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A BRILS metaheuristic for non-smooth flow-shop problems with failure-risk costs

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ABSTRACT

This paper analyzes a realistic variant of the Permutation Flow-Shop Problem (PFSP) by considering a non-smooth objective function that takes into account not only the traditional makespan cost but also failure-risk costs due to uninterrupted operation of machines. After completing a literature review on the issue, the paper formulates an original mathematical model to describe this new PFSP variant. Then, a Biased-Randomized Iterated Local Search (BRILS) algorithm is proposed as an efficient solving approach. An oriented (biased) random behavior is introduced in the well-known NEH heuristic to generate an initial solution. From this initial solution, the algorithm is able to generate a large number of alternative good solutions without requiring a complex setting of parameters. The relative simplicity of our approach is particularly useful in the presence of non-smooth objective functions, for which exact optimization methods may fail to reach their full potential. The gains of considering failure-risk costs during the exploration of the solution space are analyzed throughout a series of computational experiments. To promote reproducibility, these experiments are based on a set of traditional benchmark instances. Moreover, the performance of the proposed algorithm is compared against other state-of-the-art metaheuristic approaches, which have been conveniently adapted to consider failure-risk costs during the solving process. The proposed BRILS approach can be easily extended to other combinatorial optimization problems with similar non-smooth objective functions.

1. Introduction

Combinatorial Optimization Problems (COPs) have a large number of applications in many industries, from service to manufacturing, and from public to private sectors. For this reason, a large number of studies and scientific work have been dedicated to COPs. Solving a COP means finding an optimal or near-optimal solution among a finite (and usually extremely large) set of feasible solutions that represent combinations of several elements (Papadimitriou & Steiglitz, 1982). Examples of COPs are: scheduling problems (such as the Flow-Shop or Job-Shop Scheduling Problems); routing problems (such as the Traveling Salesman or the Vehicle Routing Problems); assignment problems (such as the Generalized Assignment or the Quadratic Assignment Problems); etc. Most of these problems can usually be formulated using Mixed Integer Linear Programming (MILP) models and are NP-complete (Garey & Johnson, 1979). Typically, however, the classical MILP methods can only solve small to medium instances in reasonable computing times, while heuristics and metaheheuristics are required to solve medium to large instances.

A good method to solve COPs should have the following characteristics (Cordeau, Gendreau, Laporte, Potvin, & Semet, 2002): accuracy, simplicity, efficiency, robustness, and flexibility. These characteristics enable the method to solve complex and large problems. The accuracy is related to the quality of results; simplicity of design and implementation considers the avoidance of complex and time-consuming fine-tuning processes; efficiency is related to the computational time employed and quality of the generated results; robustness means lower dependency on inputs and constraint changes; finally, flexibility is the ability to deal with general combinatorial optimization problems in different scenarios.

In this work, we focus on COPs with non-smooth objective function (NSOF-COPs) so the model is formulated using continuous

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variables. The presence of non-smooth objective functions increases the difficulty of solving these combinatorial optimization problems. The lack of a well-defined structure, such as gradient information, leads to issues in applying traditional mathematical tools. Therefore, studying the development of new methods to solve NSOF-COPs is an important area to explore and, moreover, it has not been covered extensively by the literature so far. In particular, due to the complexity of these problems, heuristic and metaheuristic methods seem among the most appropriate techniques for solving NSOF-COPs. Local-search heuristics might be able to find several local optimal solutions in different parts of the feasible region. This characteristic enables these methods to find good solutions, close to the optimal one, even in the case of NSOF-COPs.

Most of the articles on the Permutation Flow-Shop Problem (PFSP) consider a makespan-based objective function. This classical version of the PFSP can be formulated as a MILP model (Pinedo, 2008). However, in real practice other functions are usually employed to measure the quality of the solutions. In particular, we consider a variant of the PFSP with a non-smooth objective function that takes into account not only the makespan cost but also failure-risk cost functions due to uninterrupted operation of machines. This last cost is associated with the running time of each machine. Notice that solutions with an extremely short makespan might imply long uninterrupted operation times of a machine, which can lead to higher failure-risk costs.

The present work contributes to the field of Expert and Intelligent Systems in several ways. The first one is the consideration of a more realistic scheduling problem that incorporates a failure-risk penalty cost functions. A second contribution is the mathematical formulation for this non-smooth version of the PFSP. As far as we know, there is a lack of publications considering realistic non-smooth cost functions in scheduling problems. Finally, another contribution is the development of a solving method for this non-smooth PFSP that combines Biased Randomization with an Iterated Local Search (BRILS) metaheuristic framework. The method pertains to the class of nondeterministic or stochastic algorithms and relies on the use of oriented (biased) random sampling, i.e., it makes use of a skewed (non-symmetric) probability distribution in order to introduce some bias in the generation of random values to better guide the random search. This approach can be a natural and efficient way to deal with other realistic PFSP under more complex scenarios dominated by non-smooth objective functions.

