A STUDY ON ARTIFICIAL INTELLIGENCE IN PRODUCTION MANAGEMENT

Satyendra Arya*

*Associate Professor,
Department of General Management/Production and Operation,
Teerthanker Mahaveer Institute of Management and Technology,
Teerthanker Mahaveer University, Moradabad, Uttar Pradesh, INDIA
Email id: satyendra.management@tmu.ac.in

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ABSTRACT

Artificial intelligence and intelligent devices are becoming more prevalent in our daily lives. This tendency does not spare industry or production, implying the potential for traditional managerial functions to be gradually replaced. Despite the fact that the number of Ai technologies in operation continues to rise, the articles do not appear to give much thought to the long-term ramifications. This report offers the findings of a thorough literature evaluation on artificial intelligence in production management over the previous two decades, based on 74 articles in 5 sources. Process monitoring and implementation, as well as scheduling, are found to be high-interest applications in this regard, according to the review. Both jobs fall under the umbrella of typical managerial functions, and are thus likely to be handled by autonomous systems in the future. According to our findings, there are currently no management models available to portray the growing reliance on cyber-technical systems, and researchers must solve this issue in order to make way for tomorrow's production planning.

KEYWORDS: *Artificial Intelligence; Production Management; Operations Management; Machine Learning; Data Mining; Management Model.*

1. INTRODUCTION

Production management, along with finance and marketing, is one of the three core roles of a corporation. The value-adding process of development inside a service delivery system is governed by production management as a dispositive element. Their job is to convert data into decisions in order to manage and lead the production process toward meeting predetermined performance goals. Production management can be thought of as the control element of a feedback control system that evaluates the transformation process' performance against super ordinate goals and enforces corrective actions when deviations occur. Volatile global markets are dramatically increasing the complexity of manufacturing enterprises, despite the fact that they are critical to society as job creators and value adders. Production technology and management have already gone through three industrial revolutions — mechanization, electrification, and automation – and are now facing the fourth. Rapid technological advancements answer a demand that has arisen as a result of increasing organizational complexity[1].

As a result, we are currently witnessing the gradual fusion of the virtual and real worlds of production management. Following the foregoing lines of reasoning, a good question for the future is to what degree production management jobs can and will be replaced by artificial intelligence (AI) technology in the future. However, the widespread substitution of production management activities presents several important concerns, including: what is the technological optimum between human-made and machine-made decisions? Who will be responsible for setting performance goals? What kind of skill sets will be needed? Who is responsible for mistakes? And, maybe most significantly, how much decision-making will remain entirely human? The fourth industrial revolution is supposed to move work in manufacturing contexts toward decision-making and creative tasks.

However, just as the societal effects of technical advancements are unpredictable, so are the managerial duties and activities that may develop as automated decision-making and partially automated decision support become more common[2]. Artificial intelligence (AI) techniques are increasingly being used as alternatives to traditional methods or as components of larger systems. They've been utilized to address difficult practical problems in a variety of fields, and they're getting increasingly popular presently. They can learn from examples, are fault tolerant in the sense that they can deal with noisy and incomplete data, can solve nonlinear problems, and can predict and generalize at fast speeds once taught. Because of their symbolic reasoning, adaptability, and explanatory capabilities, AI-based systems are being developed and used in a wide range of applications around the world. AI has been employed in a variety of fields, including engineering, economics, medicine, military, and maritime[3]. They've also been used for complex system modeling, identification, optimization, prediction, forecasting, and control. By addressing a number of difficulties in solar systems application, the study gives a knowledge of how AI systems work. Forecasting and modeling of meteorological data, sizing of solar systems, and modeling, simulation, and control of photovoltaic systems are among the issues discussed. The material reviewed in this paper demonstrates AI's promise as a design tool for solar systems.

Academia and practitioners now have a once-in-a-lifetime chance to plan, lead, and influence this shift. The image of an integrated management is a necessity for achieving this. At the moment, there are no models for such integrated management, and their absence makes it difficult to successfully guide organizational change initiatives. A follow-up study was done by the same authors from 2005 to 2009. The authors added Data Mining as a fifth AI approach due to its increasing use in applications. They found that Fuzzy Logic, Case-Based Reasoning, and their combinations were employed far less frequently than Neural Networks and Genetic Algorithms, which accounted for over half of the papers in the disciplines of Scheduling and Process Planning and Control, respectively. Furthermore, the authors discovered that research on Knowledge-Based Systems is declining, and they concluded that these methods have been thoroughly researched and are no longer considered unique. They report a low use of 59 articles for this time period when it comes to the new Data Mining approach. In contrast, a recent assessment of 47 publications on the topic of Data Mining in Production Management looked at 47 publications published between 2010 and 2017.

