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# HOW ORDER PLACEMENT INFLUENCES RESOURCE ALLOCATION AND ORDER PROCESSING TIMES INSIDE A MULTI-USER WAREHOUSE

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## ABSTRACT

This paper focuses on the influence of different order placement behavior of users on the allocation of common resources inside a multi-user warehouse. Furthermore, the interdependencies between one user's resource usage on other users' order processing time is investigated. For this objective, an agent-based simulation model has been developed, depicting a rectangular warehouse with two users and one order picker. Results show that different order placement behavior and resource usage of one user have a strong influence on order processing times of other users. Furthermore, by simulating uneven order placement by one user, it can be shown that peaks in order demand influence other user's order processing times with a delay of up to two hours after the peak occurred. Thus, the results highlight the need for coordinated order placement of partners inside a multi-user warehouse.

## 1 INTRODUCTION

Horizontal cooperation is of great interest for the logistics sector: Cooperation not only offers new possibilities for logistics companies to meet customer demand and thus improve their service (Makaci et al. 2017, Moutaoukil et al. 2012). It also helps the participating logistics companies to face environmental requirements imposed by policy makers (Browne et al. 2012). Furthermore, sharing available resources allows for the reduction of costs and enables the generation of synergies which lead to economies of scale (Makaci et al. 2017, Pan et al. 2013). Therefore, horizontal cooperation is especially of interest for small and medium sized logistics service providers, who are often restricted by limited financial power (Anand et al. 2012), as cooperation allows for sharing of necessary investments and risks among partners (Elbert et al. 2012, Franklin and Spinler 2011).

Especially in the context of urban logistics, cooperative concepts such as urban consolidation centers and multi-user warehouses have already been identified as a promising field of research (see e.g., Danielis et al. 2010, van Duin et al. 2010). The city logistics sector is characterized by a large number of small and heterogeneous stakeholders (Anand et al. 2012). Yet, rising cost for land and real estates in urban areas and the resulting logistics sprawl depict a rising challenge for small and medium sized logistics service providers which can be met by forming horizontal cooperations (Aljohani and Thompson 2016).

Horizontal cooperations are often characterized by the available internal and external resources being shared among the partners within the cooperation (Xu et al. 2017). Common resources inside a multi-user warehouse are the available storage space as well as the order pickers used by all users for picking orders. However, by using the same common resources, partners can have a direct influence on the other partners' performance within the cooperation which leads to uncertainties and additional cost and time requirements (Xu et al. 2017, Lindholm 2012). For example, we assume that the extent of the usage of common order pickers can have a great impact on picking times inside a warehouse. This is especially important as order picking is still mainly performed manually and thus accounts for a major part of overall warehouse cost (de Koster et al. 2007, Petersen and Aase 2004). Also, it is assumed that warehouse users need to meet certain cutoff times such as for example scheduled truck departures and are therefore interested in a fast and reliable order picking process and a coordinated usage of common resources. However, especially in the case of city logistics, heterogeneous actors often have to deal with different and sometimes even contrary interests (Anand et al. 2012). This explains why many cooperative logistics concepts based on horizontal cooperation between partners have failed in the past due to missing willingness of partners to cooperate (van Duin et al. 2010). In order to better understand the influence different resource usage can have on other partner's performance within a logistics cooperation, this paper aims at analyzing the order picking process with shared order pickers inside a multi-user warehouse.

Furthermore, the individual behavior of partners and their role within the cooperation must be addressed for the development of a functional cooperation (Lindholm 2012). In case of the order picking process, user behavior in terms of the time and amount of orders placed by users to be picked from the warehouse is of interest. Especially if resources for order picking are limited, order placement is assumed to have a strong influence on picking times of all users within the warehouse.

However, a research gap exists concerning the influence of order placement behavior by users inside a cooperative logistics facility on the order picking process. For this reason, the paper at hand investigates the influence of different order placement behavior of users inside a multi-user warehouse on the usage of common resources in order picking and the order processing times of other users.

The scope of this research can thus be summarized by the formulation of two research questions (RQ):

- **RQ 1** How does order placement behavior of one user inside a multi-user warehouse influence the allocation of the common resource of order pickers?
- **RQ 2** How does order placement behavior of one user and the associated usage of the common resource impact the other user's order processing times?

