

## AGENT-BASED ANALYSIS OF PICKER BLOCKING IN MANUAL ORDER PICKING SYSTEMS: EFFECTS OF ROUTING COMBINATIONS ON THROUGHPUT TIME

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### ABSTRACT

Order picking is one of the most labor- and time-consuming processes in supply chains. Improving the performance of order picking is thus a frequently researched topic. Due to high cost pressure for warehouse managers the space in storage areas has to be used efficiently. Hence narrow-aisle warehouses where order pickers cannot pass as well as several order pickers working in the same area are common. This leads to congestion which is in this context referred to as picker blocking. This paper employs an agent-based simulation approach to investigate the effects of picker blocking in manual order picking systems with different combinations of routing policies for three order pickers in a rectangular warehouse with narrow-aisles. Results indicate that the best combination in terms of throughput time for three order pickers in a rectangular warehouse with blocking considerations is Largest gap (picker 1), Largest gap (picker 2), and Combined policy (picker 3).

### 1 INTRODUCTION

Order picking is one of the most labor- and time-consuming processes in warehouses (Frazelle 2002; Tompkins et al. 2010). It is the process of retrieving items/products from their storage locations depending on customer orders (de Koster, Le-Duc, and Roodbergen 2007). Order picking systems differ if humans (manual systems) or machines (automatic systems) are employed. It is estimated that more than 80 % of warehouses are operated manually (de Koster, Le-Duc, and Roodbergen 2007; Napolitano 2012). Picker-to-parts or parts-to-picker systems are frequently used in manual order picking systems. Most common are picker-to-parts systems where the products are placed in fixed storage locations and the order picker walks to single products according to the order list (de Koster 2004).

The order picking process has influence on customer satisfaction especially if the order picker collects wrong or broken products which are shipped to the customer (Gue, Meller, and Skufca 2006; Parikh and Meller 2008). Additionally order picking has an effect on the service level and performance of the supply chain (Chen et al. 2013).

In order to get efficient processes, order picking is comprehensively planned to find best arrangements of aisles and racks (*layout design*), guiding the picker through the warehouse on routes (*routing policies*), the assignment of products to storage locations (*storage assignment rules*), to combine several orders into batches (*batching*) or to divide the storage into different zones (*zoning*) (de Koster, Le-Duc, and Roodbergen 2007).

Routing policies have a major influence on the efficiency of order picking processes in terms of travel time and are regarded as primary source of management because there are relatively easy to change (Hong 2014). They are also frequently employed to measure the efficiency of order picking systems (Pan

and Shih 2008). Routing policies help sorting items on the order list and guide the order picker through the storage area.

Furthermore, travelling is one of the most time-consuming processes in order picking operations. Travelling time has the major share of the order picking process and accounts for more than 55 % of order picking time (which consists of activities like traveling, searching, picking, setup, and others) (Tompkins et al. 2010).

Thus, a main objective for warehouse managers is to reduce travel time. Although there exists an optimal algorithm for routing order pickers in a rectangular one-block warehouse that minimizes travel time, most researchers have focused on heuristic routing method as these are used in practice. The reason is that heuristics are more intuitive and easier to understand (de Koster, Le-Duc, and Roodbergen 2007). The most frequently used heuristics in practice are (e.g. de Koster, Le-Duc, and Roodbergen 2007; Petersen and Schmenner 1999):

- *S-shape (S) (or traversal)*: The picker starts at the depot and enters the first aisle on the left side which contains at least one pick, traverses it completely and leaves the aisle on the other side as he entered it. This is repeatedly done with the following aisles until all items are picked. Afterwards the order picker returns to the depot. Finally, the way of the order picker has the shape of an “S”.
- *Return (R)*: Each aisle which contains at least one pick is entered. All aisles can be left on one side only. After picking all items the order picker returns and leaves the aisle on the same side where he has entered it.
- *Midpoint (M)*: The storage area is divided into two equal halves. Subsequently the order picker enters the aisles on the side where the depot is located and collects all picks in the first half. For retrieving picks in the back half the order picker traverses the aisle on the left or right side with picks completely (as the order picker does with the last aisle before he returns to the depot). All other aisles are left on side where the order picker enters it (see return policy).
- *Largest Gap (L)*: In contrast to the midpoint policy aisles are entered until the largest gap. This is the largest distance between two consecutive picks. The decision if the order picker returns after picking and leaves the aisles, where he has entered it, depends on the largest gap instead of using the middle as a reference point. Aisles can be traversed completely, entered on one side or entered on both sides.
- *Composite (Cs)*: Composite policy is a combination of return and S-shape policy. The aim is to minimize the distance between two picks in adjacent aisles.
- *Combined (Cb)*: This policy includes an algorithm similar to the composite policy with one difference. The shortest path is calculated for the whole block of aisles before the order picker starts travelling. Therefore the combined policy produces throughput times which are at least as good as the throughput times which are resulting from the composite policy (when only one order picker is considered at a time).

Recent studies highlight the importance of considering human factors (such as cognitive and motor skills or behavior of the workers) on the performance and quality of manual order picking processes (Grosse et al. 2015). Particularly if several employees work in the same storage area, congestion and thus additional waiting time as well as additional travel times and travel distances have to be taken into account (e.g. Pan and Wu 2012; Pan, Shih, and Wu 2012). Congestion in this context is referred to as picker blocking (Parikh and Meller 2009).

