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A Systematic Review of Machine Learning Approaches for Optimizing Production Scheduling in Smart Manufacturing

Ma. Victoria Rodriguez[1*], Noel Florencondia[2], Elbert Alison Benedicto[3]
[1]*Student, Graduate School, Nueva Ecija University of Science and Technology, Cabanatuan City, Philippines*
[2,3]*Professor, Graduate School, Nueva Ecija University of Science and Technology, Cabanatuan City, Philippines*

***Abstract*: This systematic review investigates the application of machine learning (ML) approaches in optimizing production scheduling within the context of smart manufacturing. As the fourth industrial revolution, Industry 4.0, reshapes manufacturing with interconnected systems, there is a growing demand for innovative solutions to address the inefficiencies in traditional scheduling processes. The impact of various machine learning (ML) techniques, including deep reinforcement learning (DRL), genetic algorithms (GA), particle swarm optimization (PSO), and neural networks (NN), on scheduling flexibility, efficiency, and flexibility in an existing real-time production system is examined in this study. The evaluation lists the primary determinants that impact these ML models' performance, such as algorithm selection, data quality, organizational preparedness, and technology infrastructure. Notwithstanding their great potential, issues with scalability, skilled labor, data quality, and interface with existing systems continue to be obstacles to broader use. The study concludes by summarizing the need for ongoing advancements in machine learning models for infrastructure in order to enable seamless deployment in actual industrial settings and offering manufacturers suggestions on how to optimize production scheduling with AI-based solutions.**

***Keywords*: Production scheduling, smart manufacturing.**

1. Introduction

In order to enable enterprises to use automated machinery and information technology for quick and innovative product engineering, the globe has seen three industrial revolutions in the last thirty years. The manufacturing sector is essential to the advancement of both the economy and technology. Saturated markets, a startling and unexpected shift in consumer preferences, a wide range of product variations, and lower batch sizes are just a few of the numerous difficulties that manufacturing companies face in today's extremely unstable business environment. (Zhou et al., 2020)

The fourth industrial revolution, or Industry 4.0, allows decision-makers to access data from a variety of potentially interconnected plant components and machinery. The Internet of Things (IoT) in industrial production (IIoT) is one way to conceptualize I 4.0. There is a widespread trend in many fields to use new data sources to enhance system comprehension and control. This tendency is much more time-healing, in fact, given the abundance of smart manufacturing technologies that include connected machinery, real-time monitoring, and data collection via IIoT devices. (Li et al., 2020).

Research papers portray AI (Artificial Intelligence) and ML (Machine Learning) as possible remedies for these problems. The best methods for scheduling problems, according to Del Gallo et al. (2023), are neural networks, reinforcement learning, and particle swarm optimization. According to the study, AI-powered solutions improved manufacturing efficiency and resource usage.

Additionally, Shaikh et al. (2022) thoroughly examined ML applications in the form, welding, molding, and machining processes. According to the study's findings, ML technology may be used to consistently complete proactive planning activities and greatly increase operational performance and product customization.

The existing AI-based scheduling solution has issues when used for actual industrial operations. Three major issues that controllers must consider are scheduling challenges among dynamic workstations, the need for large training samples, and integrating AI with pre-existing frameworks. In a paper published in Zeng et al. (2022) investigated existing implementation issues by putting out a hybrid framework for dynamic scheduling problems that combines the attention approach and deep

This study aims to systematically review existing literature on machine learning applications in production scheduling within smart manufacturing contexts. By analyzing current methodologies, key influencing factors, and implementation challenges, the research seeks to provide a comprehensive understanding of how AI and ML can optimize production scheduling and enhance overall manufacturing efficiency.

A. Statement of the Problem

Manufacturing industries struggle with inefficient production scheduling, which results in delays, increased operational costs, and resource underutilization. The study seeks to answer the following questions:

1. What are the most effective machine learning approaches for optimizing production scheduling in

*Corresponding author: mavictoriarodriguez549@gmail.com

smart manufacturing?

2. What key factors influence the success of machine learning-based scheduling methods?
3. What challenges and limitations exist in adopting AI-driven scheduling in real-world industrial settings?

B. Objectives

1. To conduct a systematic review of existing literature on machine learning applications in production scheduling.
2. To analyze the key factors that contribute to the efficiency of AI-driven scheduling in smart manufacturing.
3. To identify challenges and best practices for implementing machine learning-based scheduling solutions in industrial environments.

C. Significance of Study

The findings of the study are beneficial to the following sectors:

To the Manufacturing Industry, the study can provide insights into the most efficient machine learning strategies for optimizing production scheduling. Hence, it can also help the industry to improve efficiency, reduce costs, and improve the utilization of resources.

To the Technology Developers, the results of the study are beneficial as it can help them understand the factors which influences the success of machine leaning systems which aids in the development of more efficient industrial applications.

To the Future Researchers, the findings of this research can be utilized for developing research in similar fields. Hence, the results can be utilized as reference for future research on Ai-driven scheduling, trends, challenges, and best practices.

