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Optimization of Production Scheduling Using Machine Learning: A Systematic Literature Review

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Abstract

Modern production systems are increasingly complex, requiring scheduling methods that can handle dynamic environments, diverse constraints, and large-scale operations. Traditional approaches often lack flexibility, while machine learning (ML)–based methods, despite their potential, still face limitations related to scalability, generalizability, interpretability, and computational efficiency. This study presents a systematic literature review of 77 primary studies published between 2014 and 2024, conducted in accordance with the Kitchenham and Charters framework. The review analyzes major research outlets, commonly applied ML techniques, reported performance, and proposed enhancements. Reinforcement learning, particularly deep reinforcement learning, dominates the literature, with methods such as Q-Learning, Deep Q-Networks, and Proximal Policy Optimization showing promise for dynamic scheduling. However, challenges remain regarding convergence speed, data requirements, reward design, and real-time adaptability. Future research should focus on scalable, adaptive, interpretable models and tighter integration with real-time data and Industry 4.0 systems.

1. INTRODUCTION

Modern production systems are becoming increasingly complex, requiring efficient and adaptable scheduling solutions to cope with dynamic environments, diverse constraints, and large-scale problems (Fülöp et al., 2022). This complexity presents significant challenges for traditional scheduling methods, which often struggle to adapt and optimize production processes effectively (Togo et al., 2022). For example, the automotive industry faces fluctuating demand, multi-stage assembly lines, and just-in-time supply chains that require real-time rescheduling to avoid costly downtime. In the semiconductor sector, scheduling must account for reentrant flows, extremely long processing times, and strict quality requirements, where even minor disruptions can lead to large productivity losses. Similarly, in chemical and process industries, safety-critical operations and highly interdependent production stages demand robust and adaptive scheduling systems. These sector-specific challenges highlight why conventional optimization techniques often fall short and why machine learning approaches are increasingly explored as viable alternatives. Consequently, the exploration of machine learning

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(ML) as a potential solution has gained significant traction within the research and industrial communities (Ghasemi et al., 2022). ML techniques enable systems to learn from data, detect patterns, and make informed decisions capabilities that align well with the complex requirements of modern production scheduling (Kim & Maravelias, 2022; Kusnadi & Pratama, 2024).

This systematic literature review (SLR) aims to deliver a thorough examination of how machine learning is currently applied to production scheduling. By analyzing a wide range of scholarly and industry-related literature, this study identifies key research trends, evaluates the performance of various ML techniques, and outlines future research directions (Togo et al., 2022). Our investigation delves into several crucial aspects, including the identification of prominent journals and influential researchers that are shaping the field. We further explore the landscape of commonly used machine learning methods for production scheduling optimization, evaluating their strengths and limitations in different contexts (Schweitzer et al., 2023). Additionally, we examine proposed method improvements and novel techniques that hold promise for advancing the capabilities of machine learning in addressing complex scheduling challenges.

Previous reviews have often presented broad surveys of machine learning applications in scheduling without fully addressing differences across industrial contexts or evaluating the practical limitations of specific methods. This review adds value by analyzing 77 studies published between 2014 and 2024, providing an updated and comprehensive picture of the field. It examines how reinforcement learning and its variants are being applied in practice, while also identifying persistent shortcomings such as poor scalability, limited adaptability to real-time disruptions, and low interpretability for industry practitioners. By combining a systematic mapping of the literature with a discussion of unresolved challenges, this review moves beyond summarizing existing work and offers clearer guidance for future research directions as well as actionable insights for industrial application. (Alexopoulos et al., 2023). Ultimately, the incorporation of machine learning into production planning is seen as a transformative force, with the potential to boost productivity, cut operational costs, and improve competitiveness across the manufacturing sector (Fülöp et al., 2022).

2. METHODS

Review Framework

A methodical approach is chosen for examining the literature on production scheduling problems using machine learning techniques. The Systematic Literature Review (SLR) approach is well established in production scheduling research. It is defined as a formal process involving the identification, evaluation, and interpretation of all relevant studies to answer targeted research questions (Kitchenham & Charters, 2007). Our study adheres to the guidelines proposed by Kitchenham & Charters (2007), while also drawing from methodologies suggested by Radjenović et al. (2013) and Unterkalmsteiner et al. (2011).

