current time to accurately forecast energy consumption during production. The paper [11] applies the DQN algorithm to production scheduling in order to coincide with the industry 4.0 goal for improved control in manufacturing. It positions itself at the junction of these achievements. Agents of Cooperative DQN, which employ deep neural networks, are strategically trained in the framework of RL to optimize scheduling methods based on user-defined objectives. The study's validation is conducted by simulating a small plant that represents an abstracted frontend-of-line semiconductor fabrication facility. The study [12] investigates the utilization of deep learning through reinforcement learning (DRL) in industrial sectors, including robotics, job shop organizing, and management of supply chain. The primary emphasis lies on employing Deep Reinforcement Learning (DRL) to achieve intelligent allocation of resources in industrial edge equipment. Kuhnle et al. [13] contributes to the subject by specifically examining the design of reinforcement learning (RL) based on development of control system of an adaptive nature. They provide an example of this system in action by employing the actual situation of order sending in a complicated shop environment. The fundamental nature of RL algorithms is sometimes perceived as opaque, which limits a full comprehension. However, their promise in highly dynamic and complex production systems, particularly in cases where domain knowledge is restricted, is stressed. The research [14] overcomes the restrictions by incorporating deep reinforcement learning (RL) into the scheduling domain. This approach eliminates the requirement for manually extracted features and successfully tackles the difficulties caused by the lack of structured datasets. This paper makes significant contributions in multiple critical aspects. In [15] authors examine the future trajectory of leading manufacturing organizations, emphasizing the vital importance of digital and information viability in the automation production process. The emergence of machine learning (ML), specifically the evolution in reinforcement learning (RL), highlights the considerable potential for revolutionary effects on the manufacturing industry. This paper targets to deliver a thorough examination of recent real-world uses of reinforcement learning (RL) in several areas, particularly focusing on its application in the industrial sector. The analysis explores the techniques of Reinforcement Learning (RL) in industrial applications, clarifying their distinct performances. Moreover, the study examines the obstacles and possibilities for using RL in automated production. It discusses the future direction of RL development to meet the changing requirements of intelligent manufacturing. The research critically examines the current body of knowledge and employs an organizational assessment to explore the practicality of implementing reinforcement learning, or RL, in manufacturing settings. The study primarily examines the utilization of Reinforcement Learning (RL) in manufacturing process structures, human-machine assist oversight and control, process inspection, preventive and post-processing, and complete material process management. The objective is to determine the suitability of RL in the intricate procedures and regulatory systems of the automated manufacturing sector, thus facilitating improved productivity and informed decision-making. This literature review offers a thorough examination of the latest advancements in the use of RL in industrial settings. It presents a coherent storyline that outlines the potential direction of intelligent manufacturing systems in the future. Within the field of semiconductor manufacturing, the need for dynamic scheduling has become extremely important. This is driven by an increasing variety of products being produced and the decreasing period of time that each product remains on the market. The scheduling problem is inherently complex, with detailed constraints and a need for quick decision-making, making it a hard challenge. The objective of this study is to fulfill these practical needs by introducing a novel approach that efficiently integrates a hybrid algorithm based on genetics with deep reinforcement learning (DRL). The primary goal is to tackle the problem of independent parallel machine scheduling involving sequence-dependent time for setup, a prevalent and substantial obstacle in semiconductor manufacturing. By utilizing the deep Q network (DQN), that integrates deep learning alongside Q learning, the scheduling agent is able to efficiently perform job allocation tasks while maintaining compliance with the constraints of dynamic scheduling. In addition, the study employs a blend of genetic algorithm methodologies to improve the effectiveness and efficacy of the process of searching throughout the agent's training. To find out the accuracy of the suggested solution, in-depth scenarios were created to conduct comparison assessments with rules of dispatching and other methods dependent upon Knowledge. The testing outcomes not only confirm the practical feasibility of the created technology but also authenticate its application in a real-world semiconductor production organization. This literature review situates the research within the wider framework of semiconductor manufacturing scheduling, emphasizing the importance of tackling dynamic difficulties and the novel incorporation of deep reinforcement learning and hybrid genetic algorithms. This study enhances the development of scheduling approaches in semiconductor manufacturing, offering a valuable framework for practical implementation. Esteso et al. [17] thoroughly examine the utilization and practical implementations of reinforcement learning, or RL, methods in the domain of production control and planning (PPC). The paper comprehensively analyzes several facets of PPC, including facility resource planning, planning for capacity, supply chain and procurement management, scheduling of production, and inventory management. This analysis thoroughly examines crucial elements of RL, including methodology, context, states, actions, and incentives, and highlights their importance. The literature review [18] situates the paper within the wider scope of RL implementations in PPC, emphasizing prevailing patterns, effective approaches, and the ability of RL to provide inventive solutions in