To investigate the influence of different order placement behavior and to answer the research questions, an agent-based simulation model with discrete event elements has been developed using the software AnyLogic 8. An agent-based simulation is considered most suitable for investigating the complex interdependencies inside a multi-user warehouse as it is able to model the behavior of multiple heterogenic actors and allows for analyzing the effects on the overall system (Bonabeau 2002).

The remainder of this paper is structured as follows: The subsequent section will give a brief overview of the existing literature on horizontal cooperation in logistics and warehousing. In the third section, the agent-based simulation model is described in detail. Subsequently, the results of the simulation study are presented. The final section gives a conclusion and outlines potential for future research.

## 2 LITERATURE REVIEW

When speaking of different companies on the same level of the supply chain working together, Mejias-Sacaluga and Prado-Prado (2002) as well as Spekman et al. (1998) distinguish between cooperation, coordination and collaboration. Nevertheless, making this distinction is in many cases not necessary as all three concepts share the same basic meaning of having two or more partners building up a relationship and sharing some of their resources (Xu et al. 2017). As the use of common resources is in the focus for the paper at hand, the same meaning is assumed for all three concepts in this work.

Most of the existing literature on horizontal cooperation in the field of logistics concentrates on organizational, economical or technical aspects. Klein et al. (2007) compare the consequences of cooperative versus competitive behavior inside strategic alliances within an integrated logistics supply chain. The authors conclude that successful logistics partners cooperate by sharing strategic information and compete in the field of IT customization. Yang and Zhou (2014) analyze the cooperative behavior of transportation companies offering free warehousing service to customers. The authors point out the importance of an effective design of contracts to enable cooperative behavior of partners. Verdonck et al. (2013) deal with the operational planning of horizontal cooperations and give a basic overview on the existing literature with focus on transportation carriers. The authors distinguish between order sharing and capacity sharing as two forms of collaboration. A case study for cooperative distribution network in rural areas in Sweden can be found in Hageback and Segerstedt (2004). Here, the authors argue that cooperation in the field of distribution have to compete with other companies in the area offering a similar service. Therefore, generating lower costs or offering better service is vital for efficient logistics cooperation. The importance of achieving synergies by engaging in horizontal cooperation is also pointed out by Cruijssen et al. (2007). They find that by cooperatively planning routes, transportation companies can achieve cost savings of up to 30 %.

While numerous studies on cooperation in distribution and transportation networks exist, the number of studies focusing on cooperation in warehousing is much smaller. Makaci et al. (2017) analyze different case studies of pooled warehouses in France. They point out that a close collaboration between actors is essential for the success of such a cooperation. Furthermore, they formulate common characteristics of pooled warehouses and derive new key performance indicators. Reaidy et al. (2015) point out that cooperative warehouses can be considered as dynamic and are therefore much more complex to manage. Their research thus aims at developing new platforms for collaborative warehouse management based on Internet of Things technology.

Both, cooperative transportation and warehousing have in common that the allocation of costs and benefits among partners has been identified by researchers as one of the most important factors for a successful cooperation: In practice, cost allocation is often mainly based on the number of items or volume stored by each user (Hariga 2011). Lozano et al. (2013) develop a linear programming model to investigate cost savings of different transportation companies within a horizontal cooperation. By integrating different behavior of the partners into the model using cooperative game theory, the authors are able to analyze different methods of allocating costs under certain scenarios. Similarly, Krajewska et al. (2008) use cooperative game theory to analyze possibilities to share profits among partners in horizontal cooperation of freight carriers. In order to solve the cost allocation problem, Cruijssen et al. (2010) propose logistics cooperation initiated by logistics service providers instead of the suppliers. According to the authors, this procedure not only allows for selecting partners with the highest potential of generating synergies but also enables a sustainable allocation of costs and benefits.