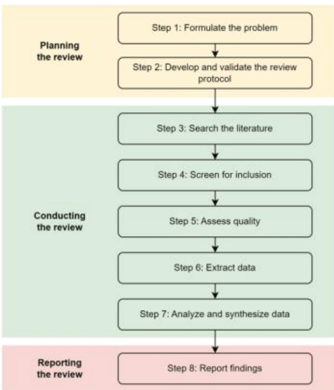

Fig 1. Systematic Literature Review Steps

As depicted in Figure 1, the SLR process is divided into three fundamental phases: planning, execution, and reporting. At the planning stage, the key requirements for carrying out a systematic review are established. The review then defines its objectives in the context of ML-based scheduling challenges. In the next phase, existing relevant literature is gathered and analyzed (De et al., 2024). To maintain transparency and reduce bias, a detailed review protocol is designed. This protocol includes steps such as setting research questions, designing the search process, defining selection criteria, assessing study quality, and integrating the collected findings (Campos et al., 2022; Febriani et al., 2023). The protocol is refined iteratively throughout the execution and reporting phases of the review.

Research Questions

To provide a structured focus for the review, the research questions were systematically formulated using the Population, Intervention, Comparison, Outcomes, and Context (PICOC) framework, as proposed by (Kitchenham & Charters, 2007). Table 1 illustrates the PICOC structure of the research questions.

Table 1. Summary of PICOC

Population	**Production scheduling, machine learning**
Intervention	Machine learning models, methods, and techniques applied to improve production scheduling processes.
Comparison	n/a
Outcomes	Evaluation of performance in production scheduling, identification of successful machine learning methods.
Context	Literature from both industry and academia, utilizing small and large datasets related to production scheduling.

Table 2 outlines the research questions along with the rationale underpinning this literature review. In the investigation of machine learning's application to production scheduling, six research questions were formulated to provide a comprehensive understanding of the field. The primary focus was on identifying significant journals (RQ1) and influential researchers (RQ2) actively contributing to this area of study.

Table 2. Research Questions on Literature Review

No	Research Question	Motivation
1	Which journals have made the most influential contributions to the field of machine learning applications in production scheduling?	Identify the most significant journals in applying machine learning techniques to production scheduling.
2	Who are the most active and influential researchers in applying machine learning to production scheduling?	Identify the most active and influential researchers who have contributed significantly to applying machine learning in solving production scheduling problems.
3	What machine learning methods are commonly used for optimizing production scheduling?	Identify trends and common machine learning methods for optimizing production scheduling.
4	Which machine learning method performs best for optimizing production scheduling?	Identify the best-performing machine learning method for optimizing production scheduling.
5	What method improvements are proposed for applying machine learning to production scheduling?	Identify proposed method improvements for optimizing production scheduling using machine learning techniques.

Furthermore, attention was given to the common machine learning methods (RQ3) utilized for optimizing production scheduling and assessing the performance of these methods (R4) to determine the most effective approach. Lastly, proposed method improvements (RQ5) were examined to highlight advancements in applying machine learning to enhance production scheduling processes. By conducting a systematic literature review, these research questions seek to shed light on the present state, emerging trends, and prospective developments of machine learning applications in optimizing production scheduling.

Search Strategy

In the third step of the search process, various tasks are undertaken, such as choosing relevant digital libraries, constructing the search string, conducting a preliminary search, adjusting the search terms, and compiling an initial list of primary studies from digital libraries that align with the search criteria. Prior to beginning the search, it is important to select suitable databases to improve the chances of retrieving highly relevant literature. This review primarily relies on the Scopus database (scopus.com), due to its broad recognition as a reputable source in the field, ensuring thorough coverage of the literature related to the research topic. The following search string was eventually used:

production AND (scheduling OR schedule) AND machine AND learning

The database queries were conducted by targeting titles, keywords, and abstracts, and were restricted to publications released between 2014 and 2024. The search covered two categories of literature: journal articles and conference papers. Furthermore, only English-language publications were considered.

Study Selection and Quality Assessment

Criteria for inclusion and exclusion were applied to guide the selection of primary studies, as outlined in Table 3.

