

An Intelligent Cooperative Approach Applied to Single Machine Total Weighted Tardiness Scheduling Problem

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Abstract. In this research work, we propose an intelligent search technique called genetic simulated annealing algorithm (GASA) to obtain an approximate solution to the single machine total weighted tardiness job scheduling problem, which is a strong *NP-hard*. The developed approach is based on two metaheuristics: genetic algorithm (GA) and simulated annealing (SA) algorithm. In this context, when GA is exploited as a global search strategy to discover solution space, SA algorithm is used as a local search technique to enhance more efficiently the visited attractive regions to improve solution quality. Numerical results using a set of benchmarks have shown the capability of the proposed method to produce better solutions compared to results given by some other recently literature works.

Keywords: genetic simulated annealing, scheduling, genetic algorithm, simulated annealing, benchmarks.

1. Introduction

The single machine total weighted tardiness (SMTWT) problem is an important special case of scheduling problem that is referred to be a strongly NP-hard problem [1][2]. It has been discussed for many years, and several effective algorithms have been presented in the literature. This problem is stated as following : There are a set of n jobs to be processed on exact one machine. The machine processes only one job at a time and without interruption. Each job i has an integer processing time p_i , a positive weight w_i and a distinct due date d_i . For a given processing order of the jobs, the earliest completion time C_i and tardiness $T_i = \max(0, C_i - d_i)$ can be computed for each job. The objective is to find the sequence of n jobs that minimizes the total weighted tardiness (TWT) which is done as following :

$$TWT = \sum_{i=1}^n w_i * \max(0, C_i - d_i) \quad (1)$$

Actually, the SMTWT problem becomes an important combinatorial optimization problem that has various real life applications such as sequencing in production process, assigning the sequence of stages in a construction project, delivering the goods with the customer's priority in supply chain and so on [3].

A various number of exact methods have been developed in literature in order to resolve the SMTWT problem for a moderate number of jobs. The well-known of them is dynamic programming paradigm and Branch-and-Bound method, optimality of the solution obtained by these approaches is guaranteed, but they are mostly constrained by available memory and required computation time, especially when the number of jobs is more than 50 [4]. To overcome these limits, metaheuristic algorithms were shown to be promising. The basic idea of this methods class, is to start by an initial solution and iteratively improve it through a series of iterations until the solution doesn't become better any longer. They include polynomial-time approximation algorithm [5], tabu search [6], [7], simulated annealing [8], ant colony optimization [9], iterated dynasearch [10], genetic algorithm [11], variable neighborhood search [12] and so on.

In this research paper, we aim to present a hybrid model based on metaheuristics to solve the SMTWT problem. The proposed approach combines the strong global search ability of genetic algorithm to discover the search space using a part of the initial population with the excellent local improvement which is given by simulated annealing using the rest of the population. The reminder of this paper is organized as follows : In section 2, some previous related works are briefly cited. Section 3 summarizes principals concepts of both

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GA and SA algorithms. Section 4 outlines the proposed GASA algorithm and its components for the SMTWT problem. In section 5, we present the obtained simulation results. Finally, conclusion and perspectives of our work are given in section 6.

2. Related Works

A brief review of some related works which are used to solve SMTWTP is presented in this section. In Ref. [4], the authors demonstrated that exact methods such as Dynamic Programming and Branch-and-Bound are inconsistently solve problems with more than 50 jobs. Potts and van Wassenhove [13] compared four dispatching rules: weighted shortest processing time (WSPT), earliest due date (EDD), modified cost over time (MCOVERT) and apparent urgency (AU). They found that AU performs best and WSPT is greatly inferior. Alidaee and Ramakrishnan [14] tested the COVERT-AU class of dispatching rules for problems of up to 200 jobs. As a result of their study, dispatch rules give a quick sequencing method, but have poor solution quality.

Crauwels et al. [15] proposed a single and multi-start versions of simulated annealing, tabu search (TS) and genetic algorithm implementations for the SMTWTP problem. The authors showed that an acceptable results are produced by simulated annealing and tabu search dominates the other methods. An iterated dynasearch algorithm, which is a local search technique that uses dynamic programming to generate the best moves, is introduced in [10]. An excellent solutions are also obtained in a short time by a natural permutation encoded GA and its multistart version using problems with 40 and 50 jobs [16].

A particle swarm optimization (PSO) algorithm to solve the single machine total weighted tardiness problem is proposed in [17]. Experimental results show that the PSO algorithm is able to find the optimal and best-known solutions on all instances of widely used benchmarks from the OR library. An heuristic search applied to the SMTWTP is discussed in [18]. In Ref. [19], the authors developed a variable structure learning automata to solve SMTWT problem. Recently, the authors in [20] proposed a new genetic algorithm to produce a best approximate solutions for SMTWT problem. The developed procedure provided a good results compared to some existing dispatching rules.

3. Preliminaries

3.1. Genetic Algorithm Overview

The basic principles of GAs were introduced by Holland in 1975 [21]. GA is an intelligent random search technique which have been successfully applied to find optimal solutions of many complex problems [22]. A genetic algorithm starts with a population of potential solutions and iteratively replaces the current population by a new population. It is based on a suitable encoding for the problem and a fitness function that is used to measure each solution quality. At each generation, a selection operator is applied to choose the parents and recombines them using a crossover operator to produce offsprings that are submitted to a mutation operator in order to perturb them locally. This will continue for many generations until the termination condition is met.

3.2 Simulated Annealing Overview

Simulated annealing was first introduced by Kirkpatrick et al. [23]. It is a stochastic method that is used to find approximate solutions to very large combinatorial problems. The annealing algorithm begins with an initial feasible configuration and proceeds to generate a neighboring solution by perturbing the current solution. If the cost of the new solution is less than that of the current solution, the new solution is accepted; otherwise, it is accepted or rejected with probability $p = e^{-\Delta C/T}$. The probability of accepting solutions depending of the temperature (T), and the difference in cost between the new solution and the current solution ($-\Delta C$). Typically, SA starts with a large value of T, which means that an inferior solution has a high probability of being accepted and the algorithm works as a random search to find a promising region in the solution space. As the optimization process progresses, the temperature decreases and there is a lower probability of accepting an inferior solution. The process is repeated until the stopping criterion is reached.

4. Materials and Methods

The mean advantage of GA is its capability to discover solution space globally according to the crossover and mutation operators, but it suffers from premature convergence and it can not escape from local