APEM journal

Advances in Production Engineering & Management
Volume 18 | Number 2 | June 2023 | pp 137–151
https://doi.org/10.14743/apem2023.2.462

ISSN 1854-6250
Journal home: apem-journal.org
Original scientific paper

Real-time scheduling for dynamic workshops with random new job insertions by using deep reinforcement learning

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A B S T R A C T

Dynamic real-time workshop scheduling on job arrival is critical for effective production. This study proposed a dynamic shop scheduling method integrating deep reinforcement learning and convolutional neural network (CNN). In this method, the spatial pyramid pooling layer was added to the CNN to achieve effective dynamic scheduling. A five-channel, two-dimensional matrix that expressed the state characteristics of the production system was used to capture the state of the real-time production of the workshop. Adaptive scheduling was achieved by using a reward function that corresponds to the minimum total tardiness, and the common production dispatching rules were used as the action space. The experimental results revealed that the proposed algorithm achieved superior optimization capabilities with lower time cost than that of the genetic algorithm and could adaptively select appropriate dispatching rules based on the state features of the production system.

A R T I C L E I N F O

Keywords:
Real-time scheduling;
Machine learning;
Deep reinforcement learning (DRL);
Spatial pyramid pooling layer;
Artificial neural networks (ANN);
Convolutional neural networks (CNN)

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Article history:
Received 7 December 2022
Revised 6 June 2023
Accepted 25 June 2023

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