the presence of intricate planning and control obstacles. Energy-efficient machining has become increasingly important in the manufacturing industry [18], as it aligns with the crucial objectives of conserving energy, reducing emissions, and saving costs. In order to address this gap, this study proposes a cohesive meta-reinforcement learning (MRL) approach for optimizing machining parameters. The objective is to detect commonalities in optimization approaches and use this comprehension to promptly adjust to novel machining assignments. The paper [19] investigates the cutting-edge methodologies and procedures employed in surface fault inspection, specifically in the domains of semiconductors, steel, and fabric manufacturing processes. The ML has made substantial progress in the last ten years. This progress is notably evident in the development of Deep Learning (DL) algorithms used in autonomous driving automobiles and electronic strategy games. Researchers are actively investigating the possibilities of ML in the industrial sector, viewing it as a crucial catalyst for the progress of old manufacturing settings towards Industry 4.0. Although there is increasing interest, the practical use of machine learning in industry is still somewhat restricted, mostly limited to a small number of multinational corporations. Bertolini et al. [20] examines this field, offering a thorough analysis to clarify the true capabilities and possible limitations for algorithms of ML in the field of operation management. Subject review has been methodically designed to aid practitioners' orientation, categorizing works from 2000 to the present based on the applicable algorithm and application domain. Within the field of industrial duties [21], quality control emerges as an area that is highly suitable for enhancement through technological advancements. Among these developments, machine vision appears as a breakthrough technology, enabling reliable and efficient 24/7 inspections that boost industrial processes' overall efficiency. The paper presents a machine vision model that surpasses defect diagnosis by incorporating continuous improvement into manufacturing processes. This literature review [22] situates the paper within the wider range of technical breakthroughs in quality control, highlighting the significant influence of vision and ML algorithms on improving the efficiency and effectiveness of industrial processes. Significantly, the review examines current works that employ deep learning methods for AOI. The article finishes by emphasizing prevailing patterns and delineating prospective avenues for further investigation. In their study, Huang [23] focuses on creating an advanced machine learning-based method for detecting defects in metal products. The system's structure incorporates picture preprocessing with computer vision library of OpenCV. Subsequently, training techniques are implemented, employing machine learning algorithms like generative adversarial networks (GAN), CNN plus chunk-max pooling. These techniques are employed to address the issue of insufficient datasets for surface defects. The evaluation processes are executed utilizing the Python programming language and GPU-accelerated embedded hardware to accomplish effective defect identification. The incorporation of machine learning (ML) [24] into the industrial sector, under the Industry 4.0 framework, has brought about significant and revolutionary alterations. Industry 4.0 focuses on implementing intelligent factories that utilize smart sensors, gadgets, and machines to constantly gather data on production operations. Hao (25) undertakes a thorough assessment of optical inspection methods in the semiconductor sector, classifying existing research according to inspection algorithms and the items being examined. The visual inspection technologies employ a variety of vision-based algorithms, such as projection techniques, filtering-based methods, learning-based approaches, and hybrid methods. Automated identification of flaws [26] on hot-rolled steel surfaces poses a significant difficulty because to considerations such as the need to locate them on large surfaces, changes in their appearance, and the rare incidence of flaws. Traditional methods, which depend on models based on physics or limited statistical data with only one threshold, face difficulties in accurately identifying these flaws. This study aims to tackle the difficulty by focusing on extracting a collection of superior defect characteristics from surface photos. The objective is to accurately differentiate between different types of surface defects when these characteristics are fed into appropriate machine learning algorithms. The study systematically evaluates the effectiveness of different wavelet feature sets, such as multiwavelet, biorthogonal spline, Daubechies 4 (DB4) and Haar, Daubechies 2 (DB2) with different levels of decomposition. The paper [27] principally concentrates on the advancement of cutting-edge technology, namely in the domain of automated fault inspection for concrete buildings. The proposed framework employs a multi-stage methodology encompassing gathering data, fault recognition, scene rebuilding, flaw evaluation, and data integration. The mobile data gathering device is highly adaptable and equipped with a 360° camera and electronic LiDAR. It excels at acquiring both images and three-dimensional spatial data in complex indoor environments. Methods of DL play a prominent role in the defect detection process, effectively examining the gathered photos for specific abnormalities in the concrete structure. The use of automated fabric flaw detection [28] has become an essential aspect of quality control in the textile production industry, leading to an increase in research efforts to develop efficient systems. This research thoroughly examines current progress in fabric defect detection, classifying them into non-motif-based and motif-based methods. Aforementioned research studies mostly discuss the role of AI in a single domain related to the modern industry. This article aims to fill a significant research gap by bringing together multiple studies on predictive maintenance, production optimization, and quality control to create an exhaustive resource. By filling this void, it offers academics a consolidated platform for conducting literature reviews across many fields and their corresponding AI implementations concurrently.