The structure of the paper is as follows: In Section 2 we present a review of non-smooth combinatorial optimization problems and probabilistic algorithms. Section 3 describes in detail the PFSP with non-smooth objective functions. The BRILS algorithm is presented in Section 4, followed by some computational experiments and comparative studies in Sections 5 and 6, respectively. Finally, conclusions and future work are described in Section 7.

2. Review on non-smooth combinatorial optimization problems and probabilistic algorithms

In this section, we review the work done in probabilistic algorithms for solving COPs. One of the most popular solution methods applied to COPs is metaheuristics, including probabilistic or randomized algorithms. These algorithms use pseudo-random numbers or random variates during the constructive and local search phases of the algorithm. An important characteristic of these algorithms is that, for the same set of inputs, the algorithm is likely to produce different outputs in different runs—unless, of course, the same simulation seed is used in these runs. Therefore, when properly designed, these algorithms can explore the solution space in a quite extensive way, thus finding many local optimal solutions. These algorithms include, among others: Genetic and Evolutionary Algorithms (Davis, 1991; De Jong, 2006; Fleurent & Glover, 1999; Hemamalini & Simon, 2010; Reeves, 2010), Simulated Annealing (Nikolaev & Jacobson, 2010; Reeves, 1995; Suman & Kumar, 2006), GRASP (Feo & Resende, 1995; Festa & Resende, 2009a; 2009b; Resende & Ribeiro, 2010), Variable Neighborhood Search (Hansen, Mladenovic, Brimberg, & Moreno-Pérez, 2010), Iterated Local Search (Lourenço, Martin, & Stützle, 2003, 2010), Ant Colony Optimization (Dorigo & Stützle, 2010), Probabilistic Tabu Search (Gendreau, Hertz, & Laporte, 1994; Lokketangen & Glover, 1998), and Particle Swarm Optimization (Kennedy & Eberhart, 1995). For a detailed review of randomized algorithms the reader is referred to Collet and Rennard (2006).

Probabilistic algorithms have been widely applied to solve several classical COPs: Sequencing and Scheduling Problems (Funke, Grunert, & Irnich, 2005; Gendreau et al., 1994; Pinedo, 2008); Vehicle Routing Problems (Laporte, 2009), Quadratic and Assignment Problems (Fisher & Jaikumar, 1981; Loiola, de Abreu, Boaventura-Netto, Hahn, & Querido, 2007; Oncan, 2007); Location and Layout Problems (Drezner & Hamacher, 2002; Mester & Bräysy, 2007); Covering, Clustering, Packing and Partitions Problems (Chaves & Lorena, 2010; Muter, Birbil, & Sahin, 2010), etc.

The interest in solving scheduling problems with more realistic assumptions has increased within the research community in the last years. The gap between theoretical and realistic flow-shop scheduling problems is discussed in Ruiz and Stutzle (2008). Their work also presents some mathematical models and heuristics to solve realistic problems. Some recent examples of relevant works regarding realistic flow-shop scheduling problems are briefly reviewed next. In Ribas, Companys, and Tort-Martorell (2015), a Discrete Artificial Bee Colony algorithm is proposed to solve the blocking PFSP with a flowtime criterion. Li and Pan (2015) describe a realistic large-scale hybrid PFSP problem with limited buffers and present a hybrid metaheuristic based on Tabu Search and Artificial Bee Colony Systems. Li, Pan, and Mao (2015) propose a discrete teaching-learning-based optimization method to rescheduling a PFSP taking into consideration realistic incidents as machine breakdown, new job arrival, cancellation of jobs, job processing variation, and job release variation. They consider a multi-objective environment, taking into account as objective function the makespan and an instability function. Sun, Cui, Chen, Wang, and He (2013) describe a general permutation PFSP where the processing time of a job is defined by a general non-increasing function of its scheduled position. They present a study with several objective functions as makespan, total completion time, total weighted completion time, etc. To solve these problems, they present an approximation algorithm based on solving a one-machine scheduling problem. All these articles consider classical objective functions as, for example, the makespan or other related completion times. As a novelty, the problem considered in this paper includes a non-smooth objective function representing not only the makespan but also the failure-risk costs.

With respect to the NSOF-COPs, only a few research publications regarding the application of probabilistic algorithms can be found. We performed an intensive search in the Thomson Reuters Web of Science (http://wokinfo.com/) and, after that, we reviewed the few papers found whenever they were related to the present work.

Within the communication systems knowledge area, the non-smooth optimization is quite relevant. Chiang (2009) presents an overview of some of the important non-smooth optimization problems in point-to-point and networked communication systems. For instance, Hamdan and El-Hawary (2002) and Oonsivilai, Srisuruk, Marungsri, and Kulworawanichpong (2009) consider the Optimal Routing problem in Communication Networks. The objective is to find the best path for data transmission in a short amount of time. Hamdan and El-Hawary (2002) describe a Genetic Algorithm combined with Hopfield Networks to solve this problem, and Oonsivilai et al. (2009) present a Tabu Search Method. However, both methods lack the capacity to obtain good solutions in a reasonable time period.