D. Scope and Limitations

The study offers a systematic evaluation of recent research on machine learning approaches for scheduling optimization in smart manufacturing environments. The study examines several machine learning methods used in production process scheduling, looks at important variables influencing AI scheduling success rates, and assesses real-world implementation issues for industrial machine learning deployment. The study's findings are based on academic publications from five to ten years ago, including conference proceedings, peer-reviewed journals, and other scholarly sources.

There are certain limitations to this research study. The only way the study works is by reviewing the body of current literature; it does not include any processes for developing, testing, or implementing a model. Because a lack of studies will restrict the generalizability of findings, the study is dependent on the availability of published research as well as its quality standards. Because different businesses have different operating constraints, the research might not have taken into consideration all unique scheduling issues in the manufacturing sector. The risk that new models or methodologies will surface after this research is concluded and might affect its long-term impact is increased by the continuous advancement of AI and smart manufacturing technology.

2. Review of Related Literature and Studies

A. Smart Manufacturing and Production Scheduling

The term "smart manufacturing" (SM), which was coined in the US but is now being used more and more around the world, has become quite popular in both industry and academics in recent years. SM systems (SMSs) are a common way for manufacturing systems to exhibit themselves. SM is a collection of manufacturing procedures that regulate manufacturing activities via the use of networked data and information and communication technologies (ICTs). (Suvarna et al., 2020).

Recent technological developments and the market's desire for highly individualized and customized goods have pushed manufacturers to create new solutions that will make them more adaptable and dynamic in the face of these emerging trends and rapidly shifting markets. The majority of current production systems rely on automated systems from the second and third industrial revolutions that were designed to achieve high performance and high delivery rates, but they lack autonomy, adaptability, and flexibility. (Alemao et al., 2021).

Zizic et al., (2022) stated that both vertical and horizontal integrations are a part of smart manufacturing. By linking the many value chain participants over the course of the product lifetime, horizontal integration enables production process optimization from suppliers to manufacturers and end usersThrough vertical integration, a number of hierarchical structures are included into the factory's production process, including workstations, human labor on the shop floor, software technologies like manufacturing execution systems, and marketing campaigns. (Ghosh et al., 2022).

Additionally, one of the most recent studies has been on AI-powered smart industrial production scheduling. For example, a thorough investigation shown how AI-powered scheduling may significantly reduce lead times, improving the responsiveness of industrial processes. Techniques like deep reinforcement learning (DRL) have proven effective in solving complex scheduling issues faster and with higher-quality results than traditional methods. However, because to their high resource requirements for computationally demanding tasks and the sizeable dataset required for training, these AI-based approaches may be limited in some industrial situations. (Suganthi et al., 2025).

Even though there have been encouraging advancements, putting AI-based scheduling systems into practice remains difficult. Since the changeover may require significant adjustments and financial outlays, integrating these technologies into contemporary manufacturing infrastructures is a serious challenge. Furthermore, scheduling systems must be flexible enough to adapt to changes in the industrial environment, such as supply chain interruptions or equipment failures. One area of active study is creating robust AI models that can handle such a range. (Serrano-Ruiz et al., 2021).

B. Machine Learning in Production Scheduling

Production scheduling is a crucial instrument in a manufacturing system that can have a big impact on the productivity of the production process, according to Takeda-Berger et al. (2020). The application of machine learning can be highly profitable in this sector since it allows computer programs to automatically derive intelligent conclusions from data in order to improve performance at the manufacturing system.

The effectiveness of the production-planning-and-control (PPC) endeavor will determine all of these factors, including competitive advantage, cost reduction, and timeline compliance. For PPC, machine learning (ML) opens up new possibilities for data-driven, intelligent decision-making. (Cadavid et al., 2018).

These machine learning methods are ideal defenses against the majority of complex production systems' most significant problems. Extremely complicated non-linear patterns in data from a variety of sources and data kinds can be addressed with this data-driven method. It can also convert unprocessed data into models that are utilized for production forecasting and scheduling. The availability of complicated and opaque data and the growing sophistication of machine learning tools are only two of the many variables that have contributed to the rise in the use of ML approaches in recent years. The goal of many machine learning approaches is to analyze vast volumes of data and process high dimensionality. (Panzer et al., 2022; Modesti et al., 2020).

Current studies on machine learning's efficacy in resolving scheduling conflicts. For example, a thorough investigation by Ruiz et al. (2021) identified critical gaps and opportunities in production scheduling and highlighted the potential of machine learning and data science techniques to improve manufacturing efficiency. Khadivi et al. (2025) have highlighted the advantages of deep reinforcement learning (DRL) in task assignment optimization, pointing out that DRL-based techniques frequently beat traditional heuristics in terms of computation speed and solution quality. Furthermore, by successfully capturing intricate interactions, Wang et al. (2023) have also presented a dual attention network framework that enhances flexibility and decision-making in flexible job shop scheduling.