Research on practical applications of cooperative logistics facilities can mainly be found in the urban logistics sector. Browne et al. (2007) for example discuss the potentials of urban consolidation centers. The authors especially point out that the allocation of costs and benefits among partners is an important aspect for a successful implementation. A study on potential benefits and challenges for a specific urban consolidation center is carried out by van Duin et al (2010): They provide an ex-ante analysis for a planned urban consolidation center in The Hague by analyzing similar concepts that were already implemented. Besides the willingness to cooperate, the authors also identify the allocation of costs and benefits as the primary challenge for the success of the urban consolidation center. However, Vanovermeire and Sörensen (2014) point out that it is often difficult to precisely analyze individual costs of different activities within the cooperation and that it can therefore be difficult to create a perception of fairness among all partners. Instead, Xu et al. (2017) argue that reasonable allocation of resources is essential for cooperations in logistics as it can have a direct influence on operating costs. For this reason, they propose a programming model that can be used to develop optimal resource allocations plans and decisions in a collaborative logistics network. Their model is even able to take uncertainties into account.

As the review of the literature shows, so far little research exists that focuses on the effects of different resource allocation within multi-user warehouses. This work therefore aims at closing this gap by showing the effect different demand behavior and resource usage of one user has on the performance of other users within a multi-user warehouse.

# 3 SIMULATION MODELLING

## 3.1 The Warehouse Model

To analyze the effect of different user's order placement behavior on the common resource usage and the other user's order processing time, a simplified agent-based simulation model of a multi-user warehouse used by only two users A and B has been developed. Restricting the model to just two users allows for better isolating and thus analyzing the resulting interdependencies between order placement behavior of one user and order picking times of the other user. Logistics cooperation of only two participants is also investigated by Vanovermeire and Sörensen (2014). The warehouse itself has been modeled as a rectangular layout with ten aisles and 100 storage positions of equal size in each aisle (i.e. 50 positions on each side of the aisle). This layout thus yields a total of 1000 different storage positions. The warehouse has one depot on one side to which items are brought after picking. Pickers can only change aisles on either end of the aisles, meaning that there are no cross-aisles within the layout. Similar layouts are widely used in warehousing literature (see e.g. Hong and Kim 2017; Grosse et al. 2014; Petersen and Aase 2004). Inside the warehouse, both users store goods which are assigned randomly to one of the available storage positions using a uniform distribution. In the simplified warehouse model, all items stored in the warehouse as well as the storage positions are of equal size. A picture of the final layout filled with equal number of items of both users is given in Figure 1.

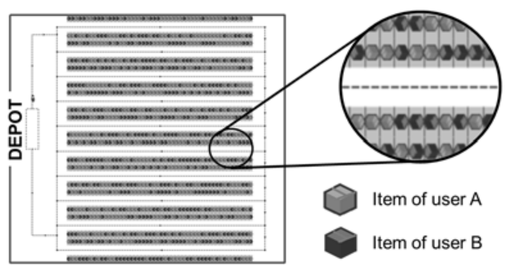


Figure 1: The warehouse layout used in the simulation model filled with the same number of items of both users A and B.

At certain points in time, each user places orders for a number of their items to be picked from the warehouse. The exact items to be picked for each order are selected randomly by using a uniform distribution assigning the same probability to all available items of the respective user. For picking the ordered items, a picker-to-parts system is used with one commonly used order picker who moves through the warehouse in an S-shape route. S-shaped routes provide efficient solutions for the picker routing problem in the given layout and are therefore widely used in practice (Hong and Kim 2017). Only one picker is modeled as this allows for analyzing the influence of limited resource availability. Furthermore, effects caused by picker interaction (e.g. picker blocking – Franzke et al. 2017) that are not in focus of the presented work can be excluded. The moving velocity of the picker is set to one meter per second as in Elbert and Müller (2017), who have analyzed walking velocities in manual order picking in detail. After being placed by users, picking orders are assigned to the picker in a FIFO scheme. The picker then picks the items starting at the depot until its maximum carrying capacity is reached or until all items of all orders have been picked. Subsequently, the picker brings items to the depot and continues picking or waits for new orders. Note that orders of both users can be picked within one tour. However, as the picker – if currently idle – starts its tour right after a new order has been placed, this only takes place if orders of both users are already waiting at the depot once the picker returns from a tour. The time the picker needs for picking each item can be defined individually for each user but is of equal deterministic value for each item of the user. Because only the picking process is of interest for this work, the refilling process is neglected in the model. Instead, items are replaced automatically at its storage locations after being picked, making sure that there are always sufficient items available for picking.