Due to longer waiting times or additional idle times, picker blocking has a considerably negative effect on the efficiency of order picking processes and increases operational costs related to order picking time (Hong, Johnson, and Peters 2012b; Heath, Ciarallo, and Hill 2013).

As picker blocking represents a major challenge for warehouse managers that causes significant operational performance loss, it is a notably researched topic. Studies investigate the influence of picker blocking on travel time (Gue, Meller, and Skufca 2006), the effects of wide- or narrow-aisles with regard to picker blocking (Parikh and Meller 2009) or apply a simulation approach (e.g. Pan and Wu 2012; Pan, Shih, and Wu 2012). In addition, the impact of blocking for different routing policies are investigated (Furmans, Huber, and Wisser 2009). Although there exist several studies on picker blocking in the literature, there are still various research gaps that have been overlooked so far, especially with regard to the use of comprehensive simulation approaches. To the best of the authors' knowledge, there is no study which investigates the impact of picker blocking on order picking time when assigning each order picker an individual routing policy. Thus, we formulate the *research question* studied in this paper as follows:

*What are the effects of picker blocking in manual operated narrow-aisle warehouses with individual routing policies for every order picker?*

The remainder of this paper is structured as follows: After identifying the research question, section 2 encompasses an overview of the relevant literature in the field of picker blocking. Section 3 contains the description of the employed method and the suitability of simulation models for investigations in the field of order picking. Furthermore, the structure of the simulation model is explained. In section 4 the results of the simulation study are presented with regard to the research question. Section 5 comprehends the conclusion of the paper, discusses the results and gives implications for further research and practice.

## 2 LITERATURE REVIEW

An estimation by de Koster, Le-Duc, and Roodbergen (2007) states that most order picking systems in practice are low-level (order picker walks to storage shelves without truck or cranes), picker-to-parts order-picking systems employing humans (and with multiple picks per route). Hence, we focus on such order picking systems in our investigation as picker blocking is of major concern in these systems.

Picker blocking is a critical factor which impacts travel time (Mowrey and Parikh 2014). It occurs in two different ways (Hong, Johnson, and Peters 2013; Gue, Meller, and Skufca 2006; Mowrey and Parikh 2014; Parikh and Meller 2009; 2010; Sainathuni et al. 2014). First, order pickers cannot pass each other due to narrow-aisles or no passing restrictions. This is referred to as *in-the-aisle-blocking*. The second one is referred to as *pick-column blocking*. It occurs when order pickers cannot reach the pick-column because other workers (order pickers or workers, who are in charge for replenishment) block it.

Furthermore, Furmans, Huber, and Wisser (2009) distinguish between level-one, level-two, and level-two opposite blocking situations within a single aisle. The first one is comparable with *in-the-aisle-blocking* or *pick-column blocking*. Level-two blocking occurs if three or more order pickers are blocked and if picker 2 blocks the pick-column of the next picker (picker 3). Level-two opposite blocking results from opposite walking directions. Latter situation requires priority rules to resolve blocking situations.

Extensive research was done in the field of manual order picking. Thus, we refer to the literature review of de Koster, Le-Duc, and Roodbergen (2007) and present an overview of literature that studies picker blocking in manual order picking systems. Ruben and Jacobs (1999) investigated influence of different storage assignment rules and construction of batches on order retrieval under consideration of blocking. Furthermore, Skufca (2005) focused on picker blocking with multiple order pickers, who are working on a closed circular path. The main result of Gue, Meller, and Skufca (2006) is that negative effects of blocking on travel times are reduced with increasing pick activity (if pick density is high and order pickers frequently stop for picking). Pan and Shih (2008) employed a throughput model to show that random storage assignment rule increases throughput because of a higher utilization of the storage area. Parikh and Meller (2008) developed a cost model and investigated picker blocking as one of four factors affecting the decision regarding batch or zone picking (other factors are: pick-rate, workload-imbalance, and sorting). Furmans, Huber, and Wisser (2009) modelled the negative effects of picker