C. Factors Influencing AI-Driven Scheduling Efficiency

When used in production scheduling, AI algorithms perform best when they are given high-quality data sources that contain all the necessary information. Inadequate scheduling results in data with errors or missing information. To obtain a comprehensive view of the manufacturing environment, it is essential to integrate data from IoT devices with supply chain platforms and enterprise resource planning (ERP) systems.This integration, which processes real-time data including supply chain information, demand patterns, and equipment status updates, makes it possible to achieve new levels of operational efficiency and more precise forecasts. (Ogunfowora & Najjaran, 2023; Chung et al.,2024).

As per Abbasi et al., (2024), because production procedures are so complicated, choosing the right artificial intelligence algorithms becomes crucial when scheduling them. Through dynamic environment learning, deep reinforcement learning (DRL) has demonstrated its capacity to improve task assignment optimization. Only when these algorithms successfully control the vast array of manufacturing process parameters can they yield outcomes that satisfy specific production requirements, necessitating constant modifications. (Fischer et al.,2024).

For AI scheduling solutions to be implemented throughout an organization, powerful computers are required in order to process large datasets and run intricate simulations. In order to fulfill the increasing demands for data processing, busy infrastructure must be able to support itself. Cloud computing is advantageous to manufacturers because its scalable capabilities allow them to perform large calculations with little investment in physical infrastructure. (Mahi et al., 2024; Soori et al., 2024).

The conditions of industrial production are always changing due to a variety of reasons, including shifting product demands, equipment availability issues, and disruptions in the supply network. To maximize operational efficiency, AI-controlled production schedules must be modified instantly. In order to manage production efficiency based on current conditions, artificial intelligence requires real-time data integration with algorithms built to react swiftly to new information. (Nweje & Taiwo, 2025; Aljoghaiman et al., 2024).

D. Synthesis

Numerous studies show how AI-based production scheduling techniques combined with smart manufacturing (SM) significantly increase industrial efficiency. According to Suvarna et al. (2020), smart manufacturing optimizes data and ICTs (information and communication technologies) through networks. With their focus on speed and performance, traditional industrial systems have issues with adaptation and autonomy that AI-based techniques solve (Alemao et al., 2021). When SM integrates both vertical and horizontal digitalization, it enables industrial goals pertaining to real-time data interchange, process improvement, and enhanced decision functions (Zizic et al., 2022; Ghosh et al., 2022).

Machine learning (ML) techniques are essential components of production scheduling that improve scheduling decision-making and address difficult operational issues. By providing data-driven scheduling automation with automated scheduling decisions, machine learning (ML) increases production productivity (Takeda-Berger et al., 2020). Research confirms that deep reinforcement learning algorithms (DRL) perform better than classical heuristics (DRL) in terms of computation and solution quality (Khadivi et al, 2025). Dual-attention networks applied with a machine-learning approach improve scheduling flexibility in manufacturing shops and production adjustment under changing working conditions (Wang et al., 2023).

The effectiveness of scheduling processes that employ artificial intelligence approaches is diminished by several obstacles. The accuracy of data directly affects the efficacy of scheduling outputs, which is not surprising given that missing or insufficient data results in insufficient scheduling outcomes (Ogunfowora & Najjaran, 2023; Chung et al., 2024). The selection of algorithms that enable adaptive self-learning systems is crucial for AI-based manufacturing process optimization because of the complexity of the industrial environment that calls for such systems (Abbasi et al., 2024; Fischer et al., 2024). The construction of a functional AI scheduling system requires a strong computational infrastructure since cloud resources and scale allow for the processing of large amounts of data and intricate simulations (Mahi et al., 2024. Soori et al., 2024). AI systems must function in real time due to supply chain disruption and dynamic response to machine faults.

In conclusion, every production-scheduling approach that combines machine learning and smart manufacturing improves productivity, adaptability, and flexibility in any industrial environment. To guarantee that the full potential of AI-driven scheduling is realized, however, problems including data quality, algorithm optimization, computing scalability, and real-time flexibility must be addressed. Building more resilient AI models with dynamic learning, real-time decision-making, and seamless integration with current manufacturing infrastructure requires more study.

E. Research Design

The study uses systematic review techniques to examine research publications regarding the application of machine learning algorithms in production schedule optimization for smart manufacturing. The evaluation of findings from scholarly articles, conference proceedings, and peer-reviewed journals is made possible by the principles of qualitative research. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) criteria are adhered to by the review process in order to preserve its transparency and structure. The key components of AI-driven production scheduling, including recent advancements and challenges as well as potential future breakthroughs, are revealed by this review of previous research.

F. Sampling Technique

To find relevant studies to include in the systematic review, the researchers used purposive sampling. The reputable databases IEEE Xplore, ScienceDirect, Springer, and Scopus, as well as Google Scholar, provide the information used in this study. The study chooses studies that focus on the use of machine learning to intelligent manufacturing and production scheduling that surfaced between 2020 and 2025. Peer-reviewed publications, studies not related to AI scheduling research, and academic approaches from the past are not included in the review. When taken as a whole, the final studies included in this research provide a thorough, up-to-date evaluation of the chosen topic.

