ARTICLE IN PRESS

Int. J. Production Economics ∎ (∎∎∎∎) ∎∎∎–∎∎∎

Contents lists available at ScienceDirect

Int. J. Production Economics

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

The effect of worker learning on manual order picking processes

Eric H. Grosse*, Christoph H. Glock

Carlo and Karin Giersch Endowed Chair "Business Management: Industrial Management" Technische Universität Darmstadt, Hochschulstr. 1, 64289 Darmstadt, Germany

ARTICLE INFO

Article history:
Received 30 January 2014
Accepted 11 December 2014

Keywords:
Order picking
Warehousing
Learning
Human factors
Picker-to-parts systems

ABSTRACT

Order picking is a time-intensive and costly logistics process as it involves a high amount of manual human work. Since order picking operations are repetitive by nature, it can be observed that human workers gain familiarity with the job over time, which implies that learning takes place. Even though learning may be an important source of efficiency improvements in companies, it has largely been neglected in planning order picking operations. Mathematical planning models of order picking that have been published earlier thus provide an incomplete picture of real-world order picking, which affects the quality of the planning outcome. To contribute to closing this research gap, this paper presents an approach to model worker learning in order picking. First, the results of a case study are presented that emphasize the importance of learning in manual order picking. Subsequently, an analytical model is developed to describe learning in order picking, which is then evaluated with the help of numerical examples. The results show that learning impacts order picking efficiency. In particular, the results imply that worker learning should be considered when planning order picking operations as it leads to a better predictability of order throughput times. In addition, the effects of learning are relevant for the allocation of available resources, such as the allocation of workers to different zones of the warehouse. The results of the numerical analysis indicate that it is beneficial to assign workers with the lowest learning rate in the workforce to the fastest moving zone to gain experience.

1. Introduction

Global competition and high cost pressure force companies to utilize every option for improving the efficiency of their operations. An area that still contains significant potentials for improvements in many companies is internal logistics and warehousing. Processes in this area have, as a consequence, come more and more under detailed scrutiny in recent years. Order picking, which is the process of retrieving items from their storage locations to fulfill customer orders, is one of the most time- and labor-intensive operations in warehousing. Therefore, identifying and realizing potentials for efficiency improvements in order picking is an important lever for increasing the efficiency of operations. Studies indicate that order picking is responsible for more than 50% of the operating costs of a warehouse (Tompkins et al., 2010), which is mainly due to the high amount of manual human work that is involved in this process step. Although more and more order picking systems are partially automatized today, manual order picking systems are still dominant in practice. Researchers have estimated that up to 80% of all order picking warehouses are operated manually (de Koster et al., 2007; Baker and Perotti, 2008; Napolitano, 2012). The reason why many companies rely on manual order picking is that the cognitive and motor skills of human order pickers cannot be imitated economically by automatic order picking systems (Roodbergen and Vis, 2009). Cognitive and motor skills, however, are human characteristics that may have a high impact on the performance of manual order picking processes, and therefore they should not be neglected when planning order picking operations.

To predict and monitor the performance of individuals, various types of learning curves have been developed in the past (e.g., Jaber and Glock, 2013). Learning curves model the performance improvement of an individual or a group performing a task over time as a result of accumulated experience. They facilitate better performance predictability, for example in inventory models that consider learning in the production rate or in setups (Jaber et al., 2009). Learning in order picking has attracted less attention in the past. A recent study of Grosse et al. (2015) revealed that worker characteristics—such as learning—have regularly been neglected, and that performance

* Corresponding author. Tel.: +49 6151 165281.
E-mail addresses: grosse@bwl.tu-darmstadt.de (E.H. Grosse), glock@bwl.tu-darmstadt.de (C.H. Glock).

http://dx.doi.org/10.1016/j.ijpe.2014.12.018
0925-5273/

Please cite this article as: Grosse, E.H., Glock, C.H., The effect of worker learning on manual order picking processes. International Journal of Production Economics (2015), http://dx.doi.org/10.1016/j.ijpe.2014.12.018

indicators of order pickers (such as the time needed to fulfill particular order picking tasks) have therefore been (wrongly) assumed to be constant. This indicates that there is an opportunity to improve existing order picking models by considering learning in the planning of order picking processes and in studying which aspects facilitate learning. This may contribute to a better predictability of order picker performance and may help to manage the system in such a way that learning is maximized and order picking time and costs are reduced (compare for production e.g., Anzanello and Fogliatto, 2011; Jaber and Bonney, 1999, 2011). For example, a dedicated storage assignment strategy may promote learning as workers get familiar with the location of stored products over time. This may lead to improved picker performance which, in turn, may reduce order lead time. If, in turn, a high number of contract or temporary workers are employed in order picking, only little learning may occur at the order pickers due to the constant labor turnover that takes place. Thus, each time a new worker enters the warehouse, he or she has to become familiar with the operations on site, which may reduce the performance of order picking systems.

