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Two stage particle swarm optimization to solve the flexible job shop predictive scheduling problem considering possible machine breakdowns

Maroua Nouiri [a,b,*], Abdelghani Bekrar [c], Abderrazak Jemai [a,d], Damien Trentesaux [c], Ahmed Chiheb Ammari [e,f], Smail Niar [c]

[a] University of El Manar of Tunis, Sciences Faculty of Tunis, LIP2 Laboratory, 2092 Tunis, Tunisia
[b] University of Carthage, Polytechnic School of Tunis, 2078 Tunis, Tunisia
[c] LAMIH, UMR CNRS 8201, University of Valenciennes and Hainaut-Cambrésis, UVHC, Le Mont Houy, 59313 Valenciennes Cedex, France
[d] University of Carthage, INSAT, 1080 Tunis, Tunisia
[e] MMA Laboratory, INSAT Institute, Carthage University, 1080 Tunis, Tunisia
[f] Renewable Energy Group, Department of Electrical and Computer Engineering, Faculty of Engineering, King Abdulaziz University, Jeddah 21589, Saudi Arabia

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ABSTRACT

In real-world industrial environments, unplanned events and unforeseen incidents can happen at any time. Scheduling under uncertainty allows these unexpected disruptions to be taken into account. This work presents the study of the flexible job shop scheduling problems (FJSP) under machine breakdowns. The objective is to solve the problem such that the lowest makespan is obtained and also robust and stable schedules are guaranteed. A two-stage particle swarm optimization (2S-PSO) is proposed to solve the problem assuming that there is only one breakdown. Various benchmark data taken from the literature, varying from Partial FJSP to Total FJSP, are tested. Computational results prove that the developed algorithm is effective and efficient enough compared to literature approaches providing better robustness and stability. Statistical analyses are given to confirm this performance.

1. Introduction

The job-shop scheduling problem (JSP) has been well studied during the past few decades. An extension of the JSP, the flexible job-shop scheduling problem (FJSP) has also received considerable attention (Xiong, Xing, & Chen, 2013). For those systems, there has been a considerable research effort on scheduling, most of which has been focused on deterministic problems, which means optimizing particular performance measures, such as makespan or tardiness with an assumption that the manufacturing environment is ideal and that no failure or breakdown ever occurs (Jensen, 2003). For example, the job processing time is generally considered constant, and all the jobs are available at a release date and no disruptions occur on the job shop (Liu, Abdelrahman, & Ramswamy, 2007; Liu, Abraham, & Grosan, 2007). Many recent efficient meta-heuristics methods are developed to get nearly optimal solutions for deterministic FJSP assuming that there is no source of uncertainties. Among these methods, one can find the hierarchical multi-space competitive distributed genetic algorithm (HmcDGA) (Ishikawa, Kubota, & Horio, 2015), simulated annealing optimization algorithm (Kaplanoğlu, 2016) and quantum behaved particle swarm optimization (QPSO) with mutation operator (Ranjan & Mahapatra, 2016). Nouiri, Bekrar, Jemai, Niar, and Ammari (2015) and Nouiri, Bekrar, Jemai, Trentesaux, et al. (2015) proposed two multi agent architectures based on PSO to solve deterministic FJSP.

However, in most of the real-world manufacturing environments, the probability for a schedule to be executed as planed is quite low, and the solutions established with the estimated data may become obsolete during the execution (Ourari & Berrandjia, 2015). In fact, many parameters related to a scheduling problem are subject to fluctuations. The disruptions may arise from new jobs arrival or job cancellations, urgent jobs to be taken into account, processing times changes, machine failures, etc. Thus, uncertainty is a very important characteristic that researchers should not deny or neglect in the problem resolution.

* Corresponding author at: University of El Manar of Tunis, Sciences Faculty of Tunis, LIP2 Laboratory, 2092 Tunis, Tunisia.
E-mail address: maroua.nouiri@gmail.com (M. Nouiri).

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Recently, research on production scheduling under uncertainty has attracted substantial attention (Wang & Choi, 2012). Nevertheless, when incorporating the data uncertainty in the formulation of the already NP-hard FJSP, the problem becomes even more difficult and complicated to solve. In this context, heuristic and meta-heuristic approaches have received attention to deal with the presence of uncertainty in the problem's data parameters (Al-hinai & ElMekkawy, 2012).

In this paper, we propose a two-stage PSO algorithm to solve the FJSP under uncertainty. We restrict the term of uncertainty to machine breakdown, which refers to the temporary unavailability of a machine. The idea is to find a predictive schedule referred as pre-schedule that minimizes the effect of machine breakdowns in the overall performance and also increases the schedule stability.

The rest of the paper is organized as follows. Section 2 presents some definitions of uncertainties, robustness and stability. The literature review of scheduling approaches addressing FJSP under uncertainties is presented in Section 3. The problem formulation and the bi-objective optimization of the FJSP are presented in Sections 4. Section 5 represents the details of the two stage PSO algorithm. Experimental results are reported in Section 6. Finally a conclusion and future work are dealt with in Section 7.

2. Definitions

Real manufacturing is dynamic and tends to suffer a wide range of uncertainties, such as random process time, random machine breakdown, random job arrivals or job cancellations (Subramaniam & Raheja, 2003). Uncertainty means that the data are incomplete or imprecise. It is related to doubts concerning the validity of knowledge if the proposition is true or not (e.g., at time x, machine y is at a standstill or if there is no disturbance and no programmed maintenance task) (Chaari, Chaabane, Aissani, & Trentesaux, 2014).