blocking in manual order picking systems with S-shape and return policies. Parikh and Meller (2009) showed the difference between narrow- and wide-aisles. They developed a model to investigate pick-column blocking in wide-aisles with one pick at each pick column as well as with one or more picks at each pick column. Resulting that for the first case (one pick at each pick column) blocking has less negative effects in wide-aisles order picking systems than in narrow-aisles order picking systems and for the latter (one or more picks at each pick column) blocking has more negative effects in wide-aisle order picking systems. Hong, Johnson, and Peters (2010) also investigated narrow-aisle order picking systems and the effect of batch picking on order picking throughput under consideration of picker blocking. Parikh and Meller (2010a) investigated effects of blocking for non-deterministic (one or more picks at each pick column) pick times in a narrow-aisle order picking system. Findings suggest that picker blocking is higher compared to deterministic (one pick at each pick column) pick times and has more negative effects with increasing pick density. Parikh and Meller (2010b) included vertical as well as horizontal traveling in their study and gave recommendations for the height of a one-pallet-deep storage system based on an analytical model. Hong, Johnson, and Peters (2012a) created a batching model for large-scale order picking situations which reduced traveling time in their model. They discuss results that narrow-aisles lead to more picker blocking and shorter travel lengths. This does not guarantee a shorter retrieval time when picker blocking is considered. Hong, Johnson, and Peters (2012b) published another batching and sequencing procedure to get shorter total retrieval times (total of travel time, pick time, and blocking delays) in narrow-aisles order picking systems due to decreased picker blocking. Chen et al. (2013, 2014) developed a routing policy based on Ant Colony Optimization for an order picking system with multiple pickers. Hong, Johnson, and Peters (2013) used a Markov chain modeling framework for assessing picker blocking in a parallel-aisle order picking system and multiple picks at each pick column. Klodawski and Zak (2013) assessed the order picking efficiency depending on different order picking layouts. Hong (2014) created a blocking model and a closed-form expression for multiple workers in a no-passing order picking system with varied speed and pick stations. The author also used a circular-passage system and showed throughput loss caused by picker blocking. Hong, Johnson, and Peters (2014) presented the reduced retrieval time and improved picker utilization in an order picking system with bucket brigade policy. The study is based on an order batching model. Mowrey and Parikh (2014) introduced a mixed-width aisle layout (combination of wide- and narrow-aisles) in their study and showed that random storage assignment rules and traversal policy are best suited for their proposed system configuration. Finally, Sainathuni et al. (2014) presented a warehouse-inventory-transportation problem for supply chains where picker blocking is incorporated. The main objective is to reduce or minimize distribution costs with coordinated decisions in warehousing, inventory, and transportation.

First simulation based approaches in order picking are presented in Pan and Wu (2012) who determined throughput time for different routing policies, storage assignment rules and different sizes of warehouses with eM-plant simulator in a picker-to-parts system. Furthermore, Pan, Shih, and Wu (2012) used eM-plant software to develop a routing heuristic for decreased picker blocking. The heuristic takes the travel distance and waiting time into consideration and outperforms existing storage assignment rules (like random storage assignment rule).

In addition, there are first works that employ the agent-based simulation (ABS) approach. Particularly, ABS seem to be well suited for investigations in the field of order picking due to the high number of factors which can influence the effects of picker blocking (Heath, Ciarallo, and Hill 2013). Hagspihl and Visagie (2014) created an ABS model in which they implemented uni-directional picking lines, varied the location of stock-keeping units (SKU), and developed a new heuristic for locating SKUs. Heath, Ciarallo, and Hill (2013) investigated the influence of picker blocking on costs and performance with regard to individual behavior of the order pickers (agents).

To the best of authors' knowledge, no study could be found which investigates blocking with routing combinations for various agents within single simulation runs.

### 3 AGENT-BASED SIMULATION STUDY

#### 3.1 Methodology

Due to the dynamic nature of picker blocking (Heath, Ciarallo, and Hill 2013) we created an agent-based simulation model (ABS) with the software AnyLogic 7.1.0. It is a relatively new approach which was infrequently applied for investigations in the field of picker blocking. Heath, Ciarallo, and Hill (2013) provided one of the first studies with ABS. They showed that it is an appropriate approach for including micro-level behavior (e.g. order pickers, who follow routing policies) and observe macro-level behavior (blocking/congestion).

AnyLogic is a commercial software tool which provides the opportunity to create ABS models (Borshchev 2013a). It offers predefined libraries, a graphical user interface and the possibility to include individual functions, which are based on JAVA (Borshchev and Filippov 2004; Macal and North 2010). Furthermore, individual behavior of single agents can be included with the help of state charts. They contain states as well as transitions and are comparable to flow charts. States can contain functions and transitions including conditions for passing to the next state. Additionally, agents can interact via messages (Borshchev 2013b).

ABS consist mainly of three parts (Borshchev and Filippov 2004; Macal and North 2010): a set of agents, their relationships (with interactions between agents), and their environment. In our model each agent represents an individual order picker with own rules or guidelines (e.g. routing policies) which allows us to include human behavior in the simulation model. With regard to our research question agents are able to block each other and though picker blocking can occur. These are the interactions or relationships between the single agents. The last part of ABS is the interaction with the environment. Here we implemented a rectangular warehouse layout with narrow-aisles (see Figure 1). Based on the layout each picker receives prescribed ways through the storage area (routing policies). Whenever blocking occurs the ABS can include individual behavior which could also increase the throughput time. Order pickers have to negotiate the priorities. This is done with the help of the next picking position. The order picker with the lowest distance to the next pick gets priority.

#### 3.2 Problem Description and Parameters

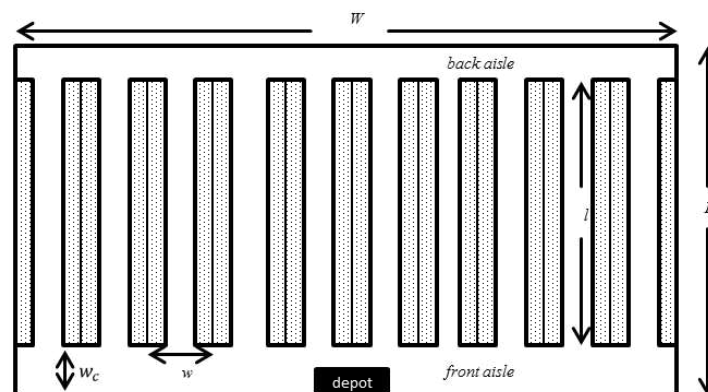


Figure 1: The rectangular warehouse layout for the simulation model has 10 aisles (Grosse, Glock, and Ballester-Ripoll 2014).