To study the effects of human learning on order picking efficiency, and to contribute to closing the research gap identified above, this paper develops an analytical model that helps to predict worker performance in order picking systems. The remainder of this paper is structured as follows: The next section reviews the related literature. Section 3 summarizes empirical evidence for learning in order picking and the impact of learning on order picking efficiency, and Section 4 formulates the assumptions made in developing the proposed model. Section 5 develops a mathematical model that considers learning in order picking, and Section 6 presents the results of a comprehensive numerical experiment. The paper concludes in Section 7.

2. Literature review

2.1. Order picking literature

The manual picker-to-part process can be described as follows (de Koster et al., 2007): The order picker receives the order usually on a pick list, i.e. a paper-based list that specifies the items to be picked with respect to item identifications, item numbers and item locations. The picker walks (typically using a trolley or cart as a tool) to the shelve locations, picks the required items and returns to the depot, i.e. the place where order picking tours start and end and where collected items are dropped off, packed and shipped. After an order has been finished, the order is usually subjected to a quality control step. Many researchers assumed that order pickers spend most of their time on traveling in the warehouse to fulfill customer orders (e.g., Tompkins et al., 2010). As a result, planning models on the design and control of manual order picking systems have a major focus on the reduction of travel time or, equivalently, travel distance. An exhaustive review of this popular research stream is not within the scope of this paper, and the reader is referred to the reviews of Gu et al. (2007) and de Koster et al. (2007). In the following, we give a short summary of the four most important planning problems that have to be addressed in the design and control of picker-to-part order picking systems, namely *layout design*, *routing*, *order batching*, and *storage assignment*. These planning problems are usually addressed with the help of analytic models; simulation models, however, have been used more and more frequently in recent years (e.g., Basile et al., 2012; Chackelson et al., 2013).

The first planning problem, *layout design*, is concerned with determining the configuration of the warehouse, which includes defining the number of aisles and cross aisles as well as their dimensions (Petersen, 2002; Roodbergen and Vis, 2006; Roodbergen et al., 2008). In many cases, warehouses have a rectangular shape. In recent studies, however, authors have analyzed alternative layouts for order picking systems without conventional parallel pick aisles, such as fishbone and flying-V layouts (Pohl et al., 2011; Çelik and Süral, 2014) or U-shaped layouts (Glock and Grosse, 2012).

Routing policies define the sequence in which the order picker retrieves required items. In a rectangular warehouse, routing order pickers is a special case of the Traveling Salesman Problem, which is why an optimal solution to the problem may be found with solution procedures that have been developed in this stream of research (Rattliff and Rosenthal, 1983; Roodbergen and de Koster, 2001). The majority of research has concentrated on developing heuristics for the routing of order pickers, as heuristics often lead to tours that are more convenient for the order picker (Hwang et al., 2004; Petersen and Aase, 2004; Theys et al., 2010). More recently, some authors have considered picker blocking and congestion in routing order pickers through the warehouse (Pan and Wu, 2012; Hong et al., 2012; Chen et al., 2013).

A problem that is closely related to the routing problem is commonly referred to as *order batching*. Order batching helps to better utilize the carrying capacity of the order picker by consolidating or splitting individual orders, which can reduce travel time in many cases (see, for a review, Henn et al., 2012). Some authors developed algorithms to solve moderate-sized batching problems exactly (Gademann et al., 2001). As the order batching problem is NP-hard, most authors have concentrated on developing heuristic procedures for assigning items to batches (Hsieh and Huang, 2011; Grosse et al., 2014).

The last optimization problem discussed here, *storage assignment*, determines how products should be assigned to storage locations. If a random storage assignment is used, items arriving at the warehouse are randomly assigned to an open location in the warehouse. Random storage is most appropriate under dynamic conditions, i.e. in situations where reliable data on item demand frequencies is not available (Tompkins et al., 2010), or in situations where a large product portfolio has to be stored and where warehouse managers desire a high utilization rate for the warehouse. A dedicated storage assignment strategy, in contrast, assigns products to fixed shelf locations based on certain item features, such as demand frequency, part number sequence or demand correlations (Frazelle, 2002; Glock and Grosse, 2012). A popular decision criterion in practice is that items with high demand and turnover frequencies should be located close to the depot (Gagliardi et al., 2008). When the number of items to be stored is high, a class-based storage method could be used. In this case, products are divided into classes and each class is assigned to a dedicated area of the warehouse. Storage within each class is random (Chan and Chan, 2011; Bottani et al., 2012). In a recent study, Grosse et al. (2013) studied the effect of storage reassignment decisions when learning and forgetting occur at the level of the order pickers. The authors investigated how changes in an existing storage assignment impact human learning and picker performance, and evaluated in which cases an existing storage assignment should be changed or not. This paper concentrated only on storage assignment and expressed learning in an aggregated form. More specifically, learning was modeled as a decreasing order picking time that occurs as the number of orders increases. To the best of the authors' knowledge, this paper is the only one that considered learning in an order picking planning model so far. The focus of the literature was instead on learning in industrial and logistics processes, which will be surveyed briefly in the next section.

2.2. Learning literature

Learning effects have frequently been the subject of research in recent years. One of the first works in this area is the one of Wright (1936), who observed that unit production costs in airplane assembly reduce as the number of units produced increases, which he attributed to learning. Performance improvement that results from human learning can be modeled with the help of so-