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THE IMPACT OF ITEM WEIGHT ON TRAVEL TIMES IN PICKER-TO-PARTS ORDER PICKING: AN AGENT-BASED SIMULATION APPROACH

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ABSTRACT

In picker-to-parts order picking the traveling of the order picker between the storage locations account for approximately 50 % of the overall time. Reducing travel times can therefore substantially improve the productivity. Hereby, current research has almost exclusively focused on minimizing the travel distance and assumed a constant velocity of the order picker. However transported item weight can significantly influence the velocity and consequently travel times as well. Hence, the paper at hand analyzes to which extent travel times vary in dependence of item weights in the warehouse. New weight class based storage assignment policies are investigated. Their aim is to locate the items in the storage area according to their weight so that the heaviest items are collected at the end of the order picker's tours. Agent-based simulation experiments confirm that the new policies can significantly reduce travel times.

1 INTRODUCTION

Over the last years warehouse operations gained increasing attention from logistics managers as well as from researchers. In the light of the continuing trend towards broader product ranges, higher service levels and shorter delivery times on the one side and the permanent pressure for improving cost efficiency on the other side, warehouses play a crucial part for the performance of supply chains (Elbert et al. 2017). With a share of 50-75 % the largest amount of the operating costs in warehouses are attributable to order picking, the process of retrieving products from storage for specific customer orders (Bartholdi and Hackman 2014). In general automation would be a possible mean to reduce labor costs. However, due to the need to handle a large variety of products with different packaging, frequently changing demand and seasonality of products, order picking processes are often difficult to automatize in an economically reasonable way (Grosse et al. 2015). Although new technologies like robot picking may bear the potential for further automatization in the future, manual order picking in a picker-to-parts-manner (order pickers travel along the storage aisles and subsequently retrieve the items on their pick lists) still clearly prevails. Approximately 90 % of the order picking systems in the United States are picker-to-parts-systems, whereas only 3 % of the warehouses use automated or robot picking, respectively (Michel 2016).

The high labor intensity of manual order picking makes an effective planning of the operative processes necessary so that the costly workforce is deployed efficiently (Glock et al. 2016). In picker-to-parts systems especially the minimization of the travel time for order pickers is decisive in ensuring a high labor productivity (Elbert et al. 2017). The time for traveling between the different storage positions accounts for 50 % of the overall order picking time and since no value-adding activities are performed during this time intervals, the reduction of travel time is a first candidate for improvement measures (Bartholdi and Hackman 2014).

Research has recognized the importance of traveling and made strong efforts in developing planning methods that can significantly reduce travel times. The resulting planning problems include, besides the layout design of the storage facilities, four different parts of the operating strategy (de Koster et al. 2007): the assignment of the items to storage positions (storage assignment), the division of the order picking area into different zones (zoning), the batching of multiple orders for a single pick tour (order batching) and the finding of shortest possible routes for a tour with given items to pick (routing). The existing approaches assume a constant velocity of the order picker. Therefore travel time is a linear function of travel distance and the planning methods concentrate on the minimization of the latter for ensuring low travel times (Gademann and van de Velde 2005).

Surprisingly, current research has not analyzed the influence of a variable velocity on travel times, although ergonomic studies verified a wealth of factors that can influence the velocity of order pickers. According to Jung et al. (2005) they can be grouped into task factors (e.g. item weight that must be transported, direction of motion, motion phases), design factors of the cart (e.g. superstructure, wheels, handles), environment factors (e.g. floors, slope, congestion) and operator factors (e.g. age, gender, anthropometry). Whereas design, environment and operator factors are external constraints regarding operating strategies, task factors have almost been completely neglected in planning models so far. However, considering the general physical relationship between time and velocity, even small changes in velocity can cause large increases or decreases in travel time (in absolute values). Despite its importance this influence factor has not been evaluated in research yet.

Especially the weight of the transported items can determine the velocity of the order picker substantially (Resnick and Chaffin 1995). Consequently, the travel time can not only depend on travel distance, but also on the sequence of picked items with different weights. The velocity during a tour can be considerably lower if heavy items are picked at the beginning. Conversely, travel time can be reduced when the items with highest weight are picked at the end of the tour. Therefore, calculated travel times in planning models can significantly differ when a weight dependent velocity is considered instead of assuming a constant velocity. Especially when the constant velocity should represent the speed of an order picker moving average item weights, serious miscalculations could occur when this constant velocity is applied for warehouses in different branches of industry (for example item weights in warehouses of the textile and clothing sector can be substantially lower than in warehouses for industrial goods).