G. Research Instrument

For systematic reviews, the research tool has two functions: it enables researchers to monitor written reports that arrange and extract important data from chosen studies. Along with the research aims, methods, important findings, and consulted study constraints, the matrix structure also includes bibliographic information about the author, publication year, title, and source. By allowing for suitable comparison of study data and spotting recurrent trends and gaps in AI-based production scheduling, the structured system helps researchers to do in-depth study analysis. To systematically arrange the collected data for proper insight categorization and synthesis, the researchers employ content analysis as their data analysis technique.

H. Data Gathering Procedure

The first step in the data collection procedure is to find pertinent sources using scholarly databases like IEEE Xplore, ScienceDirect, Springer, Scopus, and Google Scholar. The process of selecting studies involves using search terms such as "Machine Learning in Production Scheduling," "Smart Manufacturing and AI Optimization," and "AI-driven Scheduling Efficiency." Following the collection of an initial pool of studies, the articles are filtered using predetermined inclusion and exclusion criteria. The inclusion criteria concentrate on peer-reviewed conference papers and journal articles that were published between 2020 and 2025, especially those that address the effects of artificial intelligence (AI) on scheduling efficiency and machine learning applications in production scheduling. Studies that are based on outdated methods, are not academic, or have nothing to do with manufacturing and AI-driven scheduling are excluded.

After selecting the relevant studies, data extraction and analysis are done using the literature matrix. Every study is examined, and content analysis is employed to identify the key subjects, including scheduling challenges, productivity improvements, and AI model performance. The results are then combined and examined with an emphasis on recurrent trends, difficulties, and unexplored study areas. A thorough and methodical examination of the literature is made possible by this methodical methodology, which yields significant insights into the factors that contribute to machine learning's effectiveness in smart manufacturing about production scheduling optimization.

I. Data Analysis

A qualitative content analysis approach aids in the assessment of the literature of the research on machine learning production scheduling, with the use of a systematic review of a few chosen publications. The research approach identifies recurrent patterns, scientific trends, and unexplored territory in the research data collections of peer-endorsed research papers. The research foundation is an organized framework made up of standards to gauge findings in relation to the goals of the study and prioritized analyses of investigations.

A predetermined organizational structure is used in the analysis. Studies are categorized according to their core themes, which include scheduling efficiency enhancements, machine learning methodologies, and difficulties with integrating AI into smart manufacturing systems. In order to determine efficient techniques, the study investigates the performance of AI-driven scheduling strategies within each defined category.

The study assesses the restrictions and limitations described in the literature and suggests topics for further research.

By comparing the efficacy of traditional and AI-based scheduling approaches, the study verifies its conclusions. The benefits and drawbacks of using machine learning models for production scheduling optimization can be ascertained through a comparative analysis. The conclusion presents a cohesive text that illustrates how factory production performance is impacted by AI-based scheduling and offers suggestions for enhancing AI programming in subsequent studies.

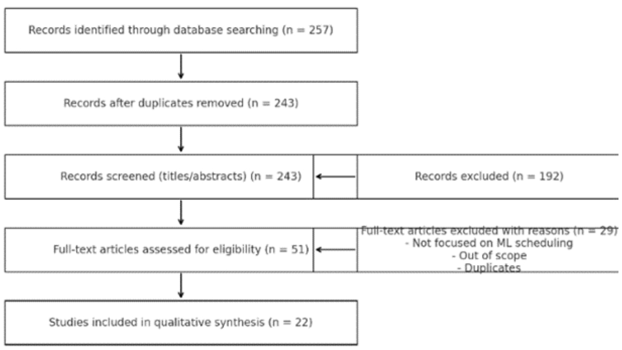

Fig. 1. Prisma flow diagram

3. Results and Discussion

A. Most Effective Machine Learning Approaches for Optimizing Production Scheduling in Smart Manufacturing

Machine learning (ML) has transformed production scheduling in smart manufacturing through data-driven systems that recognize trends and adjust their scheduling decision-making processes to increase efficiency. The most effective machine learning (ML) method to date is called Deep Reinforcement Learning (DRL). DRL has become popular because of its capacity to optimize complex scheduling problems through policy changes and continual learning. (Sahu et al., 2023). Due to research showing that DRL outperforms standard heuristics in terms of producing higher-quality solutions and speeding up operations, environmental input enables systems to make smarter scheduling decisions. This approach's ability to make decisions in real-time adds to its efficacy because production environments are subject to frequent, rapid changes. (Khadivi et al., 2025; Dong et al., 2020).