Table 3. Inclusion and Exclusion Criteria

Inclusion Criteria	Relevance to Topic: The abstracts should explicitly demonstrate the implementation of machine learning techniques within the context of production scheduling.
	Methodology Clarity: Abstracts should provide clear descriptions of the machine learning algorithms/methods used for production scheduling optimization.
	Clear Results: Abstracts must present clear findings or results related to the application of machine learning in improving production scheduling efficiency.
Exclusion Criteria	Irrelevant Topic: Abstracts lacking clear indication of the application of machine learning in production scheduling are excluded.
	Methodology Ambiguity: Abstracts with vague or unclear descriptions of the machine learning methodologies employed for production scheduling are excluded.
	Unclear Results: Abstracts not presenting clear findings or results related to the application of machine learning in production scheduling optimization are excluded

Figure 3 presents a detailed summary of the search procedure, including the number of studies identified at each stage of the process. It visualizes the steps involved in study selection and quality evaluation (Steps 4 and 5), starting with the exclusion of studies based on titles and abstracts, and subsequently on full-text content. Studies solely presenting literature reviews or lacking empirical results were excluded. Furthermore, study inclusion was determined by their relevance to production scheduling problems.

A total of 364 primary studies were initially retrieved during the first stage of the selection process. These studies underwent a thorough full-text evaluation, during which several criteria were applied, including adherence to predefined inclusion and exclusion standards, methodological soundness, alignment with the research questions, and the presence of content overlap with other works. Redundant publications by the same authors appearing in different journals were eliminated to avoid duplication. Upon completion of this evaluative process, 77 studies were selected for final inclusion. A comprehensive list of these selected studies is provided in Table 6 at the end of this paper.

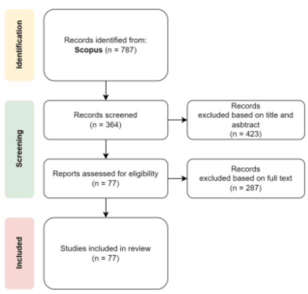

Fig 2. Search and Selection of Primary Studies

Data Extraction

The selected primary studies served as the basis for extracting data relevant to the research questions posed in this review. In Step 6, each of the 77 studies was analyzed using a customized data extraction form designed to collect essential information required for answering the research questions. The extracted attributes were determined in alignment with both the research objectives and the intended analytical framework. As outlined in

Table 4, three specific properties were employed to guide this process. The data extraction was performed iteratively to ensure both completeness and accuracy of the collected information.

Table 4. Data Extraction Properties Mapped to Research Questions

Data	Research Questions
Researchers and Publications	RQ1, RQ2
Production Scheduling Method	RQ3, RQ5
Production Scheduling Metrics	RQ4

Data Synthesis

In Step 7, the synthesized data were interpreted, and the validity of the resulting conclusions was assessed. The goal of this synthesis was to integrate evidence from the selected studies to comprehensively address the research questions. While individual findings may offer limited insight, their aggregation enhances the strength and coherence of the overall analysis. Both quantitative and qualitative data were extracted and synthesized using appropriate techniques suited to the nature of each research question. A narrative synthesis served as the principal approach, with data organized into thematic tables aligned with the research objectives. To support clarity and analytical depth, visual aids including bar charts, pie charts, and summary tables were employed to depict the distribution and performance metrics of software defect prediction methods.

3. RESULT AND DISCUSSION

Significant Journal Publications

This analysis reveals that a substantial portion, approximately 64.9%, of the research papers centered on Machine Learning Applications in Production Scheduling take the form of articles in article journals. Meanwhile, conference papers comprise the remaining 35.1% of the literature in this field.

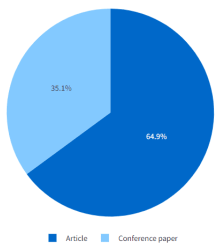

Fig 3. Distributions of Publication Types

The analysis of research publication journals in the domain of Machine Learning Applications in Production Scheduling showcases a diverse distribution across various platforms. IEEE Access stands out prominently with the highest number of publications, totaling 9 articles, indicating its significance as a venue for research dissemination in this field.

Fig 4. Distribution of Joural Publications

In addition, several other well-regarded journals make substantial contributions to the body of literature, each featuring three relevant publications. Prominent among these are the Journal of Manufacturing Systems, the Journal of Intelligent Manufacturing, and IEEE Transactions on Automation Science and Engineering, highlighting their important role as key platforms for academic dialogue and progress within this specialized field.

