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A hybrid genetic algorithm for the job shop scheduling problem with practical considerations for manufacturing costs: Investigations motivated by vehicle production

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ABSTRACT

This paper studies a job shop scheduling problem with two new objective functions based on the setup and synergy costs besides the traditional total weighted tardiness criterion. The background is found in the real-world situation of a commercial vehicle producer, where the reduction of manufacturing costs has become a significant concern like in many heavy industry firms. The cost-related objective functions have been modeled in a quite general way so that they can also be applied to other similar types of production. To tackle this multi-objective scheduling problem, the paper presents a Pareto-based genetic algorithm incorporating a local search module, which utilizes the neighborhood properties specifically developed for each objective function. The computational experiments on both real-world and randomly generated scheduling instances verify the effectiveness of the proposed approach. The research presented in this paper could shed some light on the modeling and heuristic solving of practical production scheduling problems.

1. Introduction

Production scheduling is a crucial decision process which directly affects the operational efficiency of manufacturing firms. Among others, the job shop scheduling problem (JSSP) has long been adopted as a basic model for the scheduling research (Ramasesh, 1990; Ahmed and Fisher, 1992; Sabuncuoglu and Comlekci, 2002; Liu and Kozan, 2011). However, most variants of JSSP are $\mathcal{NP}$-hard in the strong sense and thus defy ordinary solution methods. Enumerative approaches, such as the branch-and-bound algorithm of Carlier and Pinson (1989), can only conquer small-scale problem instances. The most common heuristic methods devised in the early days include dispatching rules (Sculli, 1980; Green and Appel, 1981; Kanet and Hayya, 1982; Baker, 1984) and shifting bottleneck (Adams et al., 1988; Holtsclaw and Uzsoy, 1996; Balas and Vazacopoulos, 1998; Liu and Kozan, 2012). In recent years, meta-heuristic algorithms, such as simulated annealing (SA) (Van Laarhoven et al., 1992; Zhang and Wu, 2011), genetic algorithm (GA) (Zobolas et al., 2009; Al-Hinai and ElMekkawy, 2011), scatter search (SS) (Sels et al., 2011), tabu search (TS) (Nowicki and Smutnicki, 1996; Zhu et al., 2010; Eshlaghy and Sheibatolhamdy, 2011), particle swarm optimization (PSO) (Moslehi and Mahnam, 2011), have clearly become the research focus in practical optimization methods for solving JSSPs.

In these traditional scheduling models, the objective function only includes measures on production efficiency (like makespan and due date related performances). However, in some manufacturing sectors (especially in heavy industry), the firms are also concerned with the minimization of production costs and energy consumption. In this paper, we study a multi-objective production scheduling problem which is modeled on the basis of the manufacturing system of F Company, a listed company in China which specializes in the production of commercial vehicles.

The manufacturing system of F Company mainly consists of three workshops, i.e. the body shop, the coating shop and the assembly shop. The manufacturing process of a vehicle (pickup trucks, middle buses or SUVs) passes through the three workshops in order. However, these workshops do have quite different criteria to define "good" production schedules.

(1) The body shop requires that the bodies of identical or similar types should be processed as closely as possible, so that the cost for equipment switching and setup operations can be reduced.
(2) The coating shop requires that the parts with identical or similar colors should be processed as closely as possible, so that the cost for preparing and changing the paint can be minimized.

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(3) The assembly shop requires that the vehicles with different levels of complexity should be processed in a staggered manner (difficult jobs alternating with easy jobs), so that the production intensity can be smoothed and thus the undesirable accumulation or tardiness of jobs can be reduced.

Under such circumstances, traditional single-objective scheduling models are incapable of guaranteeing a satisfactory solution set. So we must resort to multi-objective optimization models. Indeed, we will focus on a multi-objective job shop scheduling problem (MOJSSP) in this paper.

Multi-objective scheduling is quite different from single-objective scheduling in the following two aspects:

(1) There usually exist direct conflicts between different objectives under consideration. This means, in order to obtain improvement on one objective, some other objectives may have to worsen. Therefore, if the objective functions are not positively correlated with each other, there will not exist a single solution that is optimal with respect to each of the objectives.
(2) The users (production managers) require that the optimization algorithm output a set of satisfactory solutions (rather than one solution as in the single-objective case) which are sufficient in quantity and also distribute evenly. Then, the decision-maker can choose the most suitable scheduling policy from this set based on the particular scenario that he/she faces (e.g., if delivery timeliness is the current bottleneck, it may be necessary to select the schedules that are biased in favor of tardiness-related objective functions).