The authors discovered that quality improvement (23), scheduling, and defect diagnostics (each with seven applications) were the most common. The following ten publications were all in the defect analysis and other applications category. The reviews offered to this purpose cover a period of more than 32 years (do not state the period under examination, but the oldest article included was published in 1985). The employment of AI approaches in quality improvement, process planning and control, and especially scheduling appears to be a common denominator in all reviews. A similar tendency may be seen in this review. Six of the remaining nine publications, excluding the aforementioned five reviews, dealt with AI scheduling algorithms.

However, because they had already been accounted for in the most recent assessment, they have been excluded. Case-Based Reasoning was used to create a learning scheduler. That is, previous industry experience has been enshrined in a repository from which to draw.

With this information, shop-floor scheduling may be done in both a reactive and proactive manner to avoid delays caused by disruptions. To optimize execution-production order through information interchange between agents, use genetic algorithms in a multi-agent method. The method establishes upper and lower constraints for transitory times, allowing for more precise scheduling and, as a result, a reduction in overall make span. Both scheduling and costing assistance are handled in this section[4]. The authors propose methods for analyzing and discovering information from data in a manufacturing execution system so that it can be integrated into it. Different machine learning approaches are investigated, with Kernel and Ada Boost proving to be the most effective for the specific budgeting problem. However, due to a lack of data, classification was impossible for scheduling. Two references were found in terms of process quality improvement. To begin, determine the principles that govern the relationship between malfunctions/failures and corresponding delays in the production of oil and gas drilling. They use association rule mining to find linkages in massive databases between failure kinds and subsequent process delays. Second, build the groundwork for automated assembly system optimization: the study use genetic algorithms to optimize the simulation of a variety of manufacturing pull-type control policies (e.g. Kanban).

While the findings were satisfactory, the authors recognized that the algorithm they chose required a lot of manual tweaking. The approach is almost immediately usable for automated process control when combined with real-world data and machine learning techniques. Extreme learning machines were used in risk management to uncover hidden threats in industrial production environments and avert mishaps. The extreme learning machine employs neural networks and buffers incremental data in the hopes of contributing suitable weights to represent the current state of production. The authors find that this approach is more dependable in terms of accuracy and stability based on case study data. Finally, while it does not deal with production management in heavy engineering contexts, it does provide a comprehensive overview of application alternatives for the forest sector based on multi-agent topology.

Many applications, such as mill operation, supply chain planning, and risk management, have a lot in common with heavy engineering[5]. As a result, this piece is included to highlight AI's cross-industry applicability. This analysis has revealed that artificial intelligence (AI) is a recurring, and even developing, theme in production management. In general, based on the above data, academics have shown the most interest in process planning, process control, including quality improvement, and scheduling concerns, including machine operation plans and machine operator staffing. These are the most important aspects of production management. According to the references provided, AI approaches have been widely used to support these functions. When looking at the vision 2040 graphic again, it appears that scheduling and process planning and control are on the verge of shifting from phase 2 to phase 3 or higher, indicating that they have a good chance of eventually reaching autonomous decision-making.

Another major finding of this analysis is that all of the research and studies offered are limited to a single, very specific scenario or problem to be handled. However, a slew of scientific findings have the potential to break new ground in the field of production management. Despite this, no publication addresses the long-term consequences of their technological applications or advancements. This obviously supports the review paper's initial hypothesis. While academics and practitioners increasingly recognize AI's potential in the sphere of production, any long-term consequences of its implementation are being overlooked. As a result, we argue that, in light of the possibility of a step-by-step, gradual substitution of work at the managerial level, novel management models will be required in the future to capture ongoing cyber-centric developments and to protect the role of human decision-making in production management[6].

1.1 Trends in Artificial Intelligence:

The breakthrough of teaching machines how to learn from experience, referred to as machine learning (ML), by sifting through massive datasets and uncovering hidden patterns, resurrected AI in the previous few decades. While IBM's "Deep Blue" computer, which defeated world chess champion Garri Kasparow, was not an artificial intelligence in the sense of a learning machine, AlphaGo, which defeated the world's top Go-Player 19 years later, was. Experts were taken aback by this incident since AlphaGo demonstrated intuition, which had been thought to be an intractable problem for decades. By now, ML, which "sits at the intersection of computer science, statistics, and decision-making under uncertainty," has established itself as the method of choice within AI for a wide range of applications and has spread across a wide range of scientific fields, including particle research, communications psychology, genomics, astrophysics, and chemical synthesis.

Supervised and unsupervised learning algorithms, as well as reinforcement learning, are the most common ML methods. Furthermore, substantial research has been done on how to emulate human learning (i.e. learning associated skills), human cognition, and how to teach machines human preferences so that human intervention and control resources are reduced. While such rapid advancements suggest that machine learning will be one of the most transformative technologies of the twenty-first century, some mechanisms behind machine-made decisions, such as those made by deep neural networks, are still unknown and are being investigated in a field known as AI Neuroscience. Even apocalyptic scenarios are being addressed by scientists, who are highlighting important hazards and so-called accidents (defined as unplanned and bad behavior) associated with AI that must be addressed in a proactive manner. Who built safely interruptible agents that will not recognize an effort to shut them down outside, but will assume they shut themselves down, is one method to avoiding AI from seceding[7].

