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Minimizing the total completion time for parallel machine scheduling with job splitting and learning

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ABSTRACT

This paper examines parallel machine scheduling with the objective of minimizing total completion time considering job splitting and learning. This study is motivated by real situations in labor-intensive industry, where learning effects take place and managers need to make decisions to split and assign orders to parallel production teams. Firstly, some analytical properties which are efficient at reducing complexity of the problem are presented. Utilizing the analytical property of the problem, a branch-and-bound algorithm which is efficient at solving small-sized problems is proposed. For the large-sized problems, several constructive heuristics and meta-heuristics are presented. Among them, the greedy search, which can take both the current profit and future cost after splitting a job into consideration, obtains a near-optimal solution for the small sized problems and performs best in all proposed heuristics for the large sized problems. Finally, extensive numerical experiments are conducted to test the performance of the proposed methods.

1. Introduction

This paper examines parallel machine scheduling to minimize total completion time considering job splitting and learning. In this paper, a job denotes a production order, which is composed of a number of discrete identical items. A job is completed only after all items within this job are finished. In addition, a job can be split into several sub-jobs to be processed on parallel machines, which results in reduced throughput time but improved delivery time. It is noted that, when items come from the same job consecutively, the learning effects occur and single item processing time will reduce. And obviously, the learning effects among items from the same job are significant, while insignificant among items from different jobs. Once the processing of a certain job is interrupted by a different job, the learning has to be restarted when the processing of the previous job continues.

Parallel machine scheduling with the consideration of learning and job splitting at the same time is one important but rarely discussed scenario, when it comes to minimizing the total completion time in labor-intensive industries, where learning effects take place easily and job splitting is important for the manufactories to meet the delivery demands. This paper, inspired by the actual situations in footwear manufacturing, a typical labor-intensive industry, where managers need to make decisions on how to split and assign orders for effective parallel production, is going to talk about this kind of problem and its possible solutions.

In a footwear manufactory, as shown in Fig. 1, it is easy to understand that the learning effects for the same style of shoes are significant, while insignificant for different styles of shoes. Furthermore, if the manager assigned an order to a single production team, this team would accumulate producing experience through learning and would finish this order in a short total production time, which stands for the sum of the time spent by all production teams in this producing task. In contrast, if the manager split the order into sub-jobs and assigned the sub-jobs across multiple production teams, the completion time of this order, i.e., the latest completion time of the sub-jobs, could be earlier than that in the preceding case, however, the total production time could be longer due to the possible decrease in learning.

For instance, Fig. 2 shows three different schedules for parallel machine scheduling with consideration of learning effects in a footwear manufactory. This problem is very common and interesting in practice. Sch_1 aims to complete the current job as soon as possible. It schedules the jobs with a Item-split rule, which is to assign items of the job to the least heavily loaded machine one by one until all items of the jobs are assigned. In Sch_2, jobs cannot be split, which means the jobs must be processed by one machine.

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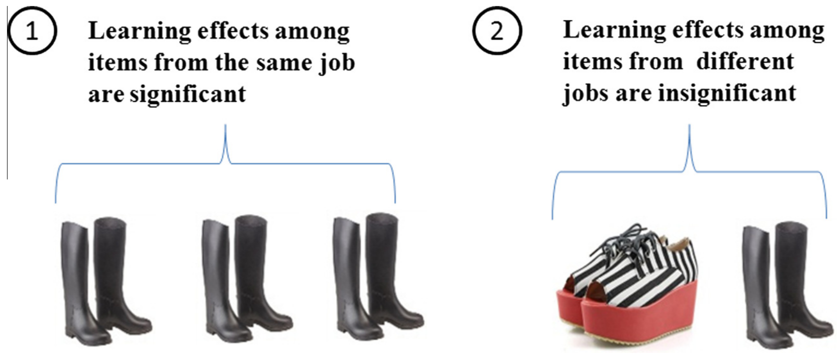

Fig. 1. Learning effects among items from the same job and different jobs.

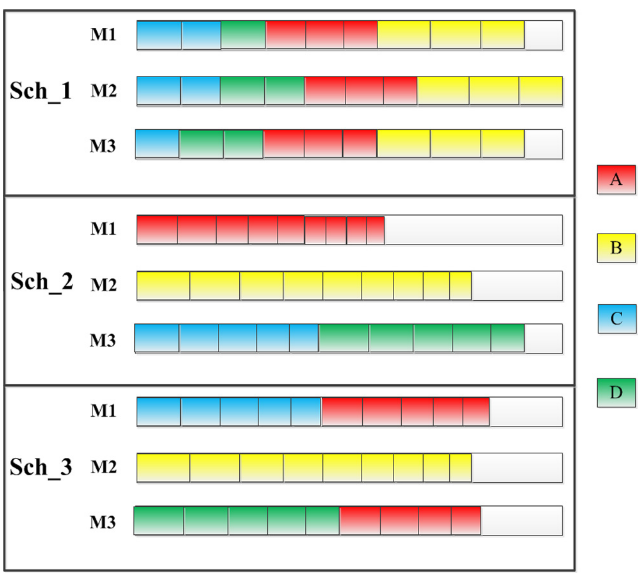

Fig. 2. A Gantt chart for a schedule for parallel machine scheduling with the consideration of learning and job splitting.

