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APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN MANUFACTURING : A REVIEW

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ABSTRACT

In recent days, It's popularly acknowledged that Artificial Intelligence (AI) is going to play a major role in influencing a large number of fields and is going to be a major source of automation and innovation. In this review paper, we present an analytical and structured literature review of the current avant-garde of AI in manufacturing and its influence. We particularly analyzed and exemplified papers from a holistic manufacturing perspective. This review provides an overall perspective on how Artificial Intelligence has bolstered Manufacturing domains and how contributions over the years have shaped the role AI has played in manufacturing. AI applications are promising and tend to act as a game-changer in tackling hindrances in metallurgy. Future research can be expected towards developing advanced combined AI applications.
Keywords: Smart Manufacturing, Manufacturing Scheduling, IIOT, ML, Computer vision, Digital Twin, Data Grid

I INTRODUCTION

Artificial Intelligence (AI) is defined as an automated and intelligent system that is capable of performing physical tasks, exhibiting cognitive behavior, and solving various complex problems without explicit human interference [1,2] The ability of engineers to design, deliver and maintain state-of-the-art equipment and tools in the healthcare, insurance, energy, oil and gas, education, aerospace, manufacturing, and transportation industries have improved significantly in recent years with the help of artificial intelligence techniques. Compared to other industries currently, AI is not conventional in Manufacturing compared to other domains. In addition, from a holistic point of view [3], expect that AI will soon become a common tool used throughout the manufacturing sector. Recently many developments in the applications of AI to manufacturing have already emerged [4]. The traditional production model of large batch production does not offer malleability towards satisfying the requirements of individual customers. A new generation of smart factories is expected to undergo new multi-variety and small-batch customized production modes [5]. For that, Artificial Intelligence (AI) is enabling higher value-added manufacturing by accelerating the integration of manufacturing and information communication technologies, including computing, communication, and control. The characteristics of a customized smart factory are to include self-perception, operations optimization, dynamic reconfiguration, and intelligent decision-making. AI technologies will allow manufacturing systems to perceive the environment, adapt to external needs, and extract process knowledge, including business models, such as intelligent production, networked collaboration, and extended service models [6,7]. These avenues are really enticing to businesses and researchers.

Of late research and business have turned their attention to cost-effective and environmentally friendly production. An integrated model based on manufacturing processes and data analytics was established as one method of analysis. The model, which is composed of many layers, can be viewed as a computer-integrated manufacturing model from which computational intelligence can take command of all production processes. Such processes require

decision-making to steer them in the right direction [8]. In these processes, all decisions pertaining to the finished product were made at the business planning level. Operation management oversaw the operational choices pertaining to process optimization. Various sensor-based monitoring techniques were used at the monitoring level. At the level of the production process and the sensing level, respectively, data collecting and real-time processing were completed using AI-Based Modeling and Data-Driven Evaluation for Smart Manufacturing Processes.
In this review, we discuss the various components of Smart Manufacturing processes and their subdomains like manufacturing scheduling and computer vision-based systems for the manufacturing process.

II SMART MANUFACTURING

Long-term and not always simple, smart manufacturing is a process. It demands an extensive understanding of the variety of cutting-edge and contemporary technology used in this process. This review discusses cutting-edge research regarding the opportunities and problems facing the use of artificial intelligence in smart manufacturing today[9]. It tries to address concerns regarding important enabling technologies for smart Manufacturing. Smart manufacturing applications include deep learning-based product quality inspection, deep learning-based remaining useful life prediction for predictive maintenance, intelligent recommender systems, machine vision systems, intelligent scheduling for dynamic permutation flow shops, real-time and explainable process monitoring, and intelligence-driven decision support systems.

