Chapter 48
Smart Make-to-Order Production in a Flow Shop Environment for Industry 4.0

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ABSTRACT

The permutation flow shop scheduling problem is one of the popular problems in operations research due to its complexity and also its practical applications in industries. With the fourth generation industrial revolution, decisional aspects in make to order flow shop environment needs to be decentralized and autonomous. One of the aspects is to consider a real-time or dynamic production environment where customers place orders into the system dynamically and the decision maker has to decide whether the order can be accepted considering the available production capacity and how to schedule the jobs of an accepted order. To answer these research questions, in this chapter, the authors introduce a new decision-making, real-time strategy intended to yield flexible and efficient flow shop production schedules with and without setup conditions, Numerical experiments based on realistic problem scenarios show the superiority of the proposed real-time approach over traditional right shifting approaches.

INTRODUCTION

The permutation flowshop scheduling problem (PFSP) is a popular scheduling problem seen in manufacturing environments such as the automobile industry, food, pharmaceuticals, steel making, sanitary ware, and furniture (Rahman et al., 2015; Rahman et al., 2013). It is a complex optimization problem,

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where the production system usually consists of a finite number of jobs or tasks that must be processed on limited machines or processors. Each machine performs a specific type of operation for each job within a certain amount of time, which is known as processing time. As a prime consideration of PF-SPs, each machine has to process all jobs in the same processing sequence of jobs. On the other hand, each job has to follow the same sequence of all machines. Therefore, the work-flow is unidirectional. A schedule is accomplished by the completion of all jobs in all machines following a particular processing sequence of jobs. There are also specific constraints that must be satisfied. For example, a job cannot visit the same machine more than once, processing times cannot be negative, and a machine cannot handle more than one job at the same time. In addition, different objectives for solving PFSPs are makespan minimization, flow time minimization, completion time minimization, tardiness minimization, earliness maximization, and through output maximization. Makespan minimization is the most widely reported objective for solving PFSPs.

For everyday production processes, flow shop scheduling problems are encountered by manufacturers worldwide in different forms depending on the constraints and optimization criteria of the production environments. Thus, efficient planning and scheduling of flow shop production has always been principal criteria for the overall success of any manufacturing enterprise. The flow shop scheduling problem is a complex optimization problem and, therefore, finding efficient and effective techniques for solving production scheduling problems has attracted researchers and practitioners in the area of operations management and combinatorial optimization (Zobolas et al., 2009; Rahman et al., 2018). In literature, many different approaches have been developed for solving PFSPs under ideal conditions. Initially, the classical optimization techniques were developed for solving PFSPs for solving small-scale problems. For solving large-scale problems, many heuristics and meta-heuristics algorithms have been proposed. However, their performance varies significantly from problem to problem.

Although some characteristics of an ideal PFSP are exponential in nature and are complex to solve, practical production systems usually offer even more complex scenarios than the idealized problems addressed in current state. These include e.g. process interruptions, variability in product specifications, smoothness in product flow throughout the production floor, level of customer satisfaction, and competitive market scenarios. Therefore, based on the type of production, flow shop scheduling problems are classified as make to order (MTO) production systems and make to stock (MTS) production systems (Rahman et al., 2015). In MTO systems, manufacturers produce the products based on customer orders and, therefore, decision makers have to take order acceptance/rejection and scheduling decisions sequentially. Many modern manufacturing industries, academic researchers, have principally focused on static MTO flow shop scheduling problems, where a set of jobs of an order is scheduled on a set of machines in the flow shop without considering realistic settings. For example, Johnson (1954) proposed an optimal algorithm for two- and for a variant of three-machine static MTO PFSPs. For solving more than two-machine static MTO PFSPs, researchers proposed classical optimization techniques, such as the branch and bound (B&B) (Ignall & Schrage, 1965), and integer programming (Selen & Hott, 1986) algorithms. However, for more than two-machine MTO PFSPs classified as NP Hard (Garey et al., 1976), these techniques can find optimal solutions for small-sized problems only. To solve larger sized PFSPs, researchers have proposed heuristics (Nawaz et al., 1983) and meta-heuristic algorithms (Zobolas et al., 2009; Grabowski & Wodecki, 2004; Tasgetiren et al., 2007; Osman & Potts, 1989; Rajendran & Ziegler, 2004; Ruiz & Maroto, 2005; Ruiz et al., 2006; Rahmnan et al., 2013; Dasgupta & Das, 2015; Abdel-Basset, et al., 2018). Pinedo (2012) has argued that most of the theoretical studies in multiple machine scheduling problems considered static settings, i.e. scheduling an n set of jobs in an m set of

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