Vieira, Herrmann, and Lin (2003) classify uncertainties in job shop into two categories: Resource-related: machine breakdown, operator illness, unavailability or failure of tools, loading limits, delay in the arrival or shortage of materials, defective material (material with the wrong specification), etc.; and Job-related: rush jobs, job cancellation, due-date changes, early or late arrival of jobs, changes in job priority, and changes in job processing time, etc. Scheduling under uncertainty allows these kinds of risks to be taken into account (Chaari et al., 2014). Therefore, the algorithms for the deterministic scheduling cannot be applied for uncertain environments (He, Sun, & Liao, 2013). Taking these aspects into account is very challenging for solving scheduling problems. Industrial requirements evolved from the usual traditional performance criteria, described in terms of static optimality or near-optimality, towards new performance criteria, described in terms of reactivity, adaptability and robustness (Chaari et al., 2014). Robustness is indicated by the expected value of the relative difference between the deterministic and actual makespan (Xiong et al., 2013). A schedule is robust if its performance degrades a small degree under disruptions, i.e., the performance of a robust schedule is insensitive to disruptions (Liu, Abdelrahman, et al., 2007; Liu, Abraham, et al., 2007). A predictive schedule is said to be robust if the quality of the eventually executed schedule is close to the quality of the predictive schedule (Bidot, Vidal, Laborie, & Back, 2009). A schedule is stable if it has a small deviation either in time or in sequence between the predicted schedule and the realized one (Wu, Storer, & Chang, 1993). Different measures of stability and robustness for classical job shop scheduling problem have been recently defined for the flexible job shop problem (Al-hinai & ElMekkawy, 2011; He et al., 2013; Jensen, 2001).

3. FJSP considering machine breakdowns: a literature review

FJSP under machine breakdowns, and in a more general way, under uncertainty condition, is an NP-hard problem and it is more complex than the one to be solved in determinist environments (He et al., 2013). This section gives a brief review of the scheduling approaches used in literature to cope with disruptions.

To structure this review, we use the new classification proposed by Chaari et al. (2014), who propose a classification scheme identifying proactive, reactive and hybrid scheduling approaches and methods.

Proactive or predictive methods (offline) construct a predictive schedule on the basis of a statistical knowledge of uncertainty, aiming at determining a schedule having a good average performance. A precomputed schedule or a predetermined schedule, called a preschedule or predictive schedule, is generated and executed until a machine breaks down. After that, a re-scheduling procedure is launched to handle the machine breakdown. The redundancy approaches are based on adding external resources or extends processing time of operation in order to absorb failures effects (Chiang & Fox, 1990). However, the effectiveness of these approaches depends on the determination of good predictability measures. Jensen (2003) uses genetic algorithms to find a robust and flexible schedule with low makespan, applicable for job shop scheduling problems. He defined a new robustness measure as well. Fattahi and Fallahi (2010) develop a multi-objective genetic algorithm based method for FJSP with dynamic arrival of jobs. Al-hinai and ElMekkawy (2012) propose a modified hybrid genetic algorithm to solve FSJP where processing times of some operations are represented by uniform distribution.

Machine breakdowns are one of the most studied disruptions in flexible job shop scheduling (He et al., 2013). Al-hinai and ElMekkawy (2011) propose a hybrid GA to solve FJSP with random machine breakdowns. The objective of the method is to obtain a predictive schedule that minimizes the effect of machine breakdowns on the overall performance. Furthermore, they propose three stability measures. Dalfard and Mohammadi (2012) focus on the multi objective FJSP with parallel machines and maintenance cost. They propose a new mathematical modeling for the problem and apply two meta-heuristic algorithms, a hybrid genetic algorithm and a simulated annealing algorithm. Xiong et al. (2013) propose a robust scheduling for a FJSP with random machine breakdowns. They use two surrogate measures and investigate their performances by a multi-objective evolutionary algorithm. He et al. (2013) apply Novel Clone Immune Algorithm to Solve FJSP with machine breakdown and propose a new stable measure to reflect the stability of machine allocation for each operation.

Recently, PSO has been used to solve the FJSP problem. Pan, Ye, and Yang (2013) propose a Quantum Particle Swarm Optimization algorithm (QPSO) to solve FJSP under uncertainty, mainly on uncertain operation time and delivery time using mathematical model. Singh, Mahapatra, and Mishra (2015) proposes a multi objective framework based on QPSO to generate predictive schedule that can simultaneously optimize the makespan and the robustness measure. Sun, Lin, Wang, Gen, and Kawakami (2015) propose a Hybrid Evolutionary Algorithm with the Bayesian Network (BN) to solve FJSP under time uncertainties. The approach combines PSO and GA as typical Evolutionary Algorithm (EA). The Bayesian Optimization Algorithm (BOA) is used to find out the relationship between the variables and, according to these relationships, to regroup, at the same time, using adaptive mechanism parameters, to dynamic adjust the parameters of PSO, minimizing the makespan of the FJSP within a reasonable amount of calculating time.

On the other hand, one can find reactive methods. In reactive scheduling, no schedule is generated in advance but decisions are made locally in real time (online). The scheduling will be generated