Computers & Industrial Engineering 87 (2015) 317–327

Contents lists available at ScienceDirect

Computers & Industrial Engineering

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

Production planning in DRC systems considering worker performance

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ARTICLE INFO

Article history:
Received 5 July 2014
Received in revised form 2 May 2015
Accepted 4 May 2015
Available online 13 May 2015

Keywords:
Quality
Learning-forgetting
Fatigue-recovery
Flexibility
Transfer policy
Human error

ABSTRACT

This paper studies the effects of some human characteristics on production planning in a Dual-Resource Constrained (DRC) system and the quality of products. Human behavior is captured by the learning–forgetting–fatigue–recovery model (LFFRM). The production process is modeled through a Quality Learning Curve (QLC) model while the quality deficits are the result of human error and machine malfunction. The system performance is presented with a twofold cost function considering direct (time) and indirect (quality) costs. The results indicate that the system performance is concave over a production run, which represents the optimum flexibility level, transfer policy, and the workstation configuration.

1. Introduction

Dual Resource Constrained (DRC) systems are working environments where the number of workers is less than the number of machines or workstations (Zamiska, Jaber, & Kher, 2007). Workers in a DRC system are cross-trained to acquire several skills that increase their flexibility and allow them to perform a variety of tasks (Thannimalai, Kadhum, Feng, & Ramadass, 2013). Cross-trained workers can usually handle situations of unexpected orders and unbalanced workloads. A flexible workforce helps reduce lead times and improve customer service (Bokhorst & Gaalman, 2009; Nembhard, Nembhard, & Gurses, 2002), however, a fully cross-trained workforce may not be feasible due to either the training costs, required specific skills, or equipment (Gel, Hopp, & Van Oyen, 2007; Robbins, Harrison, & Medeiros, 2007). In labor-intensive environments, workers accumulate experience (learning) through repetitions, but, as soon as repetitions cease, in order to take a break or transfer to another job, they start to forget their previous learning or experience. Also, while performing a job, a worker accumulates fatigue, which must be recovered by rest breaks or transferring to a less demanding job. The performance of DRC systems improves while workers learn, but is impeded when workers forget their skills and knowledge. Also, the performance of the workers declines with fatigue and improves with recovery. Therefore, the intermittent cycles of learning–fatigue and forgetting–recovery have adverse effects on the system performance. While the performance of DRC systems improves with the flexibility of workers (Azizi, Zolfaghari, & Liang, 2010; Jaber, Kher, & Davis, 2003; Jahandideh, 2012), alternating between different jobs or going on a break impedes the system's performance and influences process quality. In DRC systems, learning–forgetting, fatigue–recovery, and quality have been studied separately, but to the best knowledge of the authors, there is no study that captures the combined effects of these phenomena. The focus of this research is industrial settings where workers perform the tasks that require them to identify and select the component and follow a sequence to assemble it (Jaber & Kher, 2002). In this process, learning occurs during the assembly process and forgetting occurs when a worker shifts back and forth between different assembly stations or products. The present study, contributes to the DRC system literature by presenting a production planning model that captures aspects of human behavior such as learning, forgetting, fatigue, recovery, and error making in order to create production schedules that are more realistic and applicable to such working environments. The rest of this paper is organized as follows: in Section 2 a concise literature review of DRC systems is presented. Section 3 provides a quick background of the models that are utilized in this study. Section 4 presents the methodology of this research and results are presented in Section 5. Section 6 discusses and Section 7 concludes this study.

2. A concise literature review of DRC systems

Learning, in an assembly job, can occur in the following steps: component identification, understanding the sequence of the

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http://dx.doi.org/10.1016/j.cie.2015.05.005
0360-8352/