Genetic algorithms (GA) combined with reinforcement learning seem to be a very successful scheduling method. Through exploration efficacy and learning efficiency, the combined GA and reinforcement learning models gain from both methods, increasing scheduling accuracy and flexibility. Hybrid scheduling techniques are most useful when it's necessary to strike an effective balance between energy consumption, machine utilization requirements, and delivery time requirements. By increasing output, reducing manufacturing delays, and avoiding equipment stoppages, new models show exceptional potential. (Shaikat et al., 2025; Song et al., 2023).

An algorithm known as Particle Swarm Optimization (PSO), which functions as an efficient Machine Learning technique, has a significant positive impact on the scheduling process. PSO was able to create methods for scanning large areas while identifying ideal scheduling conditions because to the social finding patterns seen in swarms and flocks. (Del Gallo et al., 2023). Because PSO effectively optimizes production costs and better distributes resources under dynamic situations, smart manufacturing benefits from its deployment. (Saha et al., 2022).

The ability of neural network (NN) models, especially deep learning models, to model nonlinear production scheduling models is impressive due to their intricate relationship comprehension. By learning current and historical data trends, NNs are able to make well-informed decisions about work assignments, which in turn allows them to predict schedule accurately. The system remains lean due to its adaptability to changing customer needs, equipment availability, and workflow conditions. (Bhardwaj et al., 2018).

Finally, because to their immense potential for solving NP-hard problems, metaheuristic algorithms such as simulated annealing and tabu search have been widely used in production scheduling systems. Because of the related computational complexity, these algorithms offer general-purpose frameworks that perform well even in situations that are difficult for conventional optimization techniques to handle. They are suitable for real-world manufacturing applications due to their adaptability and ability to generate excellent solutions in a fair amount of time. (Daneshdoost et al., 2022; Alemao et al., 2021).

In conclusion, the most effective machine learning techniques to improve production scheduling in the field of smart manufacturing include deep reinforcement learning, hybrid reinforcement-genetic models, particle swarm optimization, neural networks, or meta-heuristic algorithms. Each of these strategies has a unique application strength and may be tailored to the particulars of a manufacturing environment, such as complex multi-objective trade-offs, real-time decision-making, or dynamic demand fluctuations. When combined, they offer a significant advancement above traditional scheduling methods toward more flexible, effective, and intelligent manufacturing processes.

B. Key Factors Influence the Success of Machine Learning-Based Scheduling Methods

The availability of high-quality data and data quality are the first of several interrelated elements that are essential for the effective application of scheduling paradigms based on machine learning (ML) in smart manufacturing. High-quality, consistent reference datasets with all the information required for ML model deployment and training are required. Inadequate, low-quality data significantly impairs schedule models' accuracy and reduces their usefulness for practical applications. Reliable and verified data collection and preprocessing are necessary for production scheduling to yield precise, scalable outcomes (Del Gallo et al., 2023; Shaikh et al., 2022).

Algorithm selection and customization are important elements of machine learning initiatives. The optimization capability of an algorithm is dependent on the specific scheduling needs as well as the complexity of the process, since each machine learning technique performs best in distinct production situations. Through their combined exploratory and adaptive learning capabilities, hybrid models that incorporate genetic algorithms and reinforcement learning are effective for better scheduling performance (Khadivi et al., 2025; Ruiz et al., 2021). The creation of factory-specific algorithms that take into account unique operational needs is necessary for the effective improvement of factory scheduling efficiency.

Any successful organization needs a long-term strategic plan that incorporates both cultural changes in business practices and technical improvements. Long-term success for these technologies depends on committed training, sufficient funding, and supportive leadership.

Integration and technological infrastructure are equally important. Current machine learning (ML) systems rely on real-time data flows from sources such as big data analytics, cloud platforms, and the Industrial Internet of Things (IIoT). Due to the continuous analysis of production floor circumstances, these systems enable responsive and adaptive scheduling. Only without adequate infrastructure can the advantages of machine learning be realized, particularly in dynamic situations (production environments change frequently) (Chung et al., 2024; Mahi, 2024).

Model interpretability and trust are two more important aspects to take into account. Many machine learning models operate as "black boxes," which may cause stakeholders to misunderstand or doubt the suggestions. Users can more readily explain model behavior thanks to the model's development using explainable AI (XAI) techniques, which boosts user confidence and acceptance of automated scheduling decisions. Only until greater openness is established will widespread adoption be feasible (Fischer et al., 2024).

Finally, scalability and adaptability are necessary to ensure that ML-based scheduling techniques continue to work as production volumes change. Scheduling models must be adaptable enough to take into account shifts in supply chain fluctuations, equipment availability, and job load because manufacturing settings are constantly changing. Long-term efficiency and resilience can be facilitated more effectively by models that can adjust to these changes in real time (Wang et al., 2023; Nweje & Taiwo, 2025).

In conclusion, high-quality data, a well-chosen algorithm, organizational commitment and preparedness, infrastructure integrity, model openness, and system scalability are all necessary for the success of ML-based production scheduling. The full potential of intelligent scheduling in smart manufacturing necessitates a comprehensive approach to these operational and technical aspects.