Models of Management (1.2):

Objectives and Management by Exception are socially driven and human-centered, focusing on mutual agreement on performance goals and the following monitoring and control of those goals. Although it has been suggested that Management by Objectives can be used as a performance review technique in highly digitalized industrial firms, there is little data to back this up. Instead, one may argue that when confronted with sincerely obedient, self-governing manufacturing systems and processes, these models will lose their utility. Forecast, plan, organize, command, co-ordinate, and control are the six distinct roles of management in general. We are currently witnessing the possibility of machines taking over the majority of these functions, rendering management textbooks obsolete. Work systems are considered a nexus of social and technological subsystems that are linked by the specification of a task in sociotechnical methods, which presume mutual interaction between social and technical subsystems, leading to the imperative that both can be maximized jointly.

The relationship between social and technical subsystems manifests itself in many forms of function division and human-machine interaction. As a result, it has been proposed that secondary duties such as system preservation (upkeep, training) and system regulation (detailed production planning, comprehensive production control, material placement, and so on) will become more important as sophisticated technologies are implemented. For the development of such a task orientation to occur, two requirements must be met: the working person must have control over operating cycles and auxiliaries, and the task must be constructed in such a manner that it elicits power to complete or continue their work. As a result, socio-technical techniques tend to presuppose a synergetic balance between technical and social systems, favoring the social over the technical. The 2040 vision, on the other hand, assumes that the technical subsystem will take over primary production management tasks, transferring a significant amount of control from humans to machines and granting it the ability to self-optimize independently of the social subsystem, a point that socio-technical approaches appear to be unable to capture at the moment[8].

1.3 A Production Management Vision for 2040:

While great effort is invested into AI research, it appears that the AI stream does not lend itself to production management. At the same time, no current academic effort that draws on AI literature to substantially address existing management paradigms has been uncovered. That is, there are major gaps in the state of the art of management literature and artificial intelligence, as well as their respective overlaps, that need to be filled in order to develop an integrated management model that includes cyber-centric aspects[9]. As a result of technological revolutions, a new form of production management will emerge at the point of interaction between human and artificial intelligence, as traditional management models are unable to cope with the growing reliance on information technology, massive amounts of data beyond human perception abilities, and non-human resources entering the workforce on a broad scale. The latter feature, in particular, has sparked debate in society, as intelligent machines are frequently associated with apocalyptic scenarios of deserted factories and entire towns ravaged by unemployment. As a result, future corporate success will necessitate a radical new management paradigm, one that shifts the focus from social to socio-technical perspectives while allowing human employees unrestricted reason for being[10].

2. DISCUSSION

A third of the papers considered relevant for this research are type reviews: evaluate 762 Internet of Things (IoT) business cases between 2009 and 2012 and indicate that RFID as the foundation for IoT is widely employed in operational functions for asset management and production management. Despite the nature of this study does not provide immediate information on management automating manual, the IoT dispersion examined here lays the groundwork for data mining activities that will eventually enable information for decision - making or autonomous decision-making, and is so included in this evaluation. They study the use of Knowledge-Based Systems, Case-Based Reasoning, Fuzzy Logic, and Neural Networks in various business operations and provide an overview of AI in OR. The authors find that Fuzzy Logic and Case-Based Reasoning have gotten much less attention than the other AI approaches, with scheduling receiving the most attention. Later, build on this review and take a more systematic approach to the study question: Between 1995 and 2004, they looked at over 1200 papers. According to their findings, Fuzzy Logic, which had previously received little attention, had gained in popularity, particularly for scheduling purposes, whereas Case-Based Reasoning remained underutilized. In the past, neural networks were commonly utilized in process planning and control. They also saw a drop in academic interest in Knowledge Based Systems.

3. CONCLUSION

This paper looked at 74 references from the last 20 years that were spread among five databases. The goal was to see if artificial intelligence has been applied in production management and if so, how. Based on 13 full-text articles, this study concluded that AI has primarily been applied to scheduling, process planning, and control. This suggests that these jobs are already receiving sufficient attention to transfer to the next level of machine help in our vision 2040, which is a steady substitution of management decision-making tasks up to autonomous machine-made decision-making. This review summarizes a large number of current research contributions on integrating AI into modern manufacturing systems. At the same time, no contribution to high-level assessments on the potential consequences of increasing the use of artificial intelligence systems in manufacturing was found. This backs up our initial hypothesis that future production management will necessitate new models capable of depicting a more cyber-centric production system.

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