We assume a standard warehouse layout with 10 aisles (see Figure 1) which is common in practice and has frequently been studied in the literature (cf. Grosse, Glock, and Ballester-Ripoll 2014). Each aisle contains 100 products (50 at each side). An order list with 20 picks is assigned to every order picker (agent). The lists contain randomly created article numbers ( $n = 1000$ ) and are constant for every

simulation run. For assigning products to storage locations we implemented a random storage assignment rule as it enables a good utilization of all aisles in the storage area (Pan and Shih 2008). Furthermore, full-turnover or class-based storage assignment rules may increase blocking (Petersen and Schmenner 1999; Petersen and Aase 2004). The depot is located in the middle of the storage area (Roodbergen and Vis 2006). After finishing one simulation run 60.000 products are picked. This is a reasonable amount of items handled per day (Hong, Johnson, and Peters 2012b).

Two times are determined by the simulation model for each order (the total of picking and walking time). The first one considers throughput time with effects of blocking while the second throughput time is determined by the simulation model without any picker blocking (i.e. if pickers could pass each other at any time) (Heath, Ciarallo, and Hill 2013).

The speed of an order picker is set constant (0.75 meter per second) as well as the time for picking at a pick-column (20 s) (Gue, Meller, and Skufca 2006; Pan, Shih, and Wu 2012).

To capture the effects of blocking in a typical order picking process we included characteristic behaviors of order pickers, which are autonomous agents (Heath, Ciarallo, and Hill 2013). The picking process starts and ends at the depot and aisles can be traversed in both directions. After picking the assigned order list each agent returns to the depot and receives the next order list (searching time is neglected). The next order picker starts after 18.5 s (when the predecessor arrives at the entrance of the first aisle). The number of order pickers in the warehouse and in one aisle is limited to three. This leads to several blocking considerations, especially when two or more order picker have to decide who has priority. Therefore, a priority rule is implemented. If one or more order pickers try to pass another worker the agent with the shortest distance to the next pick gets priority. All other agents either have to wait or have to go additional distances to let the order picker with the highest priority pass. Hence, in-the-aisle-blocking as well as pick-column blocking occurs in the simulation model. Further, we assume that order pickers follow the guidelines (routing policies) even if this will lead to picker blocking.

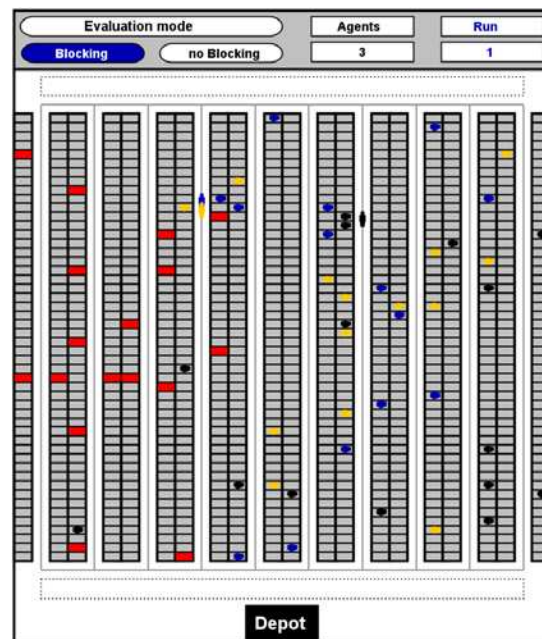


Figure 2: Screenshot of the simulation model shows that three agents retrieve products in the warehouse at the same time (order pickers, colored).

### 3.3 Validation

We validated the conceptual as well as the computer model mainly during a workshop with 33 experts in the field of logistics from several companies in Germany. We introduced our research project and explained the model in detail. Furthermore, several simulation runs and results were shown and discussed with all experts. The representatives of those companies came from different industries (automotive, chemical, logistics service provider, etc.) as well as from companies with different sizes (small, medium, and large). The high number of participants resulted from the high interest in the topic of picker blocking which obviously can be a pressing problem in practice.

Furthermore, the conceptual model is based on information taken from previously published studies as well as authors' experience and consultations with several experts which were done prior to the study.

Additionally, we used the face validation and followed the order picking process via the graphical user interface. This is suitable for easy to follow heuristics like the S-shape policy. We also compared the output data with throughput times from different heuristics (e.g. composite vs. combined). Another possibility is to start simulation runs with extreme high values. We simulated up to 90 pickers to evaluate that the computer model is valid.

## 4 RESULTS

The objective of the study was to investigate the effects of routing combinations on throughput time. Therefore we made simulation runs with all possible configurations for three order picker and six routing policies ( $6^3 = 216$  combinations). In our simulation model picker blocking can result in increased waiting or idle times as well as in additional travel distances.

Considering these effects of picker blocking, results show that the routing combination LLCb, i.e. Largest gap (Agent 1), Largest gap (Agent 2), and Combined (Agent 3) leads to best results for 1000 randomly created orders with 20 picks per order. Figure 3 depicts the mean throughput time for LLCb in comparison with combinations when the same routing policy is assigned to all pickers. The order pickers need on average 800.946 s for fulfilling an order with LLCb (standard deviation = 64.329 s; confidence interval = 2.302 s). All results are shown without picker blocking (gray color) as well as the additional time needed when blocking is considered (red color). If no blocking occurs, CbCbCb performs best in comparison to all other 215 combinations. Additionally, LLCb results in shortest mean throughput times when blocking is considered due to less waiting and idle times as well as less additional travel distances (note that all confidence intervals differ not more than 0.53 % from the mean with blocking and 0.33 % from the mean without blocking).