In the model, there are two common resources that can be analyzed in terms of usage by each user: The available space i.e. the total number of item positions available for both users and the common order picker. As usage of the available space can easily be tracked, this work focuses on the usage of the common order picker by each partner.

In summary, there are four different types of agents in the warehouse simulation model: The two users that place orders, the order picker and the items that are picked by the order picker on one hand. On the other hand, the orders themselves are also modelled as agents. These order agents are generated according to events which occur based on a predefined order arrival frequency for each user. As the number of agents is relatively small with only two warehouse users and one order picker, interaction between agents of one type is not part of the model. However, an agent-based approach has been chosen for the analysis, as it allows increasing the number of users and order pickers easily for future research. An analysis of the effects of agent interaction such as picker blocking for example on the overall warehouse performance might also be of interest in the future. Therefore, an agent-based model appears to be a suitable approach.

### 3.2 Input and Output Parameters and Model Verification

There are several input parameters that can be defined before each experiment run, allowing for a systematic analysis of different aspects. The input parameters are the

- share of available item positions of each user;
- frequency of each partner at which orders are placed, i.e. the demand of each user;
- order size i.e. the number of items in each order;
- carrying capacity of the order picker;
- time needed to pick items of each user.

Output parameters of the simulation model have been selected with focus on the picking process and the performance of the commonly used order picker. Therefore, the following output parameters, which will be explained in detail below, can be analyzed by the model:

- the order processing time of each order;
- total working time of order picker consisting of item pickup time and walking time;
- the picking time ratio.

The order processing time is calculated and saved in a database at the time at which all items of the order have been picked and arrived at the depot. It is defined as the difference between the arrival time at the depot and the time at which the order has been placed by the user. The working time of the order picker is the entire time at which the order picker is not waiting for orders at the depot. That means that the working time $t$ can be separated into walking time $t_w$ and the time $t_p$ which is used for picking up items from the corresponding locations: $t = t_w + t_p$. The picking time ratio is defined as the percentage of picker working time accountable to each of the two users. Dividing the working time to each user is done by dividing walking time and item pick time separately. Item pick time can be calculated easily for each user by simply summarizing the pick times of each item of the corresponding user that has been picked. Walking time is assigned proportionally to each user based on the total walking time $t_w^{total}$ of each tour and the number of items of each user in the tour. This means that the walking time of user A $t_w^A$ is calculated as follows:

$$t_w^A = t_w^{total} \frac{n_A}{n_A + n_B},$$

where $n_A$ is the number of items of user A and $n_B$ is the number of items of user B. The total walking time accountable for user B can then be calculated as $t_w^B = t_w^{total} - t_w^A$. For the case of this work, allocating walking times proportionally based on the number of items picked is assumed accurate as item positions are assigned randomly to both users with equal probability. Furthermore, the items to be picked with each order are also defined randomly with equal probability for each item to be picked. Nevertheless, in a case where goods are not placed randomly in the warehouse, walking times cannot be assigned by this method, as the user whose items are located closer to the depot will account for a lower share of total walking time.

The simulation model has been verified by conducting numerous simulation runs with different parameter settings. Each parameter has been altered systematically and simulation results have been carefully analyzed for the expected changes in outcome. Furthermore, in order to verify the simulated picking process, different simulation runs have been analyzed with regard to the number of items picked, ensuring that all orders that have been placed by users are also picked eventually.

## 4 RESULTS

The input parameter for displaying different order placement behavior of users in the model is the frequency at which orders are placed by each user in the warehouse. To analyze how different demand influences common resource usage, the frequency at which orders are placed is altered systematically between one and 20 orders per hour for user A. Simultaneously, the order frequency of user B is kept at a constant value of ten orders per hour for each simulation run. This allows for comparing a state at which both users have equal demand to different situations with unequal demand between warehouse users. All other parameters have been set once as described in the following section in the beginning of the study and were not changed during the experiments. Each order frequency setting has been simulated for a model time of eight hours. Yet, orders are only placed in the first seven hours of the simulation time, leaving the last hour for completing open orders.