Most Active and Influential Researchers

The selected primary studies were examined to identify researchers who have made significant contributions and are actively involved in the software defect prediction research domain. Figure 6 displays the most influential and engaged researchers in this field, organized based on the number of studies included in the primary research. Noteworthy researchers such as Grumbach, Zhou, Shiue, Marchesano, Ou, Song, Cheng, Waschneck, Tremblet, and Wang have been identified as prominent figures actively contributing to software defect prediction research.

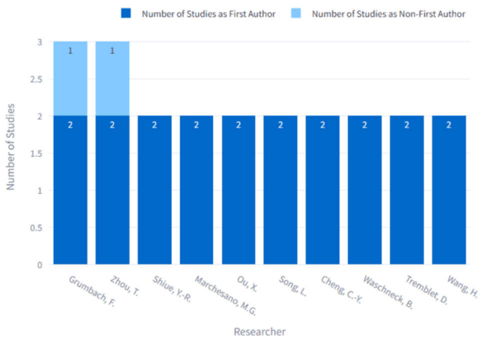

Fig 5. Top 10 Most Active Researchers

Methods Used in Production Scheduling Problems

The analysis of data extracted from selected studies within the domain of Machine Learning Applications in Production Scheduling reveals the prevalence of various learning approaches. As shown in Figure 6, reinforcement learning emerges as the predominant choice, commanding a significant majority of 79.2%.

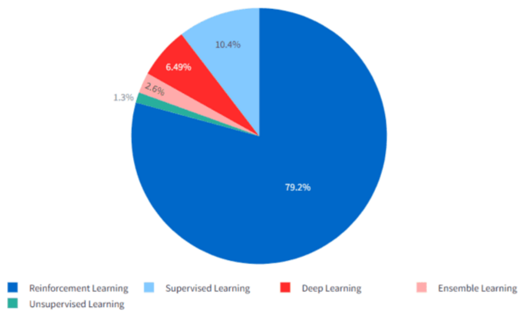

Fig 6. Distribution of Machine Learning Methods Used

In contrast, supervised learning accounts for a smaller proportion at 10.4%, indicating its comparatively lesser prevalence in this context. Deep learning follows closely behind with a moderate representation of 6.49%. Ensemble learning and unsupervised learning exhibit lower prominence among the selected studies, contributing 2.6% and 1.3% respectively.

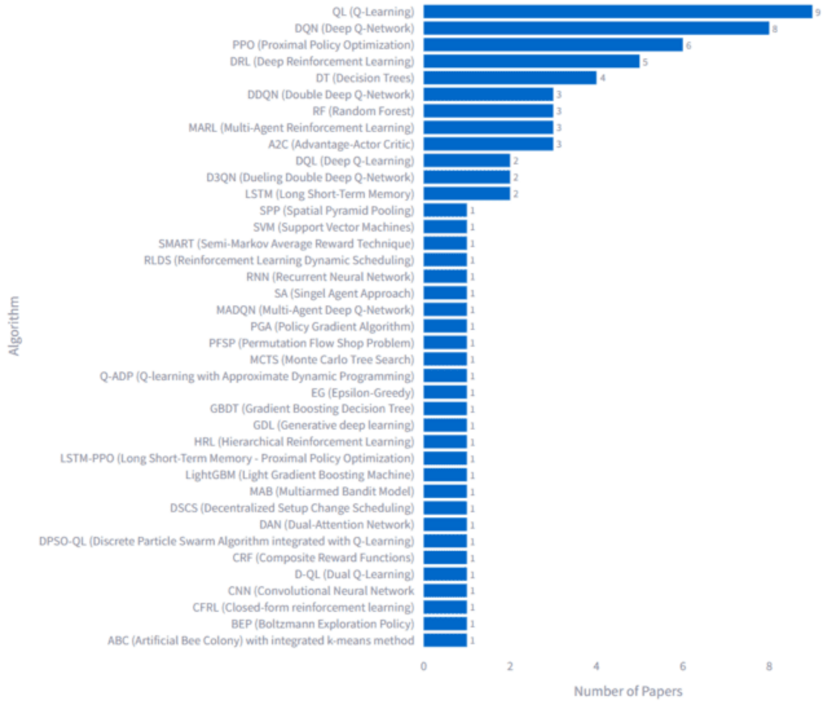

Fig 7. Distribution of Machine Learning Algorithms Used

Most Used Methods in Production Scheduling Problems

Based on the techniques presented in Figure 10, the five most commonly utilized machine learning methods for addressing production scheduling problems have been identified, as depicted in Figure 11. These methods include:

1. QL (Q-Learning)
2. DQN (Deep Q-Network)
3. PPO (Proximal Policy Optimization)
4. DRL (Deep Reinforcement Learning)
5. DT (Decision Trees)

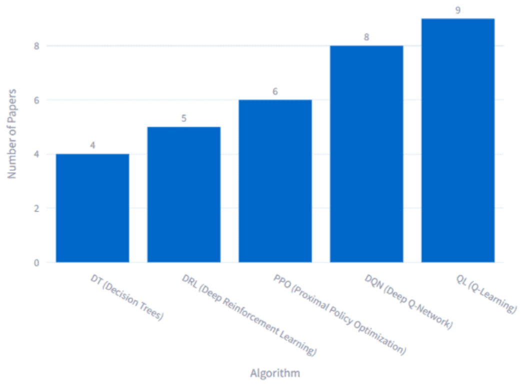

Fig 8. Most Used Machine Learning Algorithms

Q-Learning, as explored by (Alicastro et al., 2021; Kardos et al., 2020; Martínez Jiménez et al., 2020; Ou et al., 2018; Shiue et al., 2018; Tejer et al., 2024; H. Wang et al., 2021; Y.-F. Wang, 2020; J. Zhang & Cai, 2023), stands out as a model-free reinforcement learning algorithm. It is unique because it learns the value of actions in different states without needing a model of the environment. This makes QL highly versatile, as it can adapt to environments with uncertain transitions and rewards. Its effectiveness in discrete action spaces has been noted, offering a robust solution for many scheduling problems. Nevertheless, Q-learning encounters difficulties when dealing with high-dimensional state or action spaces, primarily due to the curse of dimensionality, and tends to converge slowly in complex environments. Additionally, achieving optimal performance can require extensive tuning of hyperparameters.

DQN, investigated by (Gil & Lee, 2022; Lang et al., 2020; Luo, 2020; Marchesano et al., 2021, 2022; Paeng et al., 2021; Waschneck, Reichstaller, Belzner, Altenmüller, et al., 2018; Waschneck, Reichstaller, Belzner, Altenmuller, et al., 2018), advances Q-Learning by integrating deep neural networks. This enhancement allows DQN to manage high-dimensional state spaces, positioning it as a powerful tool for complex decision-making tasks. The application of deep learning to approximate Q-values marks a significant improvement in learning efficiency, especially in environments with visual input. Despite these strengths, DQN demands substantial computational resources for training and necessitates careful implementation to avoid instability or divergence. It is also sensitive to hyperparameter settings, which can impact its performance.

(Muller et al., 2024; Rummukainen & Nurminen, 2019; L. Wang et al., 2021; S. Wang et al., 2022; Z. Wang & Liao, 2023; Y. Zhang et al., 2022) have contributed to the understanding of PPO model for production scheduling, a policy gradient method that emphasizes a balance between data efficiency and ease of implementation. PPO is distinguished by its stable and reliable performance across various applications, making it particularly effective in continuous action spaces. However, it may not be as sample efficient as some off-policy algorithms and requires meticulous tuning of clipping parameters to achieve the right balance between exploration and exploitation. High-dimensional action spaces can also pose challenges for PPO.

DRL, as discussed by (Geurtsen et al., 2023; Grumbach et al., 2022, 2023; Hubbs et al., 2020; Lee et al., 2023), merges deep learning with reinforcement learning to address complex goals in high-dimensional environments. Its capability to process high-dimensional sensory input directly and make decisions from raw data makes DRL suitable for tackling real-world problems. Nonetheless, DRL's effectiveness comes at the cost of requiring extensive data and computational resources. It also presents challenges in terms of interpretability and debugging, and is sensitive to the design of the reward function, which can lead to unexpected behaviors.

Lastly, Decision Trees, analyzed by (Benda et al., 2019; Frye et al., 2020; Tremblet et al., 2022), offer a straightforward approach to learning decision rules from data features. DTs are easy to understand and interpret, and they can manage both numerical and categorical data with minimal preparation. Nevertheless, decision trees are susceptible to overfitting and may exhibit instability, as slight variations in the input data can lead to substantially different tree structures. Additionally, their reliance on linear decision boundaries restricts their ability to model complex and highly nuanced scheduling scenarios.