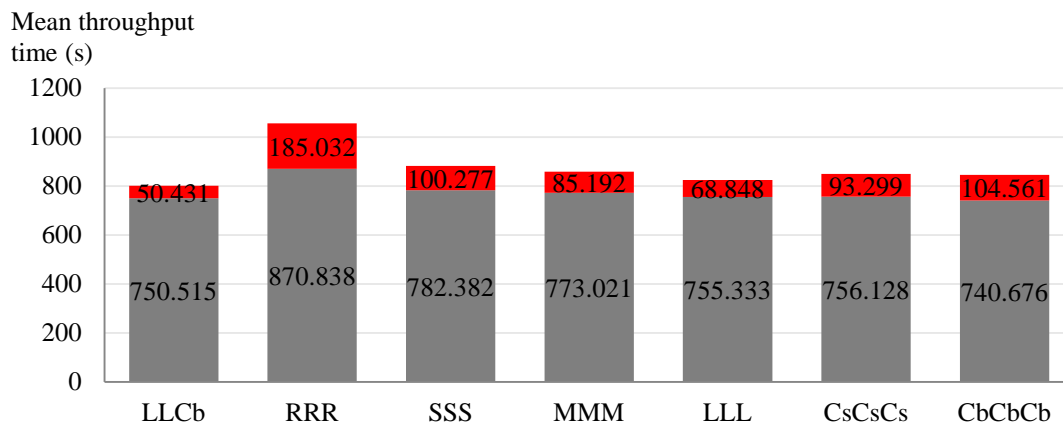


Figure 3: Mean throughput times (s) show the difference between the combination with lowest mean throughput times in comparison to combinations with only one routing policy (gray: without blocking; red: additional time with blocking).

Our results show that also other combinations of LLCb (LCbL, CbLL) lead to shorter mean throughput times in comparison to other routing combinations. The first one produces the second best mean throughput time while latter leads to the ninth best time (see Figure 4). Another important fact is that mainly sophisticated heuristics (combined, largest gap, etc.) result in shorter mean throughput times compared to S-shape or return. However, the first combination with the very common S-shape policy is ranked number 27 (LSL) but only with an increase of 2.11 % in mean throughput time (817.882 s) compared to the best combination. As Figure 4 depicts the mean throughput times for the best ten combinations are very close to each other. MCbCb, ranked number ten, has only a mean time which is 1.26 % higher than LLCb. When comparing the best (LLCb) with the lowest mean throughput time (RRR) the simulation model determines a throughput time which is 31.83 % higher. SSS which is most common in practice (de Koster, Le-Duc, and Roodbergen 2007) results in a mean throughput time of 882.659 s (standard deviation = 95.603 s; confidence interval = 3.421 s). This is about 10.2 % higher compared to LLCb.

Furthermore, combinations with return policy lead to lower mean throughput times than other combinations due to a high number of blockings during the order picking process. The longest mean throughput time results for RRR with 1055.87 s (standard deviation = 124.179 s; confidence interval = 4.444 s). This could probably increase if other storage assignment rules with busy areas are used.

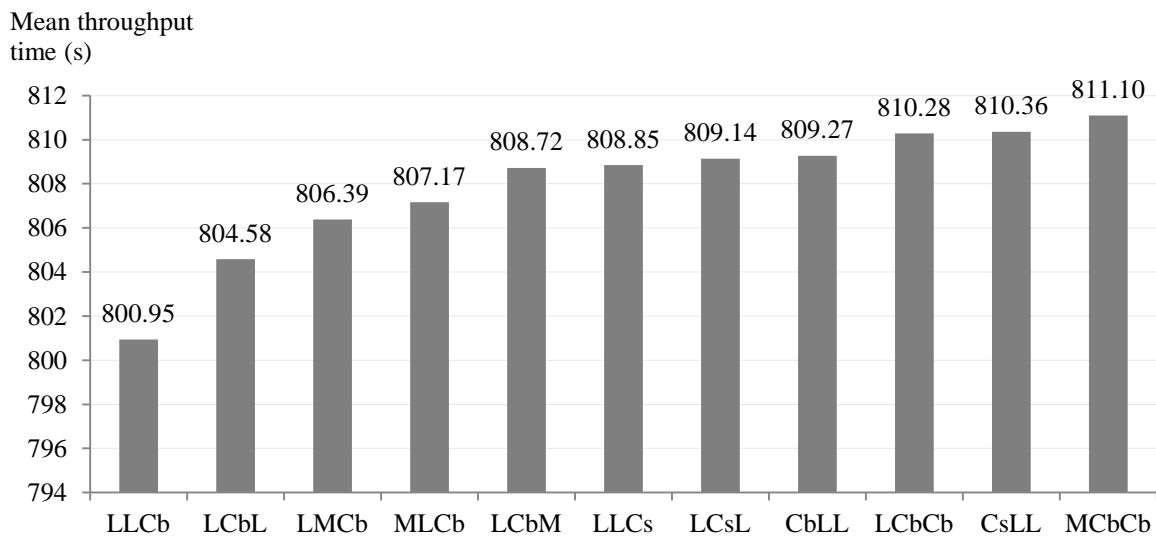


Figure 4: Mean throughput time (s) for best performing combinations with picker blocking indicate no sharp increase for the first 11 combinations.