For the share of available item positions, each user was given exactly 50 % i.e. 500 of the available 1000 storage positions in the warehouse. By choosing an equal distribution of item positions, the resource of the available space is used equally by both users. Therefore, the usage of the common order picker can be isolated and analyzed independently. The carrying capacity of the order picker has been set to 20 items and the order size to five items per order for orders of both users. The time for picking an item has been set to ten seconds for items of both users. Previous analysis of the model has shown that by choosing these values for order size and the required picking time, it is assured that all incoming orders in each order frequency configuration can be completed within the eight hours of simulated model time. Parameter values for the simulation study are summarized in Table 1.

Table 1: Parameter settings for the simulation study.

| **Parameter** | **Value for user A** | **Value for user B** |
|---|---|---|
| Number of item positions | 500 | 500 |
| Order arrival frequency | 1-20 orders per hour | 10 orders per hour |
| Order size | 5 items | 5 items |
| Pick time per item | 10 s | 10 s |
| Picker capacity | 20 items | |
| Picker speed | 1 m/s | |

First of all, the picking time ratio i.e. the total working time of the order picker accountable for each user has been analyzed in order to answer RQ 1. Results for a single simulation run for each order arrival frequency are given in Figure 2. For the data of each user, a fitted polynomial curve has been calculated using the least-square-method. This curve is also displayed as a dotted line in Figure 2. As can be seen, user A is accountable for 10 % of the picker working time when only one order per hour is placed by this user. For the case of 20 orders per hour, user A accounts for 70 % of the picker's total working time.

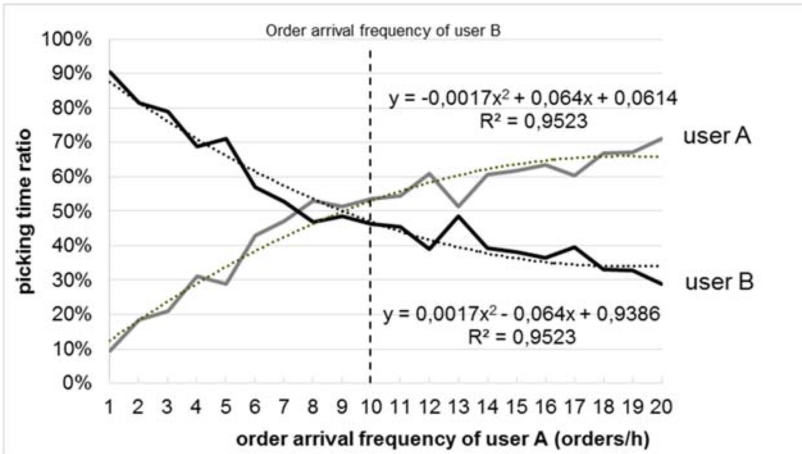


Figure 2: Picking time ratios of both users along with fitted curves for increasing order arrival frequencies of user A.

The equation for the fitted curve of user A and its derivatives are as follows:

$$y_A = -0.0017x^2 + 0.064x + 0.0614$$

$$y_A' = -0.0034x + 0.064$$

$$y_A'' = -0.0034$$

As can be seen, the picking time ratio does not increase proportional with the number of orders. Instead, for little number of orders per hour, the picking time ratio increases faster than for large values. The first derivative of the equation yields a gradient of 6.06 % for an input of one order per hour. However, for ten orders per hour, the gradient is only 3.00 %. This is caused by the fact that the order picker starts a new tour immediately after an order arrives. This means, that for low order arrival frequencies, the order picker picks each order in an individual tour. Therefore, the total working time of the order picker increases with each additional order as waiting times of the picker decrease. For higher order arrival frequencies, new orders are already waiting to be picked once the picker arrives at the depot, enabling the picker to continue picking without any delay. At some point above 20 orders per hour, the maximum picking capacity of the order picker is reached. Here, working time of the order picker cannot increase further, even if the order arrival frequency increases. Due to the FIFO rule with which orders are assigned to the picker, the picking time ratio of user A will eventually approach 100 %.

