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LEARNING-BASED SCHEDULING FOR STOCHASTIC JOB SHOP SCHEDULING WITH MOBILE ROBOTS

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ABSTRACT

This study investigates the stochastic job shop scheduling problem with finite transportation resources, focusing on the integrated scheduling of machines and mobile robots that transfer jobs between machines. The system involves uncertainty, as both processing and transfer times are stochastic. The objective is to minimize the makespan. To address challenges of scalability and stochasticity, we propose a deep reinforcement learning (DRL) approach. In the proposed framework, each action is decomposed into two sequential sub-actions—selecting a job and assigning a mobile robot—and the agent is trained to sufficiently explore and adapt to the stochastic environment. Experimental results show that the proposed DRL method significantly outperforms various combinations of dispatching rules.

1 INTRODUCTION

Job shop scheduling is a fundamental problem in manufacturing and logistics systems, where the objective is to determine the processing sequence of jobs on machines to optimize performance metrics such as makespan. In modern automated environments, however, additional constraints arise from the use of mobile robots, which are required to move jobs between machines (Ahmadi-Javid et al. 2024). This introduces a coupling between job-machine scheduling and robot dispatching, significantly increasing problem complexity and making real-time decision-making difficult for traditional heuristics or exact methods. Moreover, real-world systems are often subject to uncertainties, such as stochastic processing and transfer times, which further complicate scheduling decisions and reduce the effectiveness of conventional approaches (Lin et al. 2019).

To address these challenges, we develop a deep reinforcement learning (DRL) approach for this integrated scheduling problem, aiming to minimize the makespan under uncertainty. The decision-making process is decomposed into two consecutive steps: selecting a job and allocating a mobile robot, which helps reduce the complexity of the action space. The agent is also exposed to diverse stochastic scenarios to learn robust policies. Experimental results demonstrate that our DRL-based method significantly outperforms real-time dispatching rule combinations under various system scales and stochastic conditions.

2 DEEP REINFORCEMENT LEARNING APPROACH

In the proposed framework, scheduling decisions are made sequentially at each decision point: the system first selects a job to start its next operation on a given machine and then assigns a mobile robot to the selected job. To model this two-stage decision-making process, we design a DRL architecture in which each sub-decision is handled by a seperate fully connected actor-critic network trained with Proximal Policy Optimization (PPO) (Schulman et al. 2017).

The job selection network processes features such as the completion time of the previous operation, the expected processing time of the current operation, the current location of the job, and the expected total remaining processing time. Once a job is selected, the robot selection network evaluates candidate robots based on features including their current location, the expected completion time of any ongoing transport

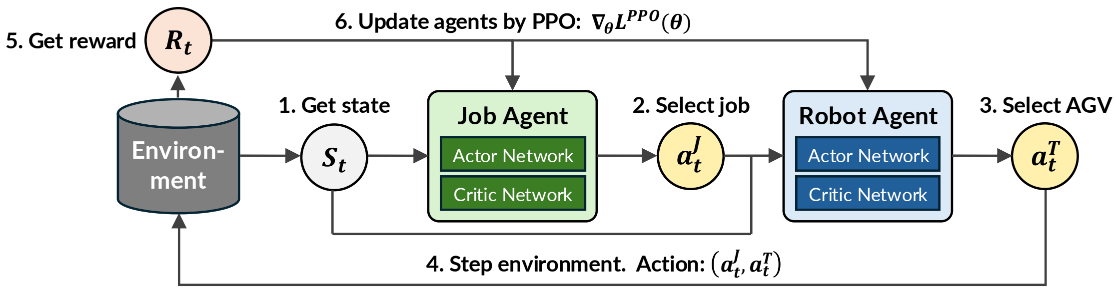

Figure 1: Overview of the proposed DRL-based scheduling framework.

task, and the expected time required to reach and pick up the selected job. The reward is defined as the negative increase in makespan and is computed after both job and robot selections are made.

3 RESULTS AND CONCLUSION

Table 1: Performance comparison between DRL and dispatching rule combinations.

Size (J × M × T)	DRL	EST+EET	EST+SPT	SPT+EET	SPT+SPT
10 × 5 × 3	953.5	1351.1	1338.3	1462.5	1475.4
20 × 5 × 3	1429.8	1956.3	1965.7	2056.6	2117.7
30 × 5 × 3	1762.2	2671.3	2715.7	2748.0	2724.7
20 × 10 × 5	2088.5	2908.2	2909.5	2992.7	2980.7
30 × 10 × 5	2862.7	4322.4	4373.0	4272.4	4338.0
50 × 10 × 5	4828.2	7155.7	7134.6	6656.1	6686.6

Table 1 compares the proposed DRL approach with various combinations of dispatching rules across different problem sizes (J: number of jobs, M: number of machines, T: number of mobile robots). The baseline methods combine job selection rules—Earliest Start Time (EST) and Shortest Processing Time (SPT)—with robot selection rules—Earliest End Time (EET) and Shortest Processing Time (SPT). The DRL approach consistently achieves significantly lower makespan values than all rule-based combinations. This highlights the scalability and robustness of the DRL approach for job shop scheduling with limited mobile robots under stochastic processing and transfer times.

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