For the schedule, the total processing time of the schedule is minimal. However, the completion time may be very large if there is job whose processing time is too long. Sch_3 is obtained by considering learning and job splitting at the same time which is studied in this paper. In this schedule, the job must be split in an appropriate way. There are three machines, e.g., M_1, M_2 and M_3, and four different styles of shoes, e.g., A, B, C and D in this example. We denote T_1, T_2 and T_3 as the total completion time of schedules Sch_1, Sch_2 and Sch_3, respectively. As we can see, because of learning effects, the single item processing time will reduce when items come from the same style of shoe consecutively. In Sch_2, Shoe A is split into two sub-jobs and assigned to M_1 and M_3. Therefore, it has a smaller completion time than that in the preceding case. However, the total processing time of Shoe A will increase. For shoes B, C and D, they are only assigned to one machine, M_2, M_1 and M_3, respectively. Comparing Sch_1 with Sch_3, we can find that, the total processing time of Sch_3 is much smaller than that of Sch_1 which is influenced by learning effects. Meanwhile, comparing Sch_2 with Sch_3, it can be found that the total processing time of Sch_3 is a little smaller than that of Sch_2. However, the total completion time of Sch_3 is much smaller than that of Sch_2, which means $T_3 < T_2$. Through the comparisons, it can be concluded that, Sch_3 is a better schedule in a footwear manufactory which can consider not only total processing time but also the total completion time.

Therefore, in order to provide a high-efficiency schedule, it is very necessary to study the parallel machine scheduling with the consideration of learning and job splitting at the same time.

There are abundant research on scheduling with learning and scheduling with job splitting exist. Biskup (1999) first considered learning in production scheduling and proved that shortest processing time (SPT) is the optimal policy to minimize total completion time in single machine scheduling. Since then, extensive research has been conducted on scheduling with learning with different definitions of learning models, machine environments, and objectives. The learning models include position-based learning models (Mosheiov, 2001b), sum-of-time based learning models (Cheng, Wu, & Lee, 2008b; Kuo, Hsu, & Yang, 2012), truncated learning models (Wu, Yin, & Cheng, 2013), other general learning models (Koulamas & Kyparisis, 2007; Mosheiov & Sidney, 2003; Okolowski & Gawiejnowicz, 2010; Wang & Wang, 2012; Wu & Lee, 2009), induced learning models (Zhang, Sun, & Wang, 2013), and so on. The machine environments covers single machine scheduling (Biskup, 1999; Cheng & Wang, 2000; Yin, Liu, Cheng, Wu, & Cheng, 2013), parallel machine scheduling (Mosheiov, 2001a), flow shop scheduling (Cheng, Wu, Chen, Wu, & Cheng, 2013; Eren & Guner, 2008; Wang & Xia, 2005) with different typical objectives such as makespan, total completion time, and tardiness. Cheng and Wang (2000) studied a single machine scheduling problem in which the job processing times will decrease as a result of learning. Yin et al. (2013) considered single-machine scheduling problems with simultaneous considerations of due date assignment, past-sequence-dependent delivery times, and position-dependent learning effects. Yin, Xu, Sun, and Li (2009) developed a general scheduling model with position-dependent and time-dependent learning effects. Yin and Xu (2011) introduced a general scheduling model with the effects of learning and deterioration simultaneously, which is a significant generalization of some existing models. Cheng et al. (2013) studied a two-machine flowshop scheduling problem with a truncated learning function in which the actual processing time of a job is a function of the job's position in a schedule and the learning truncation parameter. For a detailed literature review, please refer to Biskup (2008). Recently, researchers also proposed some new scheduling with learning problems by incorporating some other scheduling features such as multi-agent scheduling (Li & Hsu, 2012), scheduling with deterioration job (Cheng, Wu, & Lee, 2008a; Wang, 2007; Yang & Kuo, 2010), and scheduling with setup time (Cheng, Lee, & Wu, 2010; Wang, 2008). However, most of the aforementioned studies share the same assumption that the learning occurs between jobs.

Decision strategies on splitting a production task lot into sub-jobs and scheduling the sub-jobs can be found in the area of scheduling with job splitting. Splitting parallel machines ensures that jobs can be finished as soon as possible to meet delivery