Int. J. Production Economics 154 (2014) 136–145

Contents lists available at ScienceDirect

Int. J. Production Economics

journal homepage: www.elsevier.com/locate/ijpe

Learning dependent job scheduling in mass customized scenarios considering ergonomic factors

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ARTICLE INFO

Article history:
Received 13 October 2013
Accepted 12 April 2014
Available online 25 April 2014

Keywords:
Scheduling
Learning curve
Human factors
Total weight tardiness

ABSTRACT

Industrial environments that rely on Mass Customization are characterized by high variety of product models and reduced batch sizes, demanding prompt adaptation of resources to a new product model. In such environment it is difficult to schedule tasks that require manual procedures with different levels of complexity and repetitiveness. This article integrates learning curves, scheduling heuristics and ergonomic factors to sequence batches in teams of workers. For that matter, we propose the ATCE rule (Apparent Tardiness Cost with Ergonomics Factors), which simultaneously reduces the total weighted tardiness and the allocation of batches with similar complexities to the same team (measured by percentage of saturation). When applied to two assembly lines in a case study from the footwear industry, the ATCE presented outstanding performance in ergonomic terms by reducing the percentage of work saturation from 66% to 1% in Team 1, and from 62% to 0% in Team 2, compared to results yielded by the Apparent Tardiness Cost (ATC) rule. In addition, the objective function value (total tardiness) increased only 3.53% in Team 1, and 2.18% in Team 2. In addition to the case study results, we assessed the robustness of the ATCE rule through simulation experiments. In all evaluated instances, the ATCE remarkably reduced the percent of saturation compared to the ATC while slightly increasing the total tardiness.

1. Introduction

The Mass Customization (MC) strategy which has been increasingly adopted by several industrial sectors is characterized by the production of customized items with reduced batch sizes and costs (Da Silveira et al., 2001; Watcharapanyawong et al., 2011; Fogliatto et al., 2012). That makes the scheduling of production batches challenging, since MC requires rapid setup of machines and adaptation of tasks to employees which are subjected to different levels of complexity and repetitiveness, and confronted with products with varying physical characteristics. Furthermore, adaptation of workers to tasks may take place slowly, with potential generation of nonconformities, making it difficult to estimate the time required for batch completion under workers' learning effect. Thus, it is key to define an appropriate processing sequence for the different product models in order to mitigate factors such as fatigue, stress and monotony which directly impact on workers' performance (Carnahan et al., 2000). In such a context, combining learning curves, batch scheduling heuristics, and ergonomics related indices may be a promising approach to minimize production delays and reduce the ergonomic impacts on systems that continuously subject workers to new products and tasks (Anzanello and Fogliatto, 2010).

Learning curves (LCs) describe the adaptation of workers to repetitive tasks, allowing the assignment of tasks according to workers' ability and experience (Anzanello and Fogliatto, 2011b; Jaber and Saadany, 2011), and minimizing production costs (Nadeau et al., 2010; Gong and Wang, 2010; Teng et al., 2013). Approaches assessing learning effects in batch scheduling are available in the literature (e.g. Biskup, 1999; Mosheiov, 2001; Mosheiov and Sidney, 2003; Anzanello and Fogliatto, 2010), but to our knowledge there is no proposition integrating learning effects, scheduling schemes and ergonomic factors. Ergonomics plays an important role in productive systems justifying the large number of studies devoted to job rotation, such as Chan and Song (2001), Guimaraes et al. (2012), and Van den Bergh et al. (2013). Prolonged and repetitive exposure to identical or very similar procedures reduces workers' motivation to perform tasks, and may lead to Work Related Musculoskeletal Disorders (WMSD) and productivity losses (Azizi et al., 2010). Changing the task nature diversifies workers' physical and psychological demands, therefore impacting on biomechanical and psychosocial factors causing WMSD (Ellis, 1999; Kuijer et al., 1999). Although we find several

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http://dx.doi.org/10.1016/j.ijpe.2014.04.016
0925-5273/

studies tackling the job rotation issue, we understand that productivity levels are sometimes relegated in situations where workers' learning takes place.

In this paper we propose a method to reduce the total weighted tardiness in batch scheduling while minimizing the assignment of batches with similar complexity levels to the same worker team in an MC industrial setup. For that, we integrate learning and ergonomic factors to a batch scheduling heuristic. There are three steps in the proposed method. First, LCs are used to estimate the processing times of batches with different sizes and complexity levels. Second, batches are assigned to different worker teams searching for a balance in the total operation time and complexity of tasks among teams. Third, batches assigned to each team are ordered to minimize tardiness following the Apparent Tardiness Cost with Ergonomic Factors (ATCE Factors) rule, which extends Rachamadugu and Morton (1982)'s Apparent Tardiness Cost (ATC) dispatching heuristic by adding an ergonomic associated term. To the best of our knowledge, there is no approach in the scheduling literature that takes ergonomic factors into account.

