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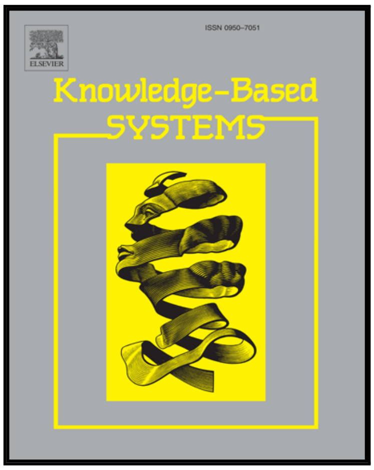

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A hybrid discrete optimization algorithm based on teaching–probabilistic learning mechanism for no-wait flow shop scheduling

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Abstract

Inspired by the phenomenon of teaching and learning introduced by the teaching-learning based optimization (TLBO) algorithm, this paper presents a hybrid discrete optimization algorithm based on teaching-probabilistic learning mechanism (HDTPL) to solve the no-wait flow shop scheduling (NWFSSP) with minimization of makespan. The HDTPL consists of four components, i.e. discrete teaching phase, discrete probabilistic learning phase, population reconstruction, neighborhood search. In the discrete teaching phase, *Forward-insert* and *Backward-insert* are adopted to imitate the teaching process. In the discrete probabilistic learning phase, an effective probabilistic model is established with consideration of both job orders in the sequence and similar job blocks of selected superior learners, and then each learner interacts with the probabilistic model by using the crossover operator to learn knowledge. The population reconstruction re-initializes the population every several generations to escape from a local optimum. Furthermore, three types of neighborhood search structures based on the speed-up methods, i.e. *Referenced-insert-search*, *Insert-search* and *Swap-search*, are designed to improve the quality of the current learner and the global best learner. Moreover, the main parameters of HDTPL are investigated by the Taguchi method to find appropriate values. The effectiveness of HDTPL components is analyzed by numerical comparisons, and the comparisons with some efficient algorithms demonstrate the effectiveness and robustness of the proposed HDTPL in solving the NWFSSP.

Key words: discrete teaching, discrete probabilistic learning, population reconstruction, neighborhood search, no-wait flow shop scheduling, minimization of makespan.

1 Introduction

Production scheduling plays an important role in the field of production management. The flow shop scheduling problem (FSSP) refers to find an optimal schedule for a set of jobs $J_1,\cdots,J_n$ being processed on the machines $M_1,\cdots,M_n$ and all the jobs follow the same order in the shop. The no-wait FSSP (NWFSSP) is an extension of the FSSP, which supposes that there should be no waiting time between consecutive operations of the jobs[1]. Nowadays, the no-wait FSSP widely exists in many industries, such as steel production, food processing, chemical processing [2]. This paper considers the NWFSSP with the criterion to minimize the makespan, which can be denoted as *Fm*|*no-wait*| $C_{\max}$ according to three-field notion $\alpha \mid \beta \mid \gamma$ proposed by Garham et al.[3], where *Fm* represents a flow shop with *m* machines, *no-wait* represents the no-wait constraint, $C_{\max}$ denotes the objective for minimizing the makespan. The previous research[4] has proved that the NWFSSP is a NP-hard problem with minimization of makespan when the number of machines is more than two. Both the academia and the industrial fields have strived to propose many heuristics[5] and meta-heuristics for solving the no-wait FSSP, such as genetic algorithm (GA)[6], particle swarm optimization (PSO)[7, 8], differential evolution (DE)[9], iterated greedy (IG) algorithm [10].

Besides the above methods, there are many literatures that focus on the NWFSSP during recent years. Moreover, much research work has started to concern extensive more complex models and more effective