Exploiting Production and Maintenance Scheduling with Deep Reinforcement Learning in Stochastic Environments

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The landscape of operations management research is transforming, catalysed by the integration of advanced computational methodologies. Notably, Deep Reinforcement Learning (DRL) emerges as a groundbreaking tool, offering unprecedented capabilities in addressing intricate operational challenges. This study explores the application of DRL within the framework of operations management, particularly focusing on areas traditionally constrained by computational limitations or complexity. We delve into the application of DRL in diverse operational scenarios, including dynamic resource allocation, predictive maintenance, and production scheduling characterized by stochastic processing times. Through a series of experimental investigations, DRL has been proved to not only surpass conventional approaches in handling multifaceted problems, but also unveil new potentials for efficiency and effectiveness in handling operations considering stochastic variables. Our findings provide a comprehensive overview of the practical applications of DRL, its efficacy in capturing the intricacies of stochastic models, and its current boundaries in the field of operations management. We conclude with a balanced and realistic evaluation, recognizing the substantial promise of DRL in advancing more responsive and smart operational systems. At the same time, we emphasize the ongoing need for research and innovation to thoroughly assess the potential of DRL in the multifaceted and dynamic challenges of operations management.

Key words: Deep Reinforcement Learning; Production Planning and control; Maintenance

1. Introduction

In the fast-paced world of modern manufacturing, strategic maintenance planning is crucial to achieving operational optimization. Efficient resource allocation and system reliability are essential for maintaining high performance in manufacturing processes (Akl et al. 2022). In particular in complex flow shop systems, where a fixed sequence of processing tasks is required, production and maintenance scheduling becomes imperative to maintain system performance (Huang et al. 2020). The dynamic nature of these systems requires quick responses to minimize downtime and prevent equipment failures, ensuring a seamless production continuum (Hu et al. 2022).

Artificial Intelligence (AI), and more specifically Deep Reinforcement Learning (DRL), a subfield of machine learning, has emerged as a powerful tool in navigating the complexities of maintenance scheduling. DRL has demonstrated significant potential in optimizing manufacturing systems, enhancing scheduling, system optimization, and control approaches (Panzer and Bender 2021).

For example, Valet et al. (2022) proposed a deep RL-based opportunistic maintenance scheduling approach. Considering the operational status of the production system, this approach schedules

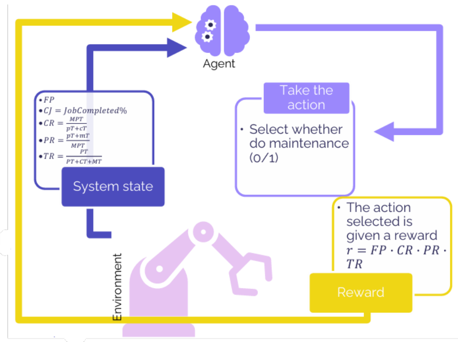

Figure 1. Proposed Approach

maintenance tasks during periods of low demand, minimizing the impact on production and improving maintenance effectiveness. Similarly, Yan et al. (2022) developed a double-layer Q-learning algorithm for dynamic scheduling with preventive maintenance in digital twin-enabled manufacturing systems. This approach considers the uncertainties and dynamics of the production system to maximize production efficiency while minimizing maintenance costs. Furthermore, Mao et al. (2022) developed a hash map-based memetic algorithm to minimize the total flow time of jobs while considering multiple maintenance activities. Although this approach did not explicitly integrate RL, the integration of such techniques could enhance the scheduling optimization process by enabling adaptive decision-making based on real-time data and system dynamics. Moreover, Kosanoglu et al. (2022) proposed a DRL-assisted simulated annealing algorithm for maintenance planning. This approach combines the benefits of both DRL and simulated annealing, allowing efficient exploration of the solution space and finding optimal maintenance schedules.

Despite the advantages of using DRL and AI in maintenance scheduling, several challenges remain. Nunes et al. (2023) reviewed the challenges in predictive maintenance, emphasizing the need for accurate data, effective machine learning models, and appropriate maintenance strategies. Advancements in AI techniques are crucial to overcoming these challenges and improving predictive maintenance practices in manufacturing systems.

2. Contribution of The Work

In this work, we introduce an integrated simulation tool and DRL algorithm to efficiently schedule and plan maintenance events in a production line flow shop. This approach combines the strengths of simulation and DRL to optimize maintenance processes and maximize productivity. The simulation tool creates a virtual environment that replicates the production line flow shop, allowing modeling and simulation of machine operations, job flows, and maintenance events. The DRL algorithm is the core intelligence of the proposed approach as it is displayed in Fgure 1. It learns optimal decision-making policies by interacting with the simulated environment and maximizing cumulative rewards. The algorithm considers machine failure probabilities, job priorities, and scheduling constraints to make informed decisions about maintenance scheduling. This multifaceted strategy not only underscores the novelty of our method but also its potential to contribute significantly to the field, bridging gaps identified in existing literature. By leveraging the strengths of AI and simulation, this approach offers a comprehensive solution to optimize maintenance processes, enhance resource allocation, and improve overall system reliability.

3. Conclusions and Future Research

Future research should continue to address the challenges of predictive maintenance and explore further integration of advanced AI techniques to improve decision making in dynamic manufacturing environments. Our findings provide a comprehensive overview of the practical applications of DRL, its efficacy in capturing the intricacies of stochastic models, and its current boundaries in the field of operations management. We conclude with a balanced and realistic evaluation, recognizing the substantial promise of DRL in advancing more responsive and smart operational systems, while emphasizing the ongoing necessity for research and innovation to thoroughly assess the potential of DRL in the multifaceted and dynamic challenges of operations management.

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