A Simulation Optimization Method for Optimal Design and Operation of an Integrated-Automated Manufacturing System

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Abstract

In recent manufacturing system design, workstations are coupled with centralized Work-In-Process(WIP) storage and material handling using AS/RS. This system called as integrated-automated manufacturing system have proven to be very effective. Through the use of AS/RS, the storage and material handling functions of the production systems have been integrated with the manufacturing operations, thus obtaining better space utilization, real time inventory tracking, better production control, and great flexibility to accommodate process changes. In this paper, we suggest a simulation optimization method for optimal design and operation of the integrated-automated manufacturing system called direct-input-output manufacturing system(DIOMS).

Most approach for manufacturing system have been studied on either system design problems or operational problems. But, these two problems are interrelated, because the design of the system must be based on the way of the system operation and conversely, the operational problem depends on the design of system. We should consider both system design and operational problems. Suggested method in this paper considers both system design and operational problems using the simulation optimization method. We consider operating policy including input sequence control, dispatching rule for AS/RS, machining center-based part type selection rule, and storage assignment policy and system design including the number of each machine type, machine layout and rack size of AS/RS.

In many simulation optimization methods for manufacturing system design, the layout of the manufacturing system is given and only the set of values for certain parameters of the system is determined. This, however, is not true when seeking optimum designs for most practical systems.

The methodology described in this paper is a simulation optimization process where the qualitative variables, the quantitative variables and the layout of the system are optimized.

We propose a method for simulation optimization using stochastic genetic algorithm(GA) to get the best design and operating policies in a DIOMS.

The first step in the method is to get the set of good alternatives using stochastic GA and simulation. In using GA for optimization, each point in the solution space is represented by a string of decision choices. Each position in the string represents the decision alternatives regarding one aspect of the system. This aspect could be a quantitative variable such as the number of machine and a sequence variable such as machine layout, and qualitative variables such as a priority rule. Each position can take a number of values or assume one of the possible choices for a particular aspect of the system. The optimization process starts with a random sample from the solution space. The string for point in the sample is translated into a simulation model and its fitness value (its response) is evaluated by running the simulation model. A new population is formed from these samples by using a selection rule based on the fitness values obtained for each point. The second step is to get the best solution of m alternatives obtained in the first step using the screen-and-selection method.

The suggested procedure has two distinct features in the step as follow :

1) Search : to seek out better solutions. unlike any other algorithms, our algorithm uses information on the variance of simulation output to adjust the number of replications taken at each solution during the search. This provides adequate (but not excessive) error control during the search, keeping it from blindly devolving into a random search.

2) Selection : In order to provide the user with a statistical guarantee as to which of the visited solutions is the best, our algorithm uses a screen-and-selection procedure recently developed by Nelson et al. This procedure screens out clearly inferior solutions (those which are very unlikely to be the best), and then performs additional replications on the remaining solutions to determine which is the best. The procedure guarantees that the returned solution is within δ of the best solution visited by the search with probability $1-\alpha$. The user-defined parameter δ is the smallest difference in expected performance that is practically significant to the user, while $1-\alpha$ is the overall confidence level that user desires. Small δ and large $1-\alpha$ imply that more simulation effort will be expended to achieve the user's goals.