Figure 5 depicts the mean throughput times for the best performing combinations when blocking is neglected. They are divided into times without blocking (grey) and additional time needed when blocking is considered (red). Results indicate that planning for minimal travel distances falls too short if blocking is neglected. Our results imply that picker blocking should be considered in narrow-aisle warehouses to avoid managerial decision failures and unexpected outcomes.

The shortest additional time caused by blocking results at LMR-combination with 40.21 s (without blocking = 799.676 s (standard deviation = 66.813 s; confidence interval = 2.391 s); with blocking = 839.886 s (standard deviation = 73.305 s; confidence interval = 2.623 s)).



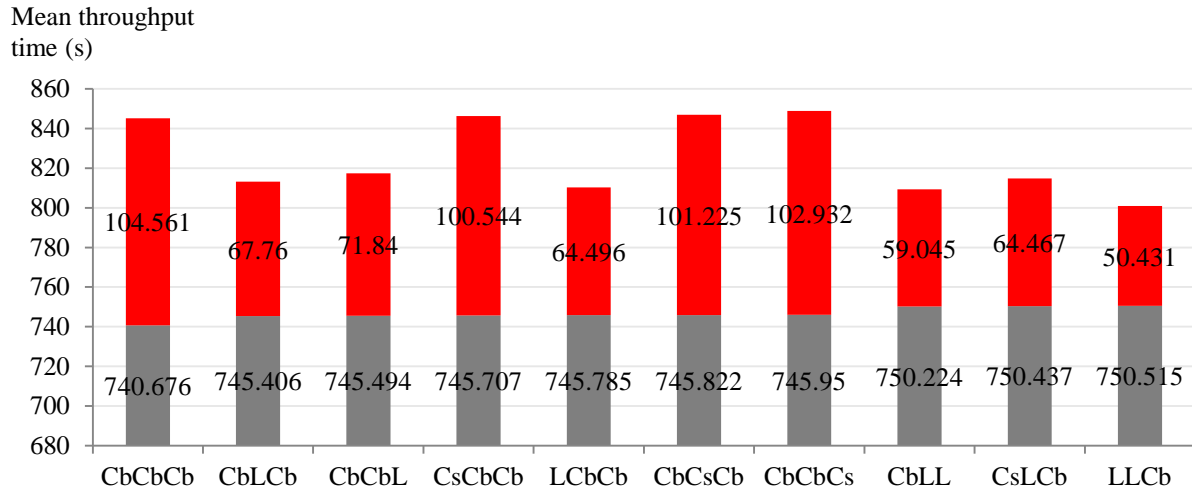


Figure 5: Mean throughput times (s) show the best performing combinations without considering picker blocking (gray) in comparison with additional time (s) caused by blocking (red).

Considering only one routing policy for all order pickers, the best combination (LLL) has position 48. It has a mean throughput time of 824.181 s (standard deviation = 68.484 s; confidence interval = 2.362 s). Furthermore, Figure 6 depicts the percentage increase of mean throughput times with blocking in comparison with the best performing combination (LLCb). While the increase in mean time is lower for the first combinations, the increase for combinations with higher mean throughput time is more dramatic.

Percentage increases of mean throughput times

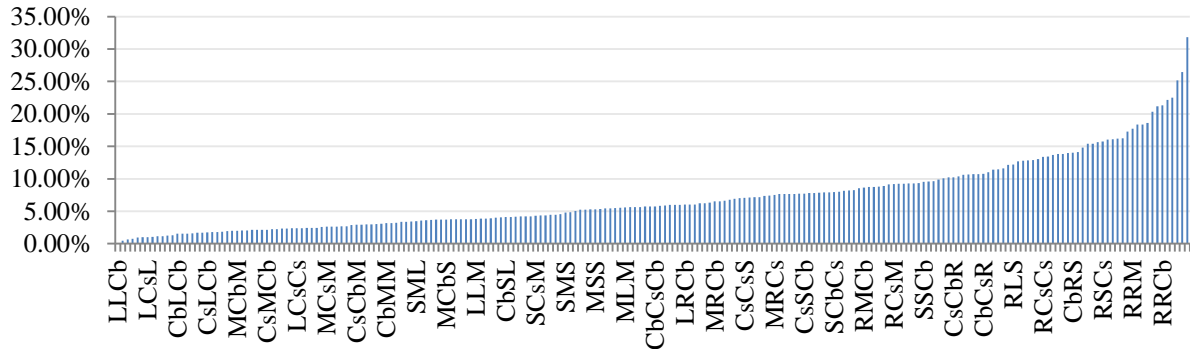


Figure 6: Depicts percentage increase of mean throughput times in comparison with the best performing combination (LLCb).