C. Challenges and Limitations Exist in Adopting AI-Driven Scheduling in Real-World Industrial Settings

AI-driven scheduling systems are challenging to implement successfully in industrial settings due to a number of issues. The intricacy of AI models is the main obstacle to their integration into the infrastructure of current legacy systems. In industrial facilities with established infrastructure systems, modern AI technology causes interoperability problems that lower operational performance (Windmann et al., 2024).

In an industrial setting, obtaining sufficient quality data is a critical issue. For AI models to function properly during training and prediction tasks, large databases with trustworthy data are required. According to Monostori et al. (2016), noise, inconsistency, and incompleteness in industrial data impair AI model performance since they prevent real-world application.

Because AI models are still difficult for humans to understand, ADB systems encounter challenges. Since many AI algorithms operate opaquely, stakeholders have difficulty comprehending decision-making processes. When well-defined decision explanations are essential, industrial stakeholders become distrustful of and refrain from deploying AI-driven solutions due to the lack of clarity in AI systems (Wuest et al., 2016).

The nature of AI models' scalability and adaptability reflect new problems. Because production processes and operating requirements are always changing, industrial locations must adapt. The requirement for AI models to adjust to various changes limits their scalability because retraining and updating processes require substantial resources, which postpone scaling (Lu, 1990).

The final major obstacle to deploying AI-driven scheduling systems is the lack of skilled workers capable of developing, maintaining, and deploying AI systems. Employees with expertise in both industrial processes and artificial intelligence technology are needed to implement AI-driven scheduling. Jourdan et al. (2021) state that interdisciplinary competence is a significant barrier to effective adoption.

4. Summary, Conclusion, and Recommendations

A. Summary of Findings

This systematic review examined recent literature on the use of machine learning (ML) approaches to optimize production scheduling within smart manufacturing environments. A total of 22 relevant studies published between 2020 and 2025 were included in the qualitative synthesis, following a rigorous selection process based on the PRISMA methodology. According to the assessment, a number of machine learning techniques have shown a great deal of promise in improving scheduling effectiveness, adaptability, and responsiveness in actual industrial systems.

One of the most effective methods is deep reinforcement learning (DRL), which excels in dynamic contexts and can schedule in real time. The remarkable performance of models that integrate reinforcement learning and genetic algorithms (RL-GA) may be ascribed to their increased adaptability and optimization capabilities. The scheduling capabilities of evolutionary algorithms, such as particle swarm optimization (PSO) and neural networks' capacity for pattern recognition and prediction, were confirmed by experts. It has been demonstrated how useful a combination of tabu search and simulated annealing is for locating nearly optimal solutions to scheduling problems of the NP-Hard class.

The success of these machine learning-based techniques depended on a wide range of factors. For the model to be properly trained, detailed data that was of the highest quality and consistency had to be delivered in real time. The chosen machine learning algorithm must supplement the production environment's requirements in order to achieve optimal performance. With the help of cloud computing and IoT integration made possible by a suitable technological foundation, robust and flexible scheduling solutions were created. The interpretability of AI models was the most crucial factor in allowing people to trust the technology and embrace its solutions. For these scheduling methods to be implemented successfully, the organization needed to be prepared, which included management support, constructive interdepartmental teamwork, and capable personnel.

AI-driven scheduling solutions, while promising, have a number of disadvantages and limitations in industrial settings. Modern AI technologies are difficult to install because of the technical obstacles that sometimes accompany interaction with legacy systems. Issues with data, like noise, inconsistency, and incompleteness, can skew model accuracy and impair performance. The lack of transparency in complicated models, particularly those based on deep learning, may cause stakeholders to lose faith in them and oppose their adoption. Furthermore, scalable and flexible modeling paradigms are necessary due to the dynamic nature of manufacturing systems, yet maintaining them can be costly.

In conclusion, even if machine learning (ML) has revolutionary potential for smart manufacturing production scheduling, its successful implementation and long-term effects depend on resolving these crucial success criteria and obstacles.

B. Conclusion

The thorough understanding of machine learning applications for maximizing production scheduling features in intelligent manufacturing systems is established by the systematic review. Neural networks, deep reinforcement learning, hybrid algorithms, and other cutting-edge machine learning techniques offer significant scheduling advantages that are reflected in responsive, adaptable, and effective production processes. Because these modern scheduling techniques can make decisions in real time and handle complex industrial scenarios, they outperform traditional scheduling techniques. The successful implementation of these technologies depends on a number of critical factors, including the quality and accessibility of data, the algorithms' applicability, the organizations' preparedness, and the technological infrastructure. According to studies, these techniques perform well in controlled research settings; nevertheless, their widespread use in industrial contexts is hampered by problems with integration systems, interpreter illiteracy, scalability limitations, and labor market concerns. In order to successfully adopt machine learning techniques for production scheduling, enterprises must recognize both their advantages and disadvantages.