assembly process, and assembling the parts (Zamiska et al., 2007). While transferring between different jobs, a worker has the opportunity to practice his skills and thereby learn. However, in DRC systems, a flexible workforce may suffer from forgetting as a result of performing different jobs. Previous studies indicate that productivity loss is a side effect of flexible workforces in DRC systems because of forgetting (Jaber & Neumann, 2010; Zamiska et al., 2007). As the flexibility of a system increases, forgetting increases, which incurs additional costs to the system since the worker must re-learn the task that he revisits. Previous studies suggest that learning and forgetting must be modeled simultaneously in order to take advantage of the flexibility policies (Kher, Malhotra, Philipoom, & Fry, 1999). Several studies investigated the effect of flexibility and worker transfer policies in DRC systems to maximize the effect of learning and minimize that of forgetting. McCreery and Krajewski (1999) developed a model for an assembly line with learning and forgetting effects to investigate the use of workforce flexibility as a means to improve the performance of the line. They found that as task complexity increases, deployment of workers should be restricted and only low cross training is needed. Kher et al. (1999) and Kher (2000) studied worker training issues associated with learning and forgetting in DRC systems. They found that in the presence of high forgetting rates, applying flexibility policies may not be feasible and if the forgetting rate is high, flexibility reduces worker efficiency. These studies suggest that in the presence of learning and forgetting, the benefit of worker flexibility is situational. If the flexibility cost is low, incremental flexibility improves the shop performance, however, if the learning losses are high, flexibility may worsen inventory and customer service performance. Jaber et al. (2003) investigated the flexibility with the task similarity factor in the presence of learning and forgetting. They found that reducing the frequency of worker transfer to other tasks, reduces forgetting losses. Yue (2005) studied worker flexibility in parallel DRC systems with learning and forgetting effects. They found that in the case of fast learning/forgetting, flexibility may not improve the performance of the system since more flexibility requires more learning and incurs more forgetting. However, to manage the workload, a certain amount of flexibility is desired (Kim & Nembhard, 2010). Jaber and Kher (2005) investigated workforce cross-training in DRC systems by assuming that the production process may go out of control and produce defects that need rework. Their results indicated that in highly motor tasks, no upfront training is recommended. In another study Zamiska et al. (2007) applied a dual-phase learning forgetting model (DPLFM) to consider the motor and cognitive contents of learning of a task. This study, corroborated the result of Jaber et al. (2003), that it is not necessary to increase both the transfers and upfront training in the presence of slow learning rates since only one of them suffices to counter the forgetting losses. For high forgetting rates, both transferring the workers and providing upfront training is necessary to confront the forgetting effects. In general, these two studies indicate that the slower the learning is, the greater the need will be for a combination of reduced transfer policies or increased upfront training to confront the forgetting losses (Zamiska et al., 2007). Kim and Nembhard (2010) investigated the minimum staffing levels in parallel DRC systems in the presence of heterogeneous and individual learning and forgetting with a fixed production horizon. They observed that: first, a best workforce subset (the collection of best performing workers) requires fewer workers than an average subset (a collection of average performing workers) and second, restricting the extent of cross-training requires more workers. Guimarães, Anzanello, and Renner (2012) studied the effect of rotation between tasks of different complexities on the workers' learning rate and performance. They have adopted two scenarios: the first scenario is when workers transfer from an easy task to a difficult task. The second scenario describes the transfer of workers from a difficult task to an easy one. Their results showed that there is no major difference in the performance of workers in the two groups and they concluded that the sequence of task complexity does not change the workers' learning rate and performance. Azizi and Liang (2013) developed a model to assign a work and training schedule and for rotating workers between tasks while minimizing the total cost of training, flexibility, and productivity loss. Their findings indicate that the length of rotation interval has a significant impact on the total cost and the shorter the interval is, the higher is the total cost. The above studies primarily investigated transfer policies in DRC systems subject to learning and forgetting effects. They did not consider the relation between the transfer policies and quality of the product or physical capabilities of workers.

A flexible workforce reduces the lead times and inventories and also reduces fatigue, boredom, repetitive stress, and injuries (Hopp & Oyen, 2004; Jorgensen, Davis, Kotowski, Aedla, & Dunning, 2005). For instance, Carnahan, Redfern, and Norman (2000) developed an integer programming model for job scheduling to reduce the potential of worker back injuries. Using a genetic algorithm, they created job rotation schedules to maintain the productivity while controlling the exposure to musculoskeletal strain. Tharmmaphornphilas, Green, Carnahan, and Norman (2003) developed a model to reduce the likelihood of worker hearing loss by rotating the workers through different jobs during the day. They were able to reduce the maximum daily dose of time-weighted average sound level, to which any worker was exposed to, by 58.8% with improved schedules. In another study, Aryanezhad, Kheirkhah, Deljoo, and Mirzapour Al-e-hashem (2009) investigated safe skill-based job rotation scheduling by integer programming to simultaneously minimize maximum occupational noise exposure injuries and the potential of worker low back pain. They found that considering only one objective (noise dosage or back injury), may sacrifice the other one where finding the feasible solution was not possible. Lodree, Geiger, and Jiang (2009) conducted a job scheduling accounting for physical and/or cognitive human characteristics. They identified human characteristics related to task sequencing and established a framework for task-sequencing for any working environment with productivity and safety objectives. They argued that learning–forgetting, performance measurement related to accuracy (quality), fatigue and cumulative workload, as well as individual differences and limits, play an important role in task sequencing. Therefore, many of the traditional scheduling methods are not applicable when tasks are performed by humans. Although the authors asserted that the integration of the classical scheduling models with human performance modeling leads to the accurate characterization of the task outcome, DRC system models suffer from the absence of a comprehensive model that include these aspects of human behavior.

High loads, recurrent or prolonged loading generate fatigue that is a source of error, accidents, and quality issues (Bevilacqua, Ciarapica, & Mazzuto, 2012; Dinges, 1995, 2010; Sherman, 2003). Fatigue is usually alleviated by transferring a worker to a less physically demanding task or by giving the worker a rest break (Horton, Nussbaum, & Agnew, 2012; Jaber & Neumann, 2010). There are very few studies that have used workers' fatigue and recovery as a constraint for obtaining transferring schedules in DRC systems. The study by Jaber and Neumann (2010) is believed to be the first that modeled worker fatigue and recovery in a DRC job-shop to address the flexibility issues associated with the workload. Jaber and Neumann (2010) developed a mixed-integer linear programming (MILP) model with a twofold target function of productivity and physical loading. To simplify the MILP model, they have considered four practical cases with combinations of two tasks with breaks. The results suggested that if productivity is preferred over fatigue, full recovery after the second task is recommended. On the