A technology-driven strategy called "smart manufacturing (SM)" uses equipment that is connected to the Internet to oversee the manufacturing process. SM's objective is to find ways to automate processes and use data analytics to boost industrial efficiency. Some smart manufacturing systems Industrial Internet of Things(also known as IIoT) are used which have sensors embedded in manufacturing equipment during deployments in order to gather information about the machines' performance and operational state[10]. Manufacturing engineers and data analysts can hunt for indicators that certain parts may break by evaluating the data coming off an entire factory's worth of machines, or even across numerous sites. This enables preventative maintenance to prevent unscheduled downtime on devices. Manufacturers might also look for patterns in the data to see where production is slowed down. A Strategy like this can serve to benefit the machines as well[11].

In the smart manufacturing process machines will be better equipped to communicate with one another as smart manufacturing spreads and more of them are networked through the Internet of Things, potentially supporting higher degrees of automation. The extensive expansion of IoT sensor deployment in manufacturing processes has increased the demand for efficient and effective data management strategies.

Automation that is effective and intelligent can result from embracing machine learning and artificial intelligence to benefit from production data. Not only AI, ML and IOT but there are also a large number of other technologies that will help in enabling smart manufacturing which include Drones and driverless vehicles, Blockchain, Edge computing, Predictive analytics, and Digital twins [12].

The goal is to give manufacturers a cutting-edge solution for managing manufacturing processes and to get insight into the different factors that make it possible for them to use efficient predictive technologies [13,14]. Advanced Process Control is an important research area in Semiconductor Manufacturing to improve the quality of products, especially in knowledge discovery. For example, High-Density Plasma Chemical Vapor Deposition appears to be a process area in semiconductor manufacturing predestined for the application of Data Mining. Promising results can be achieved by utilizing machine learning algorithms such as Support Vector Regression. The recent extension of Support Vector Machines overcomes pure classification and deals with multivariate nonlinear input data for regression.[15].

AI in Smart Manufacturing

AI applications integrated in customer relationship management, supply chain management, and enterprise information systems functional architecture, Planning and scheduling of production, logistics and inventory, Accounting and financial management, PLM, and Personnel paying particular attention to the manufacturing enterprises[16]. Improved capabilities are noted and suggested as AI

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solutions. AI-enabled decision-making implements better judgment Automated automation utilizing logic-based or machine-learning model systems[17]. It is an enterprise transformation process that results in the fusion of the four most significant disruptive technologies, notably the Internet of Things for Industry, Distributed Agent Systems, and Artificial intelligence meets cloud computing.

Digital twin and Smart Manufacturing

A digital twin can also be beneficial. Using simulation, machine learning, and reasoning to aid in decision-making, a digital twin is a virtual version of an object or system that spans its lifecycle and is updated from real-time data. Implementations of the digital twin can support smart manufacturing by fusing the real and digital worlds[18]. Machine learning-based applications of artificial intelligence are often regarded as innovative manufacturing technology. Certain fundamental ML techniques have been mentioned in **Figure 1**. However, ML techniques need a lot of high-quality training datasets, and for supervising ML, manual classification of those datasets is frequently necessary. Especially in a highly complicated and dynamic production environment, such an approach is expensive, labor- and time-intensive, and prone to errors. To overcome this Maheshwari and Brintha [19] have provided a framework for carrying out the suggested DT-driven method for creating ML models. The suggested framework was used in a use case with practical industrial application. The use case demonstrated how the suggested concept may be applied to the training of vision-based components orientation recognition employing simulations of DT models, which can then be applied to the adaptive control of the manufacturing process.