The proposed method is illustrated in a case study from the shoe manufacturing industry, involving two worker teams and 198 production batches of different sizes and complexities. We compare the ATCE and ATC rules with respect to the value of the weighted tardiness, and percentage of saturation (i.e. number of batches of same complexity assigned in sequence over all scheduled batches). Although ATC and ATCE rely on different objective functions, our scope here is to evaluate whether the inclusion of an ergonomics factor into the ATC rule promotes job complexity rotation without significantly impacting on jobs tardiness. We also assess the robustness of the proposed ATCE through simulation experiments; such experiments proved the ATCE to be an effective dispatching rule for reducing the percent of saturation without significant increase in the total tardiness objective function.

There are two main contributions in this paper. The first is the insertion of an ergonomic related term into the ATC rule. That reduces the sequencing of batches requiring similar tasks in short production periods, thus avoiding ergonomic stress due to task repetition. The second contribution is the use of LCs to estimate the processing time required by different teams of workers to complete tasks with distinct complexity levels, yielding more precise scheduling in customized manufacturing applications.

2. Background

In this section, we review the fundamentals on Learning Curves (LCs) and scheduling. LCs are mathematical representations of a worker's performance when exposed to a repetitive manual task or operation (Jaber and Bonney, 2001; Ngwenyama et al., 2007; Reid and Mirka, 2007; Anzanello and Fogliatto, 2011a). According to Teplitz (1991) and Alamri and Balkhi (2007), workers demand less time to perform a task as repetitions take place, either due to familiarity with the task or because shortcuts to task completion are discovered.

Given its efficiency in describing empirical data, Wright's potential model is the best known LC function in the literature

$$l = C_1 z^b \tag{1}$$

where z represents the number of units produced, l denotes the average accumulated time (or cost) to produce z units, C_1 is the time (or cost) to produce the first unit, and b is the slope of the curve, such that $-1 \le b \le 0$ (Wrigh, 1936). Parameter b is the learning rate parameter, measuring how fast a worker becomes familiar with the task under analysis. Due to its simplicity, several modifications in Wright's model have been proposed to improve its applicability to more complex situations. A noteworthy extension is proposed in Jaber and Khan (2010): Wright's model is modified based on the propositions of Jaber and Guiffrida (2004), and a composite LC is derived to address not only the time required to execute repetitive tasks, but also the time required to rework products with quality problems. Jaber and Khan (2010) also assess how modifications in the composite LC parameters impact on production yield and quality.

Despite Wright's model wide empirical application (Jaber et al., 2008), the hyperbolic LC has enabled a more robust and complete description of workers' learning process (Anzanello and Fogliatto, 2007). The 3-parameter hyperbolic model was originally proposed by Thurstone in 1919 and improved by Kientzle (1946);

$$y = k\frac{(x+p)}{(x+p+r)} \tag{2}$$

where y denotes workers' learning performance in terms of units produced after x minutes of accumulated practice in the task, k (units/min) is the maximum performance, r (min) denotes the learning rate (time elapsed until half the maximum performance is reached), and p (min) quantifies the impact of previous experience in performing the task (Anzanello and Fogliatto, 2007). Anzanello and Fogliatto (2007) compared the 3-parameter hyperbolic with several LC models when assigning families of products to worker teams; such a model was recommended given its adherence to workers' performance data and prediction ability. The same LC yielded the best results in Nembhard and Uzumeri (2000); the authors assessed 11 LC models with respect to efficiency in describing workers' learning profiles, stability, and number of parameters. The hyperbolic LC model was also tested in Anzanello and Fogliatto (2011a) aimed at clustering product models according to their requirements in terms of workers' abilities.

As for scheduling fundamentals, teams of workers are seen as unrelated parallel machines in this paper. In that scenario, the processing time of a task depends on the machine in which the job is processed, and there is no association between machines (Pinedo 2008). Since unrelated parallel machines give raise to complex scheduling problems (Weng et al., 2001), several approaches have been proposed to their solution, including Mokotoff and Jimeno's (2002) approach for makespan minimization using partial enumeration, Chen and Wu's (2006) heuristic for total tardiness minimization through insertion of resource and process restrictions into the formulation, and Bozorgirad and Logendran's (2013) proposition for simultaneous minimization of work-in-process inventory and total weighted tardiness.

More aligned with the propositions of this paper, the impact of the learning process on scheduling problems has received increasing attention. Biskup (1999) minimized flow-time and weighted completion time under a common due date assuming learning as a function of the job position in single machine applications. Focused on more complex productive scenarios, Mosheiov (2001) applied an LC with identical parameters for all tasks in applications comprised of several machines, while Mosheiov and Sidney (2003) minimized the makespan in unrelated parallel machines by incorporating task dependent LCs. With similar purposes, Anzanello and Fogliatto (2010) tested several scheduling heuristics for simultaneous minimization of earliness and tardiness in unrelated parallel worker teams affected by learning effect, while Bentefouet and Nembhard (2013) assessed the impact of worker's learning variability in flow shop scheduling. Finally, Li et al. (2013) evaluated the influence of a time-dependent learning effect in flow shop scheduling problems aimed at minimizing five distinct objective functions.

The Apparent Tardiness Cost (ATC) is one of the several scheduling heuristics successfully applied in manufacturing. The seminal ATC dispatches batches by taking into account their processing time, due date and subjective priority (Rachamadugu and