In order to investigate the influence on order processing times of each user and to thus answer RQ 2, the mean order processing time per order of both users from 100 simulation runs per order arrival frequency along with the calculated standard errors are given in Table 2.

Table 2: Mean order processing times from 100 simulation runs for each order arrival frequency of user A and a constant order arrival frequency of ten orders per hour for user B (standard error given in brackets).

| **Order arrival rate of user A (orders/h)** | **1** | **2** | **3** | **4** | **5** | **6** | **7** |
|---|---|---|---|---|---|---|---|
| Orders completed of user A | 7 (3) | 14 (4) | 21 (4) | 28 (6) | 35 (6) | 42 (7) | 48 (6) |
| Orders completed of user B | 71 (9) | 70 (8) | 70 (8) | 69 (8) | 69 (7) | 70 (8) | 70 (9) |
| Mean order processing time of user A (s) | 294 (56) | 303 (42) | 326 (41) | 328 (35) | 337 (33) | 359 (36) | 376 (35) |
| Mean order processing time of user B (s) | 289 (24) | 304 (25) | 316 (30) | 332 (29) | 339 (31) | 357 (34) | 371 (34) |
| **Order arrival rate of user A (orders/h)** | **8** | **9** | **10** | **11** | **12** | **13** | **14** |
| Orders completed of user A | 56 (8) | 64 (7) | 70 (7) | 78 (9) | 83 (9) | 91 (10) | 98 (9) |
| Orders completed of user B | 69 (8) | 72 (9) | 71 (7) | 71 (7) | 69 (8) | 70 (8) | 71 (9) |
| Mean order processing time of user A (s) | 388 (41) | 417 (47) | 426 (43) | 450 (46) | 469 (51) | 495 (57) | 524 (82) |
| Mean order processing time of user B (s) | 385 (38) | 414 (44) | 430 (40) | 454 (43) | 467 (54) | 498 (65) | 520 (80) |
| **Order arrival rate of user A (orders/h)** | **15** | **16** | **17** | **18** | **19** | **20** | |
| Orders completed of user A | 106 (11) | 113 (11) | 118 (10) | 128 (10) | 134 (12) | 141 (13) | |
| Orders completed of user B | 71 (8) | 70 (9) | 70 (8) | 70 (9) | 69 (8) | 71 (9) | |
| Mean order processing time of user A (s) | 559 (90) | 593 (105) | 618 (92) | 695 (148) | 755 (167) | 853 (269) | |
| Mean order processing time of user B (s) | 560 (100) | 594 (108) | 621 (104) | 693 (158) | 759 (178) | 852 (288) | |

For an order arrival frequency of user A of one order per hour, the mean order processing time is 294 s for user A and 289 s for user B. For 20 orders per hour, mean order processing times yield 853 s for user A and 852 s for user B. Although the frequency at which orders of user B are placed is always equal to 10 orders per hour, mean order processing times are almost the same for both users in each simulated case. This means that the mean order processing time of user B rises with an increasing number of orders per hour of user A. For low numbers of orders per hour of user A, the mean order processing times increase slower compared to larger numbers of orders per hour. This again is caused by the picker approaching its maximum picking capacity as well as the FIFO rule of order assignment: For larger order arrival frequency, more orders have to wait to be picked as it becomes more unlikely that picking of an order can start just after the order has been placed.

For further analysis, the influence of the time at which orders are placed has also been investigated. To do so, the order arrival rate of user A is not defined as a static value for the entire simulation run as has been the case before. Instead, the order arrival frequency is now varied over the turn of the model's runtime according to four predefined schedules. In these schedules, a peak in order arrival frequency is simulated at 12:00 h with order arrival frequencies of between 30 and 60 orders per hour. Yet, the mean order arrival frequency for the entire day for user A lies at approximately thirteen orders per hour in each schedule. Furthermore, to compare flexible order arrival frequencies to the before case of constant order arrival frequencies, a configuration with a constant order arrival frequency of thirteen orders per hour of user A has also been simulated. The order arrival frequencies of user A in each schedule are displayed in Figure 3a. The order arrival frequency of user B does not change over time and – as before – lies at a constant value of ten orders per hour in each of the simulated cases. Each order arrival frequency configuration has been simulated 100 times and the mean values of the resulting mean order processing times of user B have been calculated. In Figure 3b, mean order processing times of user B for each 30-minute block between 8:30 h and 16:00 h are presented for the given schedules. In addition, Table 3 gives the calculated values along with the resulting standard error.

