Proceedings of the 2024 Winter Simulation Conference
H. Lam, E. Azar, D. Batur, S. Gao, W. Xie, S. R. Hunter, and M. D. Rossetti, eds.

APPLICATION OF DEEP REINFORCEMENT LEARNING BASED ON GRAPH REPRESENTATION TO PRODUCTION SCHEDULING OPTIMIZATION

Young-in Cho[1]

[1] Dept. of Naval Architecture and Ocean Eng., Seoul National University, Seoul, REPUBLIC OF KOREA

ABSTRACT

In this study, we propose a deep reinforcement learning (DRL) based scheduling framework with discrete-event simulation (DES). In the proposed method, a heterogeneous graph is employed for state representation to effectively capture the relational information between entities like machines, buffers, and jobs. As case studies, we apply the proposed method to dual crane scheduling problems and quay-wall allocation problems in the shipbuilding industry.

1 INTRODUCTION

In the field of production scheduling, DRL has been given much attention because it can achieve long-term optimization within fast computational time, overcoming the limitations of the traditional approach (Kayhan and Yildiz 2023; Panzer and Bender 2021). DRL combining graph neural networks (GNN) has improved the performance of scheduling algorithms by extracting richer latent representations based on graph-encoded states (Hameed and Schwung 2023). This paper proposes the DRL framework for production scheduling based on DES with state representation of heterogeneous graphs. We evaluate the effectiveness of the proposed method to real-world scheduling problems in the shipbuilding industry.

2 PROPOSED METHOD

The proposed DRL framework for production scheduling based on DES is shown in Figure 1. The agent obtains training samples, solving thousands of scheduling problems repetitively according to the Markov decision process (MDP) composed of three signals (state, action, and reward) where states are encoded as heterogeneous graphs. Based on the obtained samples, a reinforcement learning algorithm is applied to learn a near-optimal scheduling policy by adjusting the parameters of the scheduling agent modeled as deep neural networks with GNN layers.

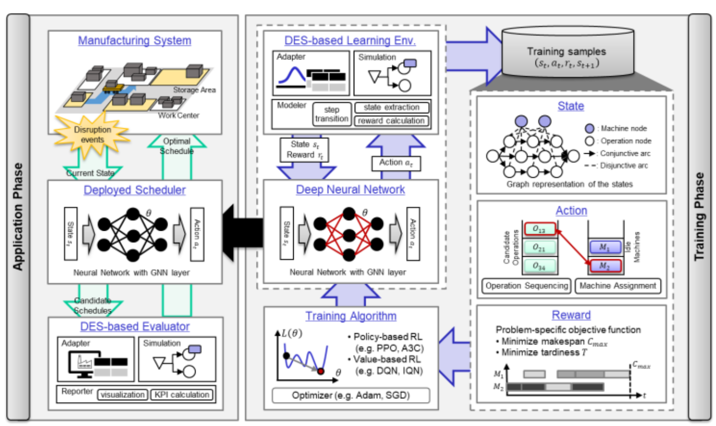

Figure 1: DRL framework.

3 CASE STUDY

In this study, we apply the proposed method to two representative scheduling problems in the shipbuilding industry. The summary of the problem description, Markov decision process formulation, and experiment results are presented in **Figure 2**.

In dual crane scheduling problems, the agent learns a scheduling policy of allocating tasks to two overhead cranes and sequencing the tasks to minimize the total working time (makespan). The agent makes decisions based on heterogeneous graph representation where the cranes and piles are included as nodes. For a crane node, the current and target location of the crane M_i is encoded as a node attribute $h^0(M_i)$. For a pile node, the location of the pile J_j and target locations where the steel plates stacked in the pile are to be moved are contained in a node attribute $h^0(J_j)$.