## 5 DISCUSSION AND CONCLUSION

This paper studied picker blocking in manual operated order picking systems. The objective was to investigate the effects of picker blocking in a rectangular manual operated narrow-aisle warehouse with individual routing policies for different order pickers. To address this research gap, an agent-based simulation model was developed which was found to be suitable to depict the dynamic nature of congestion and manual order picking processes. The results of a comprehensive simulation study demonstrated that combining routing policies can lead to lower mean throughput times in comparison to

assign one routing policy to all order pickers. Furthermore, our results implied that considering picker blocking for planning order picking processes is an important issue. Particularly, routing policies, which result in shortest lead times if only one order picker works in the storage area, lead to lower mean throughput times if several workers pick in the same storage area and blocking is possible.

The simulation model determined lowest mean throughput times for combination LLCb (i.e. Largest gap (Agent 1), Largest gap (Agent 2), and Combined (Agent 3)) in comparison to all other routing combinations. Implementing the return policy in a manual order picking warehouse led to longest mean throughput times in our study due to an increased number of blockings.

This study has several limitations. We tried to implement only some aspects of typical human behavior in our agent based model which can be expanded in future studies. We further assumed that the order pickers deviate from the guidelines (e.g. routing policies) only in case of blocking. In practice, order pickers are sometimes interrupted and errors can result (Brynzér and Johansson 1995). Thus, during the order picking process several deviations can occur (e.g. broken, wrong, or missing products). Those were neglected in our study to focus on the effects of picker blocking.

This study gives various implications for further research. First, it could be an interesting field to add more pickers to the storage area or to increase the idle time when blocking occurs because the order pickers stop, e.g. for talking. However, this would enormously increase the possible combinations of routing policies at the same time and thus increase computation effort. Second, it could be an exciting topic to vary the starting time for each order picker after the first worker begins the tour. This could have an influence on blocking and would imply a need for managerial decisions on order release dates. In addition, account should be taken of acceleration and deceleration in a further study because both of them have an effect on throughput time in practice (Heath, Ciarallo, and Hill 2013).

With regard to managerial implications, our results showed that it could be beneficial to implement a routing combination for different order pickers. As one of the most common routing policies in practice is S-shape, our results indicated that warehouse managers should rather implement combinations of more sophisticated routing heuristics (such as Largest gap, Combined, etc.) instead of using heuristics like return policy which leads to a high number of blockings. Results further indicate that planning for minimal travel distances falls too short if blocking is neglected.

## REFERENCES

- Borshchev, A., and A. Filippov. 2004. "From System Dynamics and Discrete Event to Practical Agent Based Modeling: Reasons, Techniques, Tools." In *Proceedings of the 22nd International Conference Of The System Dynamics Society* edited by M. Kennedy, G. W. Winch, R. S. Langer, J. I. Rowe, and J. M. Yanni, No. 22. Oxford, England: Keble College.
- Borshchev, A. 2013a. "Multi-Method Modelling: AnyLogic." In *Proceedings of the 2013 Winter Simulation Conference*, edited by R. Pasupathy, S.-H. Kim, A. Tolk, R. Hill, and M. E. Kuhl, 4089-4100. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.
- Borshchev, A. 2013b. *The Big Book of Simulation Modeling: Multimethod Modeling with Anylogic 6*. AnyLogic North America.
- Brynzér, H., and M.I. Johansson. 1995. "Design and Performance of Kitting and Order Picking Systems." *International Journal of Production Economics* 41(1): 115-125.
- Chen, F. H., H. Wang, C. Qi, and Y. Xie. 2013. "An Ant Colony Optimization Routing Algorithm for Two Order Pickers with Congestion Consideration." *Computers & Industrial Engineering* 66(1): 77-85.
- Chen, F. H., H. Wang, Y. Xie, and C. Qi. 2014. "An ACO-Based Online Routing Method for Multiple Order Pickers with Congestion Consideration in Warehouse." *Journal of Intelligent Manufacturing* 25(1): 1-20.