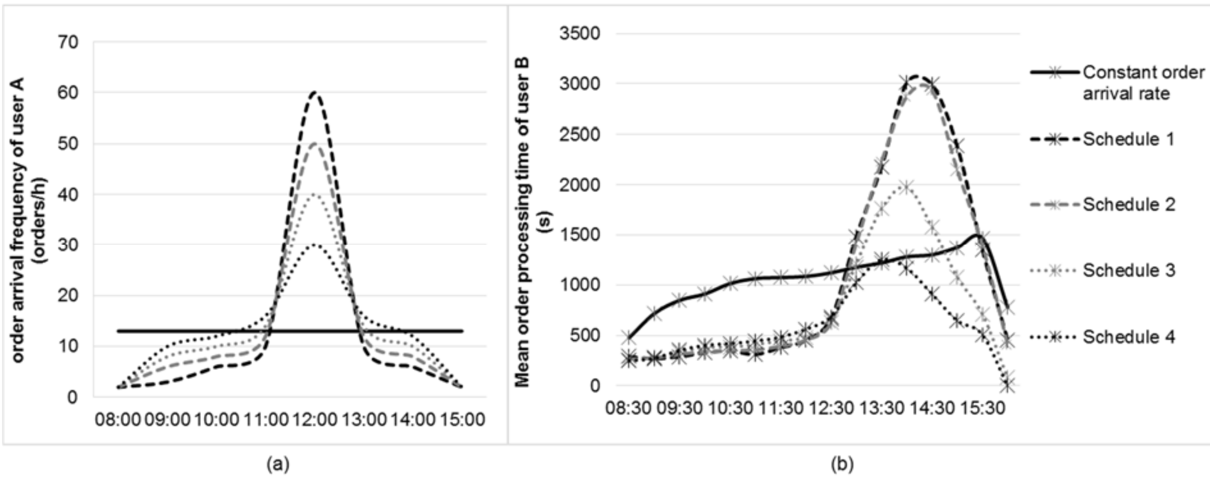


Figure 3: Different input order arrival frequencies of user A (a) and the resulting mean order processing times of user B (b) from 100 simulation runs with a simulated eight-hour day each.

In the case of a constant order arrival frequency of 13 orders per hour of user A, mean order processing times of user B lie between 479 and 1466 s. As can be seen in Figure 3, even for a constant order arrival frequency, a peak in mean order processing times can be observed at around 15:00 h. This is caused by earlier orders still waiting to be picked due to limited order picking capacity. Yet, in the case of schedule 1 with a peak order arrival frequency of 60 orders per hour of user A, mean order processing times of user B reach a maximum value of 3010 s, which is more than twice the value compared to order processing time under constant order arrival frequency at this time. Interestingly, the peak in order processing times of user B is reached in the 30-minute block between 13:30 h and 14:00 h for schedule 1, i.e. almost two hours after the peak in order arrival frequency occurred. In schedule 2 with a peak order arrival frequency of 50 orders per hour of user A, order processing times of user B reach up to 2933 s in the block between 14:00 h and 14:30 h. For schedule 4 with a peak order arrival frequency of 30 orders per hour, the highest mean order processing time of user B is measured between 13:00 h and 13:30 h with 1250 s, which is less compared to the maximum mean order processing time for a constant order arrival frequency of user A.

