Chapter I Heuristics and Metaheuristics for Solving Scheduling Problems

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ABSTRACT

Manufacturing scheduling plays a very important function in successful operation of the production planning and control department of an organization. It also offers a great theoretical challenge to the researchers because of its combinatorial nature. Earlier, researchers emphasized classical optimization methods such as linear programming and branch-and-bound method to solve scheduling problems. However, these methods have the limitation of tackling only small-sized scheduling problems because of the consumption of high computational (CPU) time. As a result, heuristics as well as various efficient optimization methods based on the evolutionary computing paradigm such as genetic algorithms, simulated annealing, and artificial immune system have been applied to scheduling problems for obtaining near optimal solutions. These computational tools are currently being utilized successfully in various engineering and management fields. We briefly discuss the overview of these emerging heuristics and metaheuristics and their applications to the scheduling problems. Given the rise in attention by the researchers, more emphasis has been given to explore artificial immune system in details.

INTRODUCTION

Scheduling is concerned with the assignment of time to a set of jobs for processing through a group of machines (or their service sector equivalents) in order to best satisfy some criteria. A great deal of

research has been carried out and will continue to be done on manufacturing scheduling problems (Baker, 1974). The reason is that scheduling offers a great theoretical challenge for researchers because of its combinatorial nature. Also, from the practical point of view, it plays a significant role in the successful operation of production, planning, and control department.

The general flowshop scheduling problem is known to be nondeterministic polynomial (NP)-complete (Gonzalez & Sahni, 1978). For solving scheduling problems, simple exact analytical methods such as integer programming (Sriker & Ghosh, 1986) or branch-and-bound (Lomnicki, 1965) have the limitation of dealing with only small-sized problems because of large computational effort. Heuristic polynomial-time algorithms (Campbell Dudek, & Smith, 1970; Johnson, 1954; Nawaz, Enscore, & Ham, 1983) probably are the most suitable means to solve large scheduling problems that are frequently encountered in many real-world situations. In general, heuristics provide good satisfactory (but not necessarily optimal) solutions in reasonable time and use problem-specific information.

The problems of manufacturing scheduling (Sarin & Lefoka, 1993) may be segregated based on (1) requirements, (2) complexity of the processes, and (3) scheduling objectives. Requirements may be produced either by open shop (customer orders) or closed shop (inventory replenishment). The complexity of the processes is primarily determined by the order in which the different machines appear in the operations of individual jobs. Broadly, manufacturing scheduling can be classified as flowshop scheduling and jobshop scheduling. In flowshop scheduling, it is generally assumed that all jobs must be processed on all machines in the same technological or machine order. In jobshop scheduling, the jobs may be processed following different machine orders. There is no common path of movement of jobs from machine to machine. Each machine is likely to appear for processing each operation of each job. The scheduling objectives are evaluated to determine the optimum schedule of jobs. Some of the objectives include makespan, total flow time, average job tardiness, and number of tardy jobs.

A variety of scheduling problems has been developed over the past years to address different production systems. The two commonly scheduling problems found in the scheduling literature of the past 50 years are flowshop scheduling and jobshop scheduling. Scheduling problems may be deterministic/stochastic and static/dynamic (Simons, 1992). The problem is deterministic or stochastic when the time required to process a task over respective machine takes a fixed or a random value. The scheduling problem is considered as static if ordering of jobs on each machine is determined once and will remain unchanged as opposed to the dynamic case that can accommodate changes of job ordering for accessing new jobs to the system.

A four-parameter notation (Conway, Maxwell, & Miller, 1967) is generally used to identify the individual scheduling problems, written as α / β / γ / δ .

 α denotes the job-arrival process. For dynamic problems, α will denote the probability distribution of the times between arrivals. For static problems, it is assumed that they arrive simultaneously unless stated otherwise.

 β describes the number of machines (m) used in the scheduling problem.

γ refers to the flow pattern of jobs through machines in the shop. The principal symbols are F for flowshop scheduling, R for randomly routed jobshop problem, and G for completely general or arbitrary flow pattern of jobs.

 δ describes the criterion by which a schedule of jobs will be determined. The symbols to represent the scheduling criterion are F_{max} (minimize the maximum flow-time or makespan). As an example of this notation, Johnson's (1954) problem is described as n / 2/ F/ F_{max} which means flowshop scheduling with n jobs and 2 machines so as to minimize the maximum flow time or makespan. Similarly, for a generalized flowshop problem, the notation will be n/ m/ F/ F_{max} .

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