C. Recommendations

According to the results of this analysis, manufacturing sectors and technology developers should adopt a systematic and progressive approach when implementing ML-based scheduling systems. Companies must invest in creating outstanding data processing systems and creating connecting tools to ensure seamless system integration. The industry should employ exacting standards when choosing scheduling algorithms, which calls for thorough validation and appropriate model testing. To reduce their dependence on commercial vendors, organizations should implement internal training programs that encompass both AI and production process knowledge in order to create two forms of competence. Explainable AI solutions, which companies must create and use to gain the trust of their end users, should enable people to profit from transparent AI systems. Lightweight, scalable, self-adaptive machine learning models that exhibit dependable performance in uncertain production environments are essential for the advancement of both academic and industrial research. These suggested standards support ethical, sustainable, and useful approaches to incorporating AI scheduling technology into intelligent manufacturing processes.

References

[1] Abbasi, M., Nishat, R. I., Bond, C., Graham-Knight, J. B., Lasserre, P., Lucet, Y., & Najjaran, H. (2024). A Review of AI and Machine Learning Contribution in Predictive Business Process Management (Process Enhancement and Process Improvement Approaches).

[2] Alemão, D., Rocha, A. D., & Barata, J. (2021). Smart manufacturing scheduling approaches—Systematic review and future directions. *Applied sciences, 11*(5), 2186.

[3] Aljoghaiman, A., & Mirzaliev, S. (2024). Adoption of artificial intelligence and digital supply chain for enhancing supply chain performance: mediating role of green supply chain process. *Operational Research in Engineering Sciences: Theory and Applications, 7*(3).

[4] Bhardwaj, A., Di, W., & Wei, J. (2018). Deep Learning Essentials: Your hands-on guide to the fundamentals of deep learning and neural network modeling. Packt Publishing Ltd.

[5] Cadavid, J. P. U., Lamouri, S., Grabot, B., & Fortin, A. (2019). Machine Learning in Production Planning and Control: A Review of Empirical Literature. *IFAC-PapersOnLine*, 52(13), 385–390.

[6] Chung, J., Fayyad, J., Younes, Y. A., & Najjaran, H. (2024). Learning team-based navigation: a review of deep reinforcement learning techniques for multi-agent pathfinding. *Artificial Intelligence Review, 57*(2), 41.

[7] Daneshdoost, F., Hajiaghaei-Keshteli, M., Sahin, R., & Niroomand, S. (2022). Tabu search based hybrid meta-heuristic approaches for schedule-based production cost minimization problem for the case of cable manufacturing systems. *Informatica, 33*(3), 499-522.

[8] Del Gallo, M., Mazzuto, G., Ciarapica, F. E., & Bevilacqua, M. (2023). Artificial intelligence to solve production scheduling problems in real industrial settings: Systematic Literature Review. *Electronics, 12*(23), 4732.

[9] Dong, H., Dong, H., Ding, Z., Zhang, S., & Chang, T. (2020). *Deep reinforcement learning*. Singapore: Springer Singapore.

[10] Fischer, D., Hüsener, H. M., Grumbach, F., Vollenkemper, L., Müller, A., & Reusch, P. (2024). Demystifying Reinforcement Learning in Production Scheduling via Explainable AI.

[11] Ghosh, S., Hughes, M., Hodgkinson, I., & Hughes, P. (2022). Digital transformation of industrial businesses: A dynamic capability approach. *Technovation, 113*, 102414.

[12] , N., Longard, L., Biegel, T., & Metternich, J. (2021). Machine learning for intelligent maintenance and quality control: A review of existing datasets and corresponding use cases.

[13] Khadivi, M., Charter, T., Yaghoubi, M., Jalayer, M., Ahang, M., Shojaeinasab, A., & Najjaran, H. (2025). Deep reinforcement learning for machine scheduling: Methodology, the state-of-the-art, and future directions. *Computers & Industrial Engineering*, 110856.

[14] Li, Y., Carabelli, S., Fadda, E., Manerba, D., Tadei, R., & Terzo, O. (2020). Machine learning and optimization for production rescheduling in Industry 4.0. *The International Journal of Advanced Manufacturing Technology, 110*(9), 2445-2463.

[15] Lu, S. C. (1990). Machine learning approaches to knowledge synthesis and integration tasks for advanced engineering automation. *Computers in Industry, 15*(1-2), 105-120.

[16] Monostori, L., Kádár, B., Bauernhansl, T., Kondoh, S., Kumara, S., Reinhart, G., & Ueda, K. (2016). Cyber-physical systems in manufacturing. *Cirp Annals, 65*(2), 621-641.

[17] Mahi, R. (2024). Optimizing supply chain efficiency in the manufacturing sector through ai-powered analytics. *International Journal of Management Information Systems and Data Science, 1*(1), 41-50.

[18] Modesti, D., Henrique, P., Carvalhar Fernandes, E., & Borsato, M. (2020). Production planning and scheduling using machine learning and data science processes. In *SPS2020* (pp. 155-166). IOS Press.