- De Koster, R. 2004. "How to Assess a Warehouse Operation in a Single Tour." Report, RSM Erasmus University, Rotterdam.
- De Koster, R., T. Le-Duc, and K. J. Roodbergen. 2007. "Design and Control of Warehouse Order Picking: A Literature Review." *European Journal of Operational Research* 182(2): 481-501.
- Frazelle, E. A. 2002. *World-Class Warehousing and Material Handling*. New York: McGraw-Hill.
- Furmans, K., C. Huber, and J. Wisser. 2009. "Queueing Models for Manual Order Picking Systems with Blocking." *Logistics Journal* 1(1): 1-16.
- Grosse, E. H., C. H. Glock, and R. Ballester-Ripoll. 2014. "A Simulated Annealing Approach for the Joint Order Batching and Order Picker Routing Problem with Weight Restrictions." *International Journal of Operations and Quantitative Management* 20(2): 65-83.
- Grosse, E. H. C. H. Glock, M. Y. Jaber, and W. P. Neumann. 2015. "Incorporating Human Factors in Order Picking Planning Models: Framework and Research Opportunities." *International Journal of Production Research* 53(3): 695-717.
- Gue, K. R., R. D. Meller, and J. D. Skufca. 2006. "The Effects of Pick Density on Order Picking Areas with Narrow Aisles." *IIE Transactions* 38(10): 859-868.
- Hagspihl, R., and S. E. Visagie. 2014. "The Number of Pickers and Stock-Keeping Unit Arrangement on a Unidirectional Picking Line." *South African Journal of Industrial Engineering* 25(3): 169-183.
- Heath, B., F. Ciarallo, and R. Hill. 2013. "An Agent-Based Modeling Approach to Analyze The Impact of Warehouse Congestion on Cost and Performance." *International Journal of Advanced Manufacturing Technology* 67(1): 563-574.
- Hong, S., A. L. Johnson, and B. A. Peters. 2010. "Analysis of Picker Blocking in Narrow-Aisle Batch Picking." In *Proceedings of 2010 International Material Handling Research Colloquium (IMHRC)*, edited by K. Ellis, K. Gue, R. d. Koster, R. Meller, B. Montreuil, and M. Oglep, Charlotte, NC: The Material Handling Institute.
- Hong, S., A. L. Johnson, and B. A. Peters. 2012a. "Large-Scale Order Batching in Parallel-Aisle Picking Systems." *IIE Transactions* 44(2): 88-106.
- Hong, S., A. L. Johnson, and B. A. Peters. 2012b. "Batch Picking in Narrow-Aisle Order Picking Systems with Consideration for Picker Blocking." *European Journal of Operational Research* 221(3): 557-570.
- Hong, S., A. L. Johnson, and B. A. Peters. 2013. "A Note on Picker Blocking Models in a Parallel-Aisle Order Picking System." *IIE Transactions* 45(12): 1345-1355.
- Hong, S., A. L. Johnson, and B. A. Peters. 2014. "Order Batching in a Bucket Brigades Order Picking System with Consideration of Picker Blocking" In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk, S. Y. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, and J. A. Miller, 4105-4106. Piscataway, New Jersey: IEEE.
- Hong, S. 2014. "Two-Worker Blocking Congestion Model with Walk Speed  $m$  in a No-Passing Circular Passage System." *European Journal of Operational Research* 235(3): 687-696.
- Kłodawski, M., and J. Żak. 2013. "Order Picking Area Layout and its Impact on the Efficiency of Order Picking Process." *Journal of Traffic and Logistics Engineering* 1(1): 41-45.
- Macal, C. M., and M. J. North. 2010. "Tutorial on Agent-Based Modelling and Simulation." *Journal of Simulation* 4(3): 151-162.
- Mowrey, C. H., and P. J. Parikh. 2014. "Mixed-Width Aisle Configurations for Order Picking in Distribution Centers." *European Journal of Operational Research* 232(1): 87-97.
- Napolitano, M. 2012. "2012 Warehouse/DC Operations Survey: Mixed Signals." *Modern Materials Handling* 51(11): 48-56.
- Pan, J. C. H., and P. H. Shih. 2008. "Evaluation of the Throughput of a Multiple-Picker Order Picking System with Congestion Consideration." *Computers & Industrial Engineering* 55(2): 379-389.
- Pan, J. C. H., and M. H. Wu. 2012. "Throughput Analysis for Order Picking System with Multiple Pickers and Aisle Congestion Considerations." *Computers & Operations Research* 39(7): 1661-1672.

- Pan, J. C. H., P. H. Shih, and M. H. Wu. 2012. "Storage Assignment Problem With Travel Distance and Blocking Considerations for a Picker-To-Part Order Picking System." *Computers & Industrial Engineering* 62(2): 527-535.
- Parikh, P. J., and R. D. Meller. 2008. "Selecting Between Batch and Zone Order Picking Strategies in a Distribution Center." *Transportation Research Part E: Logistics and Transportation Review* 44(5): 696-719.
- Parikh, P. J., and R. D. Meller. 2009. "Estimating Picker Blocking in Wide-Aisle Order Picking Systems." *IIE Transactions* 41(3): 232-246.
- Parikh, P. J., and R. D. Meller. 2010a. "A Note on Worker Blocking in Narrow-Aisle Order Picking Systems when Pick Time is Non-Deterministic." *IIE Transactions* 42(6): 392-404.
- Parikh, P. J., and R. D. Meller. 2010b. "A Travel-Time Model for a Person-Onboard Order Picking System." *European Journal of Operational Research* 200(2): 385-394.
- Petersen, C.G., and R. W. Schmenner. 1999. "An Evaluation of Routing and Volume-Based Storage Policies in an Order Picking Operation." *Decision Science* 30(2): 481-501.
- Petersen, C.G., and G. Aase. 2004. "A Comparison of Picking, Storage, and Routing Policies in Manual Order Picking" *International Journal of Production Economics* 92(1): 11-19.
- Roodbergen, K.J., and I.F.A. Vis. 2006. "A Model for Warehouse Layout." *IIE Transactions* 38(10): 799-811.
- Ruben, R. A., and F. R. Jacobs. 1999. "Batch Construction Heuristics and Storage Assignment Strategies for Walk/Ride and Pick Systems." *Management Science* 45(4): 575-596.
- Sainathuni, B., P. J. Parikh, X. Zhang, and N. Kong. 2014. "The Warehouse-Inventory-Transportation Problem for Supply Chains." *European Journal of Operational Research* 237(2): 690-700.
- Skufca, J. D. 2005. "k Workers In a Circular Warehouse: A Random Walk on a Circle, Without Passing." *SIAM Review* 47(2): 301-314.
- Tompkins, J. A., J. A. White, Y. A. Bozer, and J. A. Tanchoco. 2010. *Facilities Planning*. 4th ed. New York, NY: Wiley.

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