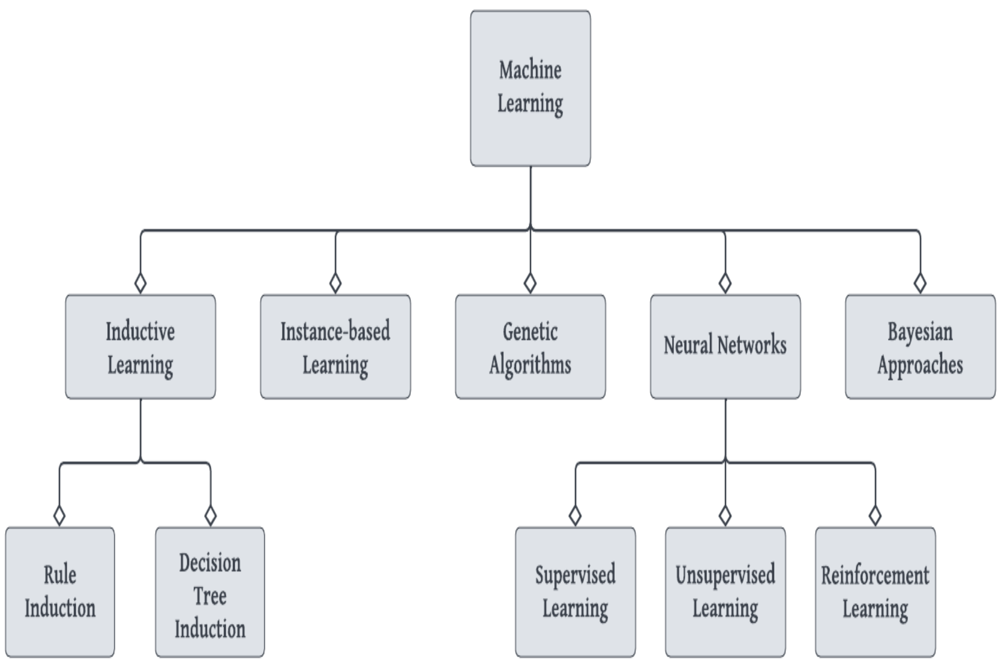

Fig.1. Fundamental ML techniques used in Smart Manufacturing

Data Grid and Smart Manufacturing

A data grid is a collection of computers that work together directly to schedule the processing of big operations. They played an important role in Industry 4.0. The new industrial revolution is called Industry 4.0. A massive amount of data is produced by linking every piece of equipment and activity via network sensors to the Internet. Machine learning and deep learning are two artificial intelligence subsets that are used to analyze the data created and generate insightful data about the manufacturing industry, while concurrently introducing Industrial AI.

From a simulation perspective as well, AI algorithms are growing prominent. Generally, simulations have been preferred to make difficult problems more tractable. It can contribute to elaborate new algorithms, undergird decision makers by utilizing Artificial Neural Networks and abating the risks in investments, and run the systems exposed to changes and disturbances more efficiently. From a simulation point of view, one can advocate Knowledge Based Hybrid Systems if intelligent systems are combined and used together.

ML and DL Algorithms

Ratnayake et al [20] et al reviewed the use of ML and DL algorithms employed in industry 4.0. They focused their study on smart grid applications, where ML and DL models were presented and their efficiency and effectiveness were examined. An example of the application of the DL algorithm in Manufacturing would be considering the factors such as Noise Factors and Design Indicative Factors to compute the speed of an automated guided vehicle. Last but not least, big data, scalability, and cybersecurity concerns as well as trends in the field of data analysis within the context of the new Industrial era were also emphasized and explored.

The way many engineering and manufacturing experts approach their work has changed with the introduction of large data, high processing speed, cloud computing, and artificial intelligence techniques. For engineers and producers, these technologies present exciting, cutting-edge solutions to difficult real-world problems. The availability of a wide range of theories, algorithms, and techniques makes it difficult to select the best AI approach for the correct engineering or manufacturing process and settings.

Specialized manufacturing

The conventional production model of mass production in big batches does not provide flexibility for meeting the needs of specific consumers. New multi-variety and small-batch customized production modes are anticipated to be supported by a new generation of intelligent factories. In order to do this, artificial intelligence (AI) is facilitating better value-added production by quickening the integration of manufacturing and information communication technologies, such as computing, communication, and control. Self-perception, operational optimization, dynamic reconfiguration, and intelligent decision-making are features of a tailored smart factory. Manufacturing systems will be able to sense their surroundings, adjust to external demands, and extract process knowledge, including information about business models like intelligent production, networked collaboration, and extended service models.