Each of these methods offers distinct strengths and weaknesses when applied to production scheduling. The selection of an appropriate approach is influenced by the specific characteristics of the scheduling task, such as the operational environment, the complexity of the state and action spaces, and the computational resources available. This variety of techniques highlights the need for ongoing research and innovation in machine learning to effectively respond to the dynamic and increasingly complex demands of production scheduling.

Proposed Method Improvements for Production Scheduling Problems

The Deep Q-Network (DQN) method, a type of Deep Reinforcement Learning (DRL), has been proposed for developing self-optimizing scheduling policies in production scheduling tasks (Marchesano et al., 2021). In this approach, a DQN dynamically selects the most suitable dispatching rule for scheduling jobs on machines within a flow shop production line.

Traditional Reinforcement Learning (RL) typically involves determining optimal actions based on received rewards, while DRL, including DQN, utilizes Deep Neural Networks (DNNs) to approximate the value function and handle high-dimensional state and action spaces (Marchesano et al., 2021). This enables the DQN to adapt its decisions based on changes in the production line's conditions, which is crucial in dynamic manufacturing environments like Industry 4.0, where quick and efficient scheduling decisions are essential.

The use of a Deep Q-Network (DQN) model enables production schedulers to leverage deep reinforcement learning for informed decision-making in job scheduling within flow shop environments. The DQN is trained through experiential learning, utilizing a predefined set of dispatching rules and adaptively selecting the most suitable rule in response to the current system state (Marchesano et al., 2021).

Within the framework of DQN operation, the model receives a given state as input and generates Q-values corresponding to all feasible actions, thereby estimating the expected value of each action in that state (Paeng et al., 2021). The network architecture includes hidden layers connected to input vectors constructed from state representations, with parameters set to be the same for each block to enhance training efficiency. The output layer corresponds to possible actions, utilizing the ReLU function for activation except for negative Q-values (Paeng et al., 2021).

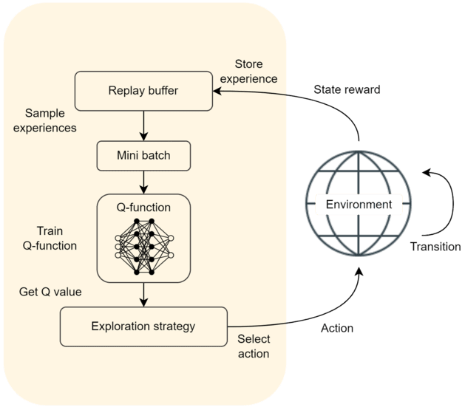

Fig 9. Deep Q-Network Algorithm

During training, the DQN repeatedly undergoes a scheduling process, observing state and action spaces, selecting actions probabilistically, calculating rewards, storing transitions in a replay buffer, sampling transitions, calculating loss, performing gradient descent steps, and synchronizing networks at intervals (Paeng et al., 2021). In terms of performance, the DQN approach has shown strong effectiveness in reducing tardiness for both parallel machine scheduling and dynamic flow shop scheduling. It surpasses conventional techniques including Iterated Greedy (IG), rule-based strategies, LBF-Q, and TPDQN by achieving lower total tardiness across various benchmark datasets (Paeng et al., 2021). Despite its advantages, the DQN method requires re-training procedures when the number of families changes, indicating a potential area for improvement (Paeng et al., 2021).

The Double Deep Q-Network (D2QN) is an advanced reinforcement learning algorithm that builds upon the Deep Q-Network (DQN) framework by introducing a dual-layer architecture for optimizing multiple objectives in dynamic job shop scheduling problems. In D2QN, two interconnected agents, namely the higher DDQN (goal selector) and the lower DDQN (actuator), work collaboratively to enhance decision-making processes and achieve more efficient scheduling outcomes (Li & Wang, 2023).

The operation of D2QN involves the higher DDQN analyzing a five-element state vector input to determine an optimization goal, which is then passed on to the lower DDQN. The lower DDQN, equipped with six input states, selects a dispatching rule that maximizes reward scores based on the output from the higher DDQN. This dual-layer architecture enables D2QN to simultaneously optimize multiple objectives, providing a more effective solution compared to traditional heuristic rules and metaheuristic algorithms (Li & Wang, 2023).

