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Verification of intelligent scheduling based on deep reinforcement learning for distributed workshops via discrete event simulation

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A B S T R A C T

Production scheduling, which directly influences the completion time and throughput of workshops, has received extensive research. However, due to the high cost of real-world production verification, most literature did not verify the optimized scheduling scheme in real-world workshops. This paper studied the verification of scheduling schemes and environments, using a discrete event simulation (DES) platform. The aim of this study is to provide an efficient way to verify the correctness of scheduling environments established by programming languages and scheduling results obtained by intelligent algorithms. The system architecture of scheduling verification based on DES is established. The modelling approach via DES is proposed by designing parametric workshop generation, flexible production control, and real-time data processing. The popular distributed permutation flowshop scheduling problem is selected as a case study, where the optimal scheduling scheme obtained by a deep reinforcement learning algorithm is fed into the production simulation model in Plant Simulation software. The experiment results show that the proposed scheduling verification approach can validate the scheduling scheme and environment effectively. The utilization and Gantt charts clearly show the performance of scheduling schemes. This work can help to verify the scheduling schemes and programmed scheduling environment efficiently without costly real-world validation.

A R T I C L E   I N F O

Keywords:
Production scheduling;
Distributed flowshop scheduling;
Discrete event simulation (DES);
Deep reinforcement learning;
Production simulation;
Modelling;
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