III MANUFACTURING SCHEDULING

Activities performed in a manufacturing firm done in order to fulfill the objective of management and controlling the execution of the production process could be abbreviated with the term Manufacturing Scheduling. The term schedule describes the time frame in which certain activities have to be performed so that the factory's resources are utilized efficiently in order to satisfy a production plan. In other words, it details how factories can use their machines to produce projects, within a certain time frame[21].

The character and content of scheduling research have always kept pace with the theoretical developments in operations research and computer science areas. Scheduling research adopted mathematical programming techniques such as linear programming, integer programming, and later multiple objective programming. The need for practical implementations took the research towards implementing branch and bound techniques. The adoption of simulation led to the use of queueing networks[22].

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Complexity Theory and Manufacturing Scheduling

Apart from the development aspects of computer hardware and software, the primary impact of computer technology on the schedule was the development of complexity theory. This theory led to a cleaner classification of scheduling problems on the basis of solution feasibility. Developments in artificial Intelligence (AI) and expert system technologies paved the way for a host of new approaches to tackling the scheduling problem AI has led to distributed AI, where solutions to scheduling problems are explored using intelligent problem-solving agents distributed across the factory. The distributed paradigm is closer to the natural way of problem-solving as it can even mimic the existing organizational structure.

Dispatching rules and Manufacturing Scheduling

Using dispatching rules is a typical method of scheduling jobs dynamically in a flexible manufacturing system (FMS), whose structure can be understood from **Figure 2**. The issue with this approach is that no single rule exists that performs better than the others in all potential system states. Instead, the performance of these rules relies on the state the system is in at any given time. Utilizing the best dispatching rule at each time would therefore be interesting. A scheduling strategy that makes advantage of machine learning can be employed to reach this objective. examining the system's standard methods performed in the past! Using this method, information is gathered that can be leveraged to determine the best dispatching rule at each instant in time.

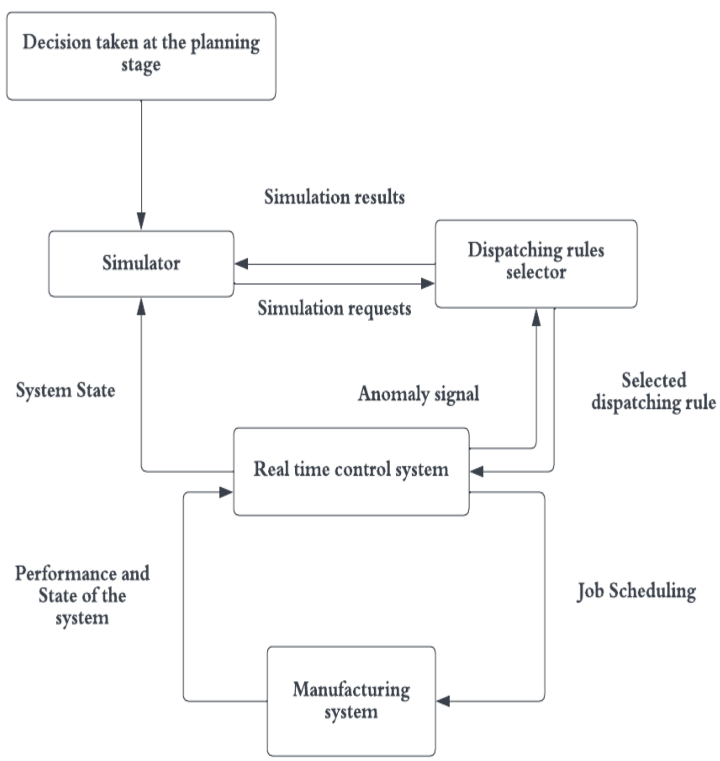

Fig.2 Components of Manufacturing Scheduling

Neural network and Manufacturing Scheduling

Neural network is a series of algorithms that endeavors to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates[23]. Neural networks can adapt to changing input; so the network generates the best possible result without needing to redesign the output criteria. The use of artificial neural networks, fuzzy systems, expert systems, pattern recognition techniques, and modern hybrid artificial intelligence (AI) approaches in manufacturing can all be seen as further steps in a process that began more than 20 years ago.