In quay-wall allocation problems, the agent learns a scheduling policy of allocating vessels to quay walls to perform the post-stage outfitting operations, where the objective is to minimize the overall cost. As a state representation, we define a heterogeneous graph with outfitting operations and quay-walls included as nodes, where the precedence and machine eligibility constraints are encoded as edges. For an outfitting operation node, information on an operation O_{jk} such as processing time, preemption, etc. is contained in a node attribute $h^0(O_{jk})$. For a quay wall node, occupying status and earliest available time of a quay wall M_i is encoded as a node attribute $h^0(M_i)$. In addition to a heterogeneous graph, an auxiliary matrix is constructed to provide the agent information on the short-term effect of each possible allocation of vessels to quay walls in terms of vessel rearrangement cost and processing cost

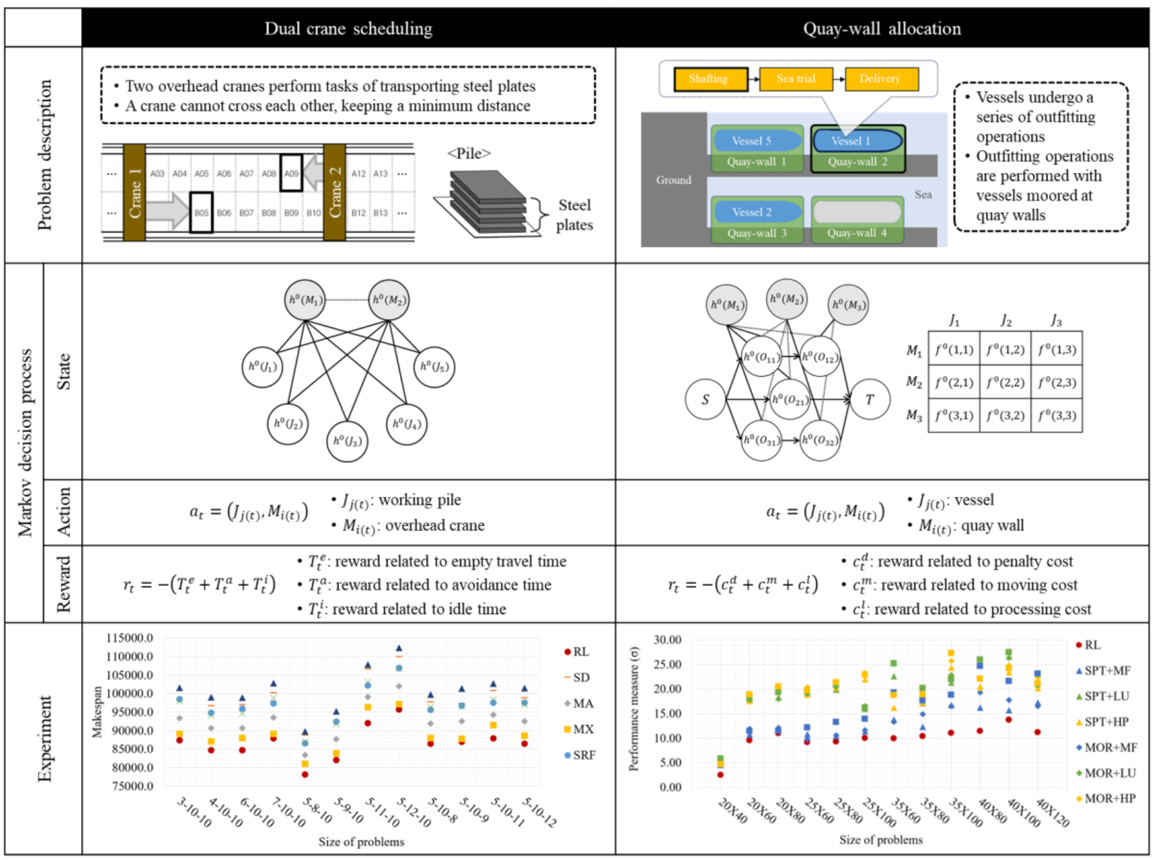

Figure 2: Case study.

REFERENCES

Hameed, M. S. A. and A. Schwung. 2023. "Graph neural networks-based scheduler for production planning problems using reinforcement learning". *Journal of Manufacturing Systems 69*:91–102.

Kayhan, B. M. and G. Yildiz. 2023. "Reinforcement learning applications to machine scheduling problems: a comprehensive literature review". *Journal of Intelligent Manufacturing*, *34*(3):905–929.

Wang, L., Z. Pan and J. Wang. 2021. "A review of reinforcement learning based intelligent optimization for manufacturing scheduling". *Complex System Modeling and Simulation*, *1*(4):257–270.