[19] Nweje, U., & Taiwo, M. (2025). Leveraging Artificial Intelligence for predictive supply chain management, focus on how AI-driven tools are revolutionizing demand forecasting and inventory optimization. *International Journal of Science and Research Archive, 14*(1), 230-250.

[20] Ogunfowora, O., & Najjaran, H. (2023). Reinforcement and deep reinforcement learning-based solutions for machine maintenance planning, scheduling policies, and optimization. *Journal of Manufacturing Systems, 70*, 244-263.

[21] Panzer, M., Bender, B., & Gronau, N. (2022). Neural agent-based production planning and control: An architectural review. *Journal of Manufacturing Systems, 65*, 743-766.

[22] Ruiz, J. C. S., Bru, J. M., & Escoto, R. P. (2021, June). Smart Digital Twin for ZDM-based job-shop scheduling. In *2021 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4. 0&IoT) (pp. 510-515)*. IEEE.

[23] Saha, S., Saha, A., Roy, B., Sarkar, R., Bhardwaj, D., & Kundu, B. (2022). Integrating the Particle Swarm Optimization (PSO) with machine learning methods for improving the accuracy of the landslide susceptibility model. *Earth Science Informatics, 15*(4), 2637-2662.

[24] Sahu, S. K., Mokhade, A., & Bokde, N. D. (2023). An overview of machine learning, deep learning, and reinforcement learning-based techniques in quantitative finance: recent progress and challenges. *Applied Sciences, 13*(3), 1956.

[25] Serrano-Ruiz, J. C., Mula, J., & Poler, R. (2021). Smart manufacturing scheduling: A literature review. *Journal of Manufacturing Systems, 61*, 265-287.

[26] Shaikh, A., Shinde, S., Rondhe, M., & Chinchanikar, S. (2022). Machine learning techniques for smart manufacturing: a comprehensive review. *Industry 4.0 and Advanced Manufacturing: Proceedings of I-4AM 2022*, 127-137.

[27] Shaikat, F. B., Islam, R., Happy, A. T., & Faysal, S. A. (2025). Optimization of Production Scheduling in Smart Manufacturing Environments Using Machine Learning Algorithms. *Letters in High Energy Physics, 2025*, 1-10.

[28] Song, Y., Wei, L., Yang, Q., Wu, J., Xing, L., & Chen, Y. (2023). RL-GA: A reinforcement learning-based genetic algorithm for electromagnetic detection satellite scheduling problem. *Swarm and Evolutionary Computation, 77*, 101236.

[29] Soori, M., Jough, F. K. G., Dastres, R., & Arezoo, B. (2024). AI-based decision support systems in Industry 4.0, A review. *Journal of Economy and Technology*.

[30] Suganthi, P., Praba, R. S., Thilaga, S., Kumar, K. A., & Deepa, J. (2025, February). A review of AI-powered production scheduling in smart factories: Impacts on lead times and resource utilization. In *AIP Conference Proceedings* (Vol. 3204, No. 1). AIP Publishing.

[31] Suvarna, M., Büth, L., Hejny, J., Mennenga, M., Li, J., Ng, Y. T., & Wang, X. (2020). Smart manufacturing for smart cities—overview, insights, and future directions. *Advanced Intelligent Systems, 2*(10), 2000043.

[32] Takeda-Berger, S. L., Frazzon, E. M., Broda, E., & Freitag, M. (2020, February). Machine learning in production scheduling: an overview of the academic literature. In *International conference on dynamics in logistics* (pp. 409-419). Cham: Springer International Publishing.

[33] Wang, R., Wang, G., Sun, J., Deng, F., & Chen, J. (2023). Flexible job shop scheduling via dual attention network-based reinforcement learning. *IEEE Transactions on Neural Networks and Learning Systems, 35*(3), 3091-3102.

[34] Windmann, A., Wittenberg, P., Schieseck, M., & Niggemann, O. (2024, August). Artificial Intelligence in Industry 4.0: A Review of Integration Challenges for Industrial Systems. In *2024 IEEE 22nd International Conference on Industrial Informatics (INDIN)* (pp. 1-8).

[35] Wuest, T., Weimer, D., Irgens, C., & Thoben, K. D. (2016). Machine learning in manufacturing: advantages, challenges, and applications. *Production & Manufacturing Research, 4*(1), 23-45.

[36] Zeng, Y., Liao, Z., Dai, Y., Wang, R., Li, X., & Yuan, B. (2022). Hybrid intelligence for dynamic job-shop scheduling with deep reinforcement learning and attention mechanism.

[37] Zhou, T., Tang, D., Zhu, H., & Wang, L. (2020). Reinforcement learning with composite rewards for production scheduling in a smart factory. IEEE Access, 9, 752-766.

[38] Zizic, M. C., Mladineo, M., Gjeldum, N., & Celent, L. (2022). From industry 4.0 towards industry 5.0: A review and analysis of paradigm shift for the people, organization and technology. *Energies, 15*(14), 5221.