In order to demonstrate the advantages of combining simulation and machine learning (ML) techniques in manufacturing artificial intelligence (AI), various architectures with partially self-developed simulation packages are described in the paper[24]. On the ML side, artificial neural networks, heuristic search, simulated annealing, and agent-based techniques are used. The outcomes of the trial run serve as an illustration of how applicable the suggested remedies are which will in turn paint a picture of how effective production using such techniques can be. Since companies are forced to consider new and inventive ways to optimize their production as market demand for improved product and process quality and efficiency grows, even minor changes in the product's state during production might result in expensive and time-consuming rework or even scrappage in the high-tech manufacturing sector. One strategy to achieve the quality requirements and maintain competitiveness is to describe each product's status throughout the whole production program, including all pertinent information involved for usage, such as in-process alterations of process parameters. The collected data should ideally be directly examined so that, in the event of a detected significant trend or incident, appropriate action, including an alarm, can be initiated.

Due to the rapidly rising complexity and high dimensionality of contemporary production programs, traditional methodologies based on cause-and-effect relationship modeling hit their limits [25]. Hence there is a need for new methodologies that can handle this complexity and high dimensionality while producing useful outcomes with moderate effort. Studies are being done on the application of ML techniques to logistics, robots, assistance and learning systems for shop floor staff, planning and control of manufacturing processes, predictive maintenance, quality control, in situ process control and optimization, and logistics. Along with data analysis, data storage plays a pivotal role[26,27]. A heterogeneous data warehouse forms a single information space of the enterprise, which serves as the basis for analytical analysis throughout the production and decision—making process[28].

IV COMPUTER VISION

Realizing precise blast furnace bearing security detection at the same time in order to ensure the equipment's security is a significant difficulty. A computer vision system based on sensor data and hybrid deep-learning techniques is a solution to this issue. To effectively separate the fault components and original components from the sensor data, the Variational Mode Decomposition (VMD) algorithm, a new time-frequency analysis technique that can break down multicomponent signals into multiple single-component amplitude-modulated signals at once is being used in the industry. The above-said artificial intelligence can be used to extract the features efficiently and precisely. We enhance the coupling mechanism and construct a hybrid deep learning-based computer vision approach that significantly increases the calculation speed and accuracy of bearing failure diagnosis by incorporating the benefits of deep learning. It is fully compatible with the feature extraction technique VMD, which fixes the issue that the bearing feature component is simple to submerge and challenging to extract in hot and noisy environments. The findings by Yang et al [29] demonstrate that training on the sensor data gathered from the experiment enables the best parameter selection for computer vision technology based on sensor data and hybrid deep learning. The various applications of the computer vision system are also discussed below.

An enhanced application of the hybrid deep learning-based computer vision system can diagnose bearing faults with a hit rate of 97.4%. Another application of Computer Vision is Granite blocks which can be traced by using a limited number of color bands that each stand for a different numerical code. Throughout the production process, this code must be read multiple times, but because human error can affect accuracy, problems with the traceability system can result.

This issue is addressed by a computer vision system that uses color detection and accompanying code decoding. The CV system employs a number of thresholds for the isolation of the colors as well as color space modifications [30]. For the purpose of identifying colors, contour detection techniques and computer vision techniques are used. Finally, the color code collected is decoded using a study of geometrical properties.

V CONCLUSION

An analytical and organized literature analysis of the state-of-the-art AI in manufacturing and its impact are presented in this review study. The approaches that can be applied, as determined by the machine learning algorithm, are reviewed. The main focus of this study includes Smart Manufacturing, Manufacturing Scheduling, and Computer Vision. We reviewed the advantages and disadvantages that come with each method and have highlighted the same in the study.

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