The rest of the paper is organized as follows. Section 2 provides a brief review on the production scheduling in automotive manufacturing and the concepts of multi-objective evolutionary algorithms. Section 3 gives a formal description of the problem studied in this paper. Section 4 presents some neighborhood properties for minimizing each of the objective functions under investigation. Section 5 proposes a genetic local search (GLS) algorithm for solving the problem. The computational results are displayed in Sections 6 and 7. Finally, some conclusions are drawn in Section 8.

2. Literature review

2.1. Scheduling in automotive manufacturing

The research on scheduling in the vehicle industry has mainly been focused on the *car sequencing problem*, which was first described by Parrello et al. (1986). The problem involves sequencing cars along an assembly line, where different options (e.g. sunroof, air-conditioning, among others) are installed on the cars according to customer orders. Each option is installed by a different station, which can handle at most a certain proportion of cars passing consecutively through the assembly line. Therefore, the cars requiring the same option have to be spaced (i.e., the "difficult" cars must be sufficiently far apart in the production sequence). Such restrictions are modeled as the *ratio constraints*. For example, for the r-th option, the ratio constraint $n_r/p_r = 4/7$ indicates that in any subsequence of 7 cars, there should be no more than 4 cars requiring this option. The decision problem is to decide whether it is possible to find a sequence which satisfies all the ratio constraints, while the optimization problem is to find a sequence with the minimum number of constraint violations.

Due to the high complexity of the car sequencing problem, the optimization softwares based on constraint programming and integer programming reach the limit when considering about 100 cars with only a few options. Therefore, recent works on this problem have focused on the meta-heuristic algorithms. In particular, genetic algorithm (Zinflou et al., 2010) and ant colony optimization (Gravel et al., 2005; Morin et al., 2009) approaches have been reported.

Remarkably, the ROADEF'2005 challenge[1] proposed by the French car manufacturer Renault aroused a new round of research on the car sequencing problem. In particular, the Renault sequencing problem differs from the above-mentioned standard car sequencing problem in the following aspects: (1) The ratio constraints (violations of which are penalized in the objective function) are further divided into two categories according to the criticality level of the options. (2) The requirement of the coating shop (i.e. minimizing the number of color switches) is considered. Based on these features and the fact that the coating and assembly shops in Renault process the same vehicle sequence, a lexicographic multi-objective sequencing problem can be defined by assigning mutually distant weights to each objective. After the competition of this year, the *European Journal of Operational Research* published a feature cluster dedicated to the leading algorithms addressing the challenge (Solnon et al., 2008). Because of the large size of the real-world instances and the strict runtime requirement (10 min), all the successful algorithms reported are based on heuristic approaches.

2.2. Multi-objective evolutionary algorithms

The potential of evolutionary algorithms for solving multi-objective optimization problems was first pointed out by Rosenberg (1967). But the first practicable multi-objective evolutionary algorithm (MOEA) should be attributed to the VEGA (Vector Evaluation Genetic Algorithm) which was proposed by Schaffer (1984) for machine learning algorithms. Remarkably, there has appeared an increasing number of literature on MOEA since the mid 1990s, especially after the launch of the biennial International Conference on Evolutionary Multi-Criterion Optimization in 2001.

From the historical perspective, the existing algorithms can be divided into two generations. The first generation is characterized by the niching technique and Pareto ranking, while the second generation is featured by the elitism strategy. The aim of niching is to reduce the occurrence of genetic drift[2] and guide GA to explore multiple optimal areas in the solution space. Pareto ranking is applied to sort the individuals in the population according to their dominance relations. Typical algorithms that belong to first-generation MOEAs include NSGA (Non-dominated Sorting Genetic Algorithm) and NPGA (Niched-Pareto Genetic Algorithm). The second generation of MOEAs introduce elitism[3] and thus improve the original NSGA and NPGA to form NSGA-II (Deb et al., 2002) and NPGA 2 (Erickson et al., 2001), respectively.

In order to enhance the searching ability, the recent trend is to combine GA with other efficient local search mechanisms, leading to genetic local search (GLS) algorithms, for example (Essafi et al., 2008).

[1] The ROADEF challenge is organized by the French Society of Operations Research and Decision Aid every two years in order to allow theoretical researchers to face up to a complex decisional problem occurring in industry.

[2] Genetic drift refers to the situation in which GA converges to a single solution due to random selection errors. This is the most serious problem that MOEA should avoid.

[3] Elitism refers to the usage of an external archive to record the elite individuals of the current generation, some of which may be passed down to the next generation.