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Development of a simulation-based decision support system for controlling stochastic flexible job shop manufacturing systems

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ABSTRACT

This paper describes a simulation-based decision support system (DSS) to production control of a stochastic flexible job shop (SFJS) manufacturing system. The controller design approach is built around the theory of supervisory control based on discrete-event simulation with an event–condition–action (ECA) real-time rule-based system. The proposed controller constitutes the framework of an adaptive controller supporting the co-ordination and co-operation relations by integrating a real-time simulator and a rule-based DSS. For implementing SFJS controller, the proposed DSS receives online results from simulator and identifies opportunities for incremental improvement of performance criteria within real-time simulation data exchange (SDX). A bilateral method for multi-performance criteria optimization combines a gradient based method and the DSS to control dynamic state variables of SFJS concurrently. The model is validated by some benchmark test problems.
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1. Introduction

Job shop is a manufacturing system with the capability of producing a wide variety of products. In a flexible job shop there are a set of machining centers in which an operation can be performed by any machine in the work center. In the last three decades, while a great deal of research works has been conducted on deterministic scheduling and control of job shop production systems, only very few researches have considered controlling such a system with stochastic parameters [19]. However, the real world manufacturing systems are stochastic. Hence, stochastic variables and constraints cannot be handled by traditional approaches [39]. A job shop system with stochastic activities (including processing times and/or inter-arrival times) is called a stochastic job shop manufacturing system [34,37]. Such a system is further characterized as a stochastic flexible job shop (SFJS) when activities are stochastic and each operation may be done by several machines. This flexibility makes job shop scheduling problems strongly NP-hard [12,13,42]. Some heuristic approaches have been proposed to solve job shop scheduling problem in later years [25,35,41,43,44].

SFJS is an extension of the classical stochastic job shops which allows an operation to be processed by different machining centers in the shop floor. Analysis of SFJS systems is more complex than traditional ones because of both stochastic and flexible nature of the manufacturing system [15,17,26]. Authors in [7] were among the first to deal with the flexibility concept in job shop manufacturing with multi-purpose machines. Because of the flexible characteristics of SFJS, control decisions should be made as soon as possible to achieve optimized performance criteria of the systems efficiently.

Manufacturing system control monitors the allocation of machines to perform a set of jobs and achieve appropriate performance criteria. Due to different operations on a product and machine requirements to process each step of production, it

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is difficult to control different events that might happen at different machining centers and achieve best practice of performance criteria [23,38]. Although in environments with stochastic events operations are assigned to machines, uncertainty does not allow achieving an optimized solution.

The control of stochastic manufacturing systems is a difficult problem with combinatorial decision spaces. Due to the complexity of stochastic manufacturing systems, heuristic algorithms have low capability to control such environments. Some heuristic algorithms were developed to solve stochastic manufacturing systems problem in recent years. For example, hybrid methodologies based on the integration of particle swarm optimization with simulated annealing (SA) for multi-objective problems [24,42], a hybrid approach which uses SA to improve the quality of the initial solutions generated by a neural network [37], integrated approaches based on mathematical and heuristic search algorithms [10,31], evolutionary algorithms developed for multi-objective stochastic job shop scheduling [22,35] can be addressed. Achieving effective solutions in heuristic methods largely depends on two mechanisms, viz. problem coding and solution generation. The main drawback of these heuristic algorithms is that they have lower searching capability especially for large scale problems and therefore convergence to a local optimum solution [4]. Moreover, there are a lot of stochastic search algorithms such as linear programming relaxation, two-stage approximation algorithm, stochastic scheduling based on a Markov chain, etc. for modeling scheduling problems which consider uncertainties. These algorithms have two main constraints:

1. They could not consider the machine flexibility and fail to work on m multi-purpose machines.
2. They consider small to medium-sized problems and their application to large-sized problems is computationally intractable.

Thus, the performance criteria of such environments should be tuned using a real-time controller [4,6,33]. An effective approach for improving performance of a manufacturing shop is to develop a simulation model that meets the desired objectives [11]. To improve the control of manufacturing shops, simulation has become an effective method due to its adaptability in modeling complex and dynamic operations. Improving the performance criteria of a manufacturing cell is still a complex issue that not only is time consuming but also demands much human expertise in its decision-making [8]. Based on this analysis, engineers would improve the initial system by changing certain parameters, such as number of machines, sequence of parts, operations, etc. This process repeats until satisfactory results are obtained [5,32,36]. Although the procedure of analyzing simulation results could rely on various guidelines and rules, decision-making still requires significant human expertise and computer resources. To efficiently use simulation in the decision process, integration of DSS with simulation has been emphasized [1,3,20].

In the SFJS problem, due to the variety of performance criteria, choosing a good system design becomes a critical decision. Discrete-event stochastic simulation optimization algorithm is able to consider maximizing or minimizing the expected value of multiple stochastic performance criteria. The problem of selecting non-dominated designs from a set of alternatives through simulation becomes a multi-performance criteria simulation optimization. Although many works have been recently done on single-objective simulation optimization, there are limited researches on multi-criteria simulation optimization. The main reason is that these techniques are suitable for deterministic and applying an appropriate simulation algorithm to optimize stochastic systems with multiple criteria is very difficult and time-consuming.

The discrete-event simulation optimization procedures perform on a discrete stochastic problem to determine the best design alternative. Statistical ranking & selection and gradient-based search are the main classes of these procedures [46–48,50,52,56]. Statistical ranking and selection methods includes two major categories, indifference zone based (IZ-based) method and optimal computing budget allocation (OCBA). The first classification is based on the concept of indifference zone which means the range of close performance where the solutions are treated as equal. The IZ-based methods are two-stage approaches in which in the first stage the sample size is determined using sample variances and in the second stage the number of additional simulation replications for each alternative is specified by sample size. The second method for ranking and selection is based on OCBA procedure. The OCBA is widely applied to determine the optimal number of simulation replications required for selecting the best system alternatives [49]. Statistical ranking and selection method can be performed effectively to select the most preferable design when the set of decision alternatives is small because the samples' size allocation procedure is based on sample variances. More recent approaches for statistical ranking and selection method considering difference of sample mean and reducing the required sample size are able only to solve average-sized problems [51,53].On the other hand, a larger part of the ranking and selection studies has focused on single measure of system performance. Ranking and selection methods solve single objective problems simply while alternatives are close performance. But, in a multi-objective problem, it would be a very difficult solution method and makes the simulation method expensive and time-consuming. For such expensive simulations, many simulation optimization tools did not work well. In contrast, the gradient-based method for solving large-sized problems can choose the best alternative with a higher convergence rate. In order to improve simulation efficiency in large-sized problems, new hybrid discrete stochastic approaches should be proposed by using the synergy of the above methods [45,52].

Considering the stated issues, the multi-criteria simulation optimization problems have not been sufficiently addressed [55]. In this paper, we applied a bilateral method for multi-performance criteria optimization mechanism. This method combines a gradient-based method to identify the search direction using sequentialized experimental designs and a DSS to control dynamic state variables of SFJS prohibiting bottleneck and concurrent balancing of resources utilization.

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