## 5 CONCLUSION

In this paper, we have presented an agent-based simulation model in order to investigate the influence of different order arrival frequencies on other users' order processing times inside a multi-user warehouse. In the simulation, a simplified rectangular warehouse with just two users and one order picker has been modeled. As expected, results of a first simulation study with constant and flexible order arrival frequencies show that order arrival frequencies indeed have a strong influence on the working times of the order picker who in this case is a common resource of both users. The simulation study moreover discovers that picking time ratio of the common order picker does not increase linearly with increasing order arrival rates. This in turn influences order processing times of the other user. Furthermore, results indicate that for the given parameter setting the effect of a peak in order arrival frequency of one user impacts order processing times of the other user with a delay of up to two hours. The results of our work thus clearly indicate that under limited availability of shared order pickers, the number of orders placed by users can have a significant impact on order processing times. Consequently, the results of the study highlight the importance of finding ways to deal with the influence of user demand on picking resource usage when planning a logistics cooperation and to promote coordinated order placement in multi-user warehouses. This can for example be done by limiting the resource usage of each partner by defining common rules or by integrating picker usage into cost allocation or pricing models of multi-user warehouses.

However, only a simplistic warehouse has been modeled in the simulation. Using only one order picker is useful for showing the effects under limited resource availability but is not assumed to be a realistic scenario. Although real-world applicability of the results is therefore only limited, we assume that having limited order picking resources available is a common scenario for most real-world warehouses. Nevertheless, repeating the simulation study with additional pickers and order data of a real warehouse is planned for future research in order to further increase applicability of results. Nevertheless, it is assumed that the interdependencies between order placement behavior of users and order processing times become much more complex if more than two users with different picking times per item are involved.

Table 3: Mean order processing times (s) of user B for different order arrival schedules of user A and a constant order arrival frequency of 10 order per hour for user B, calculated from 100 simulation runs (standard error given in brackets).

| **Order arrival frequency of user A** | **08:30** | **09:00** | **09:30** | **10:00** | **10:30** | **11:00** | **11:30** | **12:00** |
|---|---|---|---|---|---|---|---|---|
| Constant rate (13 orders /h) | 477 (144) | 717 (221) | 847 (300) | 910 (330) | 1013 (417) | 1063 (475) | 1073 (522) | 1083 (537) |
| Schedule 1 | 290 (0) | 270 (0) | 288 (0) | 329 (144) | 345 (0) | 311 (169) | 379 (0) | 451 (105) |
| Schedule 2 | 264 (0) | 276 (0) | 314 (23) | 334 (174) | 348 (166) | 356 (135) | 391 (103) | 452 (111) |
| Schedule 3 | 261 (0) | 286 (0) | 337 (1) | 380 (99) | 385 (65) | 409 (212) | 446 (96) | 481 (108) |
| Schedule 4 | 248 (0) | 272 (148) | 352 (147) | 402 (149) | 419 (96) | 444 (133) | 482 (108) | 560 (176) |

| **Order arrival frequency of user A** | **12:30** | **13:00** | **13:30** | **14:00** | **14:30** | **15:00** | **15:30** | **16:00** |
|---|---|---|---|---|---|---|---|---|
| Constant rate (13 orders/h) | 1120 (549) | 1175 (572) | 1218 (692) | 1279 (759) | 1299 (704) | 1371 (730) | 1466 (813) | 779 (1223) |
| Schedule 1 | 666 (221) | 1482 (299) | 2175 (192) | 3010 (262) | 2992 (234) | 2385 (138) | 1350 (234) | 454 (1023) |
| Schedule 2 | 623 (217) | 1412 (305) | 2227 (382) | 2870 (263) | 2933 (219) | 2150 (349) | 1393 (70) | 41 (0) |
| Schedule 3 | 627 (206) | 1208 (214) | 1759 (197) | 1978 (580) | 1580 (169) | 1079 (103) | 710 (0) | 79 (0) |
| Schedule 4 | 683 (95) | 1022 (212) | 1250 (174) | 1166 (148) | 909 (333) | 647 (371) | 506 (113) | 0 (0) |

Of course, the results presented in this work are restricted by several other limitations. Notably, orders are assigned to the picker in a FIFO scheme and the picker moves through the warehouse in an S-shaped tour. In reality though, numerous order assignment and picker routing strategies exist that should be integrated into the model in the future. Furthermore, it is planned to extend the model by integrating different cost allocation models in order to analyze which model yields a fair distribution of costs under different demand behavior of the warehouse's users. Yet, the simulation model proposed in this work is regarded as a promising first step for investigating the influence of user's order placement behavior on resource usage and cost allocation in future research.

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