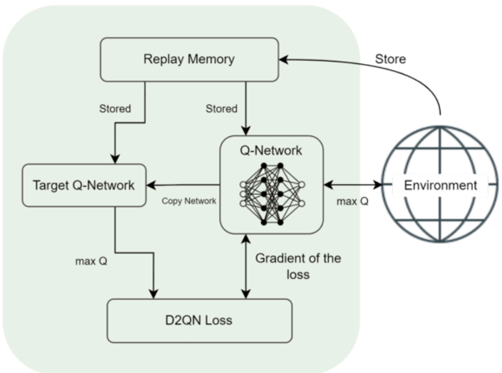

Fig 10. Double Deep Q-Network

One of the key improvements offered by D2QN is its ability to address the limitations of heuristic rules and metaheuristic algorithms in real-time scheduling and dynamic environments. By specifying optimization objectives, proposing dispatching rules, and designing a reward function tailored to the job shop scheduling context, D2QN enhances performance and efficiency in achieving near-optimal results (Wu et al., 2023).

Despite its advancements, D2QN may encounter limitations related to the complexity and size of the problem space, the quality and quantity of training data, and the selection of hyperparameters. These challenges could impact the effectiveness and scalability of D2QN in real-world applications, requiring careful consideration and potential adjustments to ensure optimal performance in dynamic job shop scheduling scenarios (Wu et al., 2023).

Dueling Double Deep Q-Network (D3QN) is an advanced reinforcement learning algorithm that combines the principles of Double Deep Q-Network (DDQN) and Dueling Network to enhance decision-making in complex environments. D3QN addresses the limitations of traditional Q-learning algorithms by utilizing deep neural networks to approximate the value function efficiently. By incorporating the concept of DDQN, D3QN enhances learning stability and convergence by incorporating a target network for computing the target Q-value and employing a delayed update strategy. This helps prevent the algorithm from overestimating or underestimating Q values, leading to more accurate decision-making (Song et al., 2023).

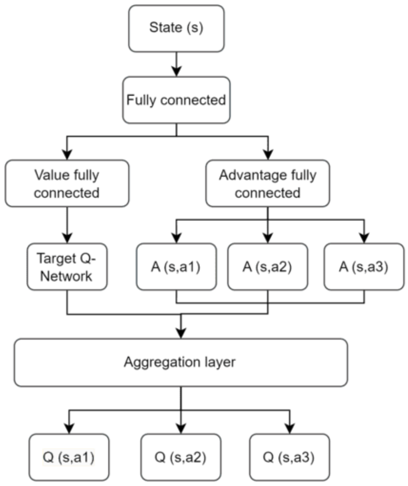

Fig 11. Dueling Double Deep Q-Network

Furthermore, D3QN integrates the Dueling Network architecture, this approach separates the Q-value function into two components: a state-value function and an action-advantage function. Such decomposition enables the network to independently learn the intrinsic value of each state and the relative benefit of individual actions, thereby minimizing irrelevant variance and enhancing learning stability. By enhancing learning efficiency and stability, the Dueling Network structure enables faster convergence and better control over estimation errors, ultimately improving the algorithm's performance in challenging scenarios (Song et al., 2023).

Despite its significant improvements over traditional Q-learning algorithms, D3QN still faces certain limitations. One notable limitation is related to the training process and the selection of experience samples for learning. In traditional experience replay mechanisms, random sampling of experiences with equal probability may lead to important experiences being overshadowed by less critical ones, resulting in slower convergence and suboptimal performance. Addressing this limitation and optimizing the prioritized experience replay mechanism in D3QN could further enhance its learning efficiency and overall effectiveness in complex decision-making tasks (Song et al., 2023).

4. CONCLUSION

In conclusion, this systematic literature review has offered significant insights into the current advancements in applying machine learning techniques to enhance and optimize production scheduling processes. The review highlighted the dominance of reinforcement learning techniques, particularly Deep Reinforcement Learning, in addressing scheduling challenges effectively. It also identified key trends, significant journals, influential researchers, and common machine learning methods used in production scheduling optimization.

Looking ahead, future research in this field could focus on exploring advanced machine learning algorithms, such as ensemble learning and unsupervised learning, to further enhance scheduling efficiency.

Additionally, investigating the integration of real-time data analytics and predictive modeling with machine learning approaches could lead to more adaptive and responsive production scheduling systems. Furthermore, studying the scalability and generalizability of machine learning models across different production environments and industries would be crucial for broader applicability.

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