**4. RESEARCH SYNTHESIS TABLE**

The provided table provides a precise summary of the major elements of all cited articles, offering a comprehensive picture of the primary focus, methodologies, and application domains within the realm of predictive maintenance, production scheduling, defect detection, and other relevant industrial applications.

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| **References** | **Key Focus** | **Method/Approach** | **Application Area** |
| [1] | Predictive maintenance, Monitoring | Machine Learning | Industrial Machine |
| [2] | Literature Review in Predictive maintenance | Machine Learning | General |
| [3] | Anomaly Detection, Predictive Maintenance, System Modeling | Machine Learning | Industrial Plants |
| [4] | Predictive Maintenance, industry 4.0 | Machine Learning, Reasoning | Industry 4.0 |
| [5] | Predictive Maintenance, IoT | Machine Learning | Industrial Machines |
| [6] | Predictive Maintenance, industry 4.0, Sustainability | Machine Learning | Industry 4.0 |
| [7] | Predictive Maintenance, Automotive Industry | Machine Learning | Automotive Industry |
| [8] | Predictive Maintenance, industry 4.0, IoT, fog Computing | Machine Learning | industry 4.0 |
| [9] | Predictive Maintenance, IIoT, Condition Monitoring | Machine Learning | Condition Monitoring |
| [10] | Predictive Scheduling, Resource Allocation | Machine Learning | Manufacturing Systems |
| [11] | Production Scheduling, Deep Reinforcement Learning | Deep Reinforcement Learning | Production Scheduling |
| [12] | Resource Allocation, Industrial IoT, Deep Reinforcement Learning | Deep Reinforcement Learning | IIoT |
| [13] | Adaptive Production Control, Reinforcement Learning | Reinforcement Learning | Production Control |
| [14] | Scheduling, Discrete Automated Production Line, Deep Reinforcement Learning | Deep Reinforcement Learning | Automated Production Line |
| [15] | Reinforcement Learning, Industrial Automation | Reinforcement Learning | Industrial Automation |
| [16] | Dynamic Scheduling, Industry 3.5, Deep RL, Hybrid genetic method | Deep Reinforcement Learning, Hybrid Genetic Algorithm | Smart Production |
| [17] | Reinforcement Learning, production Planning, Control | Reinforcement Learning | Production Planning and Control |
| [18] | Meta-Reinforcement Learning, Machining Parameters, Energy-efficient Process Control | Meta-Reinforcement Learning | Process Control |
| [19] | Surface Defect Inspection, Deep Learning | Deep Learning | Industrial Products |
| [20] | Machine Learning, Industrial Applications | Literature Review | Industrial Applications |
| [21] | Machine Vision, Defective Product Inspection | Machine Learning | Defective Product Inspection |
| [22] | AOI, Quality Monitoring, Electronics Industry | Review, Analysis | Electronics Industry |
| [23] | Intelligent Defect Detection, Machine Learning | Machine Learning | General |
| [24] | Machine Learning, Industry 4.0 | Machine Learning | Industry 4.0 |
| [25] | Automated Visual Inspection, Semiconductor Industry | Survey | Semiconductor Industry |
| [26] | Automatic fault Detection, Steel Products | Machine Learning | Steel Products |
| [27] | Automated Defect Inspection, Concrete Structures | Machine Learning, LiDAR | Concrete Structures |
| [28] | Fabric Defect Detection | Review | Textile Manufacturing |

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4. Author 1, A.B. Title of Thesis. Level of Thesis, Degree-Granting University, Location of University, Date of Completion.
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