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A probabilistic approach to the Stochastic Job-Shop Scheduling problem

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Abstract

Uncertainty exists in almost any manufacturing process, and its effect may be detrimental to the manufacturing outcomes. In the Stochastic Job Shop Scheduling Problem (SJSSP), some of the process parameters are random variables, in particular the processing time. This paper considers another facet of the SJSSP, which is the probability for success (or failure) of a manufacturing job and its effect on other jobs. The paper presents a mathematical model for determining the expected manufacturing cost, and proposes heuristics for reducing that cost. The fundamental model is based on a single resource (e.g. a single machine) and a set of manufacturing jobs, each characterized by a cost and a probabilistic distribution for success. A failure causes either a re-work of the failed job, or restarting the entire process from the first job. Since the problem is NH Hard, a set of heuristics for scheduling the jobs is proposed, and simulation results validate these heuristics.

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Keywords: Stochastic job shop scheduling, optimizing manufacturing cost, manufacturing tolerance, probablishtic process model

1. Introduction

Job-shop scheduling is a process in which a set of jobs are assigned to another set of agents that are expected to execute them according to a planned timetable. It is one of the most common problems in Operations Research (OR) and computer science, and is originally formulated as follows [1]:

Given a set of n heterogeneous jobs, each with a varying time for completion, and a set of m heterogeneous resources (humans or machines), each with varying capabilities, find an optimal assignment of all the jobs to the resources that minimizes the total time required to complete all jobs (known as the process makespan).

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There are many variations to the classic Job-Shop-Scheduling-Problem (JSSP) in the manufacturing environment, where manufacturing jobs are assigned to machines. For example, jobs and machines may have constraints (e.g. some jobs can be assigned only to particular machines), setup times of the machines can be sequence dependent, there might be different objective functions (e.g. minimum lateness, minimum idle time of machines), and the processing time of jobs on some or all machines can vary.

The JSSP is considered Non-Polynomial (NP) Hard for one or two machines, and NP Complete for three or more machines [2]. Many known problems in OR are a subset of JSSP. For example, the classic Traveling Salesperson Problem (TSP) is a special case of the JSSP with sequence dependent processing time, where the salesperson is represented by a single machine required to perform a number of jobs (visit a set of locations). The first known solution for the JSSP is the List-Scheduling Algorithm, proposed by Graham [3] in 1966, that provides a competitive ratio (the ratio between the heuristic and optimal solutions) of $\left(2-1/m\right)$, where m is the number of machines. The Coffman-Graham algorithm [4] provides a $\left(2-2/m\right)$ competitive ratio for problems with homogeneous processing times for all jobs, while Bartal et al. [5] present an algorithm for the general JSSP with a competitive ratio of 1.986. Further improvements include a competitive ratio of 1.945, proposed by Karger et al. [6], and 1.852 proposed by Albers [7]. Chen et al. [8] consider the on-line scheduling problem of two machines where some of the jobs can be re-arranged after scheduling is completed.

The solutions presented so far consider the deterministic JSSP where the characteristics of the jobs and machines are known and static (do not change during the process). However, most manufacturing systems entail some uncertainties such as in machine failures, processing times, setup times etc. This type of problems is known as Stochastic Job Shop Scheduling Problem (SJSSP). Unfortunately, most of the solutions for the deterministic JSSP are not applicable in the stochastic cases. Soroush [9] considers a manufacturing system that consists of a single machine and statistically independent processing times of all jobs. When there are more than two machines, the problem is considerably harder, as presented by Gourgand et al. [10]. They propose a recursive Markov chain algorithm for determining the expected makespan in a system that comprises of m machines and exponentially distributed jobs with a known rate. Luh et al. [11] present a solution for the SJSSP that is based on a combined Lagrangian relaxation and stochastic dynamic programming. The solution considers the uncertainties in jobs' arrival times, machines' processing times, due dates and part priorities. They prove that the computational complexity of their solution is slightly higher than the deterministic case. Golenko-Ginzburg and Gonik [12] consider a manufacturing cell with n jobs and m machines with stochastic processing times (normal, exponential and uniform distributions). Each job has a due date and a penalty cost in case it is not delivered on time, and a storage cost if it is completed ahead of time. Their solution is based on the coordinate descent search method, and is verified with extensive simulations. Tavakkoli-Moghaddam et al. [12] use a non-linear mathematical programming model for determining a near-optimal solution for the SJSSP. They propose a hybrid method that uses neural network and simulated annealing algorithm for generating a feasible solution. They compare their results with the results of Lingo 6 optimization software and show the effectiveness of the proposed model when problem size increases. Lei et al. [13] consider stochastic processing time with normal distribution, and propose a permutation-based representation of the manufacturing process to be used by Genetic Algorithm (GA) methods.

This paper considers another facet of the SJSSP, which is the probability of success (or failure) of a job and the effect it may have on previously accomplished jobs. To illustrate this idea consider the product shown in Fig. 1, which consists of three major dimensions, each with its specific tolerance. For clarity, assume the manufacturing process consists of three milling jobs corresponding to the three major dimensions, all implemented by a 3-axis CNC milling machine. Assuming the machine's resolution (a.k.a. Basic Length Unit or *BLU*) is *0.01* mm, and the repeatability – R is ±*0.01* mm. The machine's total accuracy (a.k.a. precision – P) is given by $P=0.5BLU+R=\pm 0.015mm$. Since repeatability is given in terms of statistical variability, the machine's precision is also given in terms of statistical variability. Commonly, repeatability is defined by a normal distribution where the actual repeatability value represents $\pm 3\sigma$ of the accuracy distribution. Given the machine's accuracy and repeatability, the probability for success completion of job C, denoted by P_c (tolerance of ±*0.1*) is almost *1*, for job B, denoted by P_b (tolerance of ±*0.01*) is *0.9545*, and for job A, denoted by P_a (tolerance of ±*0.001*) is only *0.15852* (these figures are determined from the normal distribution tables). The total probability of successful completion of the three jobs is therefore given by $P_t= P_a *P_b *P_c =0.1513073$.