The research gap addressed in this paper can therefore be summarized as follows: Current studies have not investigate the influence of item weight on travel times (in terms of a weight dependent velocity). In a first approach item weight can be considered in storage assignment. Depending on the routing policies that determine the sequence of visited storage locations during the tours, it could be beneficial to assign items to storage positions in ascending order regarding their weight. This means that the order picker visit the items with lowest weight first and ends his tour at storage locations where the heavy items are placed.

Therefore, the following two research questions (RQ) should be answered throughout the paper:

- RQ 1 To which extent do travel times assuming a constant velocity of the order picker differ from travel times assuming a weight dependent velocity?
- RQ 2 To which extent can the consideration of item weight in storage assignment reduce travel times when a weight dependent velocity is assumed?

Regarding RQ 2 new storage assignment policies that consider the item weight (weight class based storage assignment) are developed in this paper. As research methodology an agent-based simulation study of a generic manual picker-to-parts system is conducted. In the simulation experiments resulting travel times for different combinations of storage assignment and routing policies are calculated.

The remainder of the paper is organized as follows: In section two the current state of research is presented, the new storage assignment policies are introduced and the RQs are further operationalized in several research propositions (P). Section three describes the structure of the simulation model, modeling assumptions and the conduction of the simulation experiments for calculating travel times. In section four the results are analyzed and the RQs are answered. Finally, section five gives a conclusion, shows limitations of the research and expounds needs of further investigation.

2 STATE OF RESEARCH

2.1 Item Weight and Operating Strategy

The influence of item weight in general has already been analyzed in several research streams on ergonomics and order picking. Ergonomic literature concentrates on evaluating working conditions regarding the risk to develop musculoskeletal disorders. In this regard, a large number of observation methods (like OWAS, RULA, or the NIOSH Lifting Equation) exist that assess individual working tasks based on working posture, load/forces, and their frequency or duration (David 2005). They all determine a semi-quantitative risk index that represent the (negative) impact of the working conditions on worker health. A further approach is the biomechanical analysis of manual material handling tasks that allows the exact determination of stresses in individual body joints. For cart pushing/pulling this method enables to recommend maximum acceptable push/pull forces for avoiding overstresses of the low back and shoulder joints (Garg et al. 2014). In risk index evaluation as well as in biomechanical analysis, the item weight is only considered with regard to worker health, but not analyzed as determining factor for the velocity of the order picker and in consequence as decisive parameter for travel times.

The influence of item weight on velocity was examined by Resnick and Chaffin (1995). They could empirically verify that velocities range from 0.25 m/s up to 1.1 m/s, depending on cart weight, load/handle height, push instruction and the physical strength of the subjects. Increasing the weight by factor 10 (from 45 kg to 450 kg) results in a reduction of peak velocity by 47 % for a hard push instruction and a reduction of 25 % for an easy push instruction, respectively. Summarizing current research item weight has mainly been analyzed with regard to ergonomic aspects. However, a consideration in research on operating strategy is completely missing so far (Grosse et al. 2015). Despite the knowledge about the general influence of item weight on velocity, it has not been elaborated to which amount travel times are affected (difference to the assumption of a constant velocity) and in which way the operating strategy should be adapted for exploiting potential travel time reductions by considering item weight.

As a first approach for closing this research gap, the paper at hand is focusing on storage assignment and routing as part of the operating strategy. The combination of both determines the sequence in which items with different weights are picked during the tours. Hence, assuming a weight dependent velocity can provide new results for preferable storage assignment and routing policies regarding the minimization of travel times.

In storage assignment random storage and class based storage are commonly used policies in practice (de Koster et al. 2007) and are therefore well suited for a first analysis of the influence of weight dependent velocity. In warehouse with random storage incoming items are assigned randomly to an empty location. This policy provides a high space utilization, but on average results in higher travel times (Bartholdi and Hackman 2014). Frequently demanded items could be stored in large distance to the depot, where the order picker starts and ends the tours.

On the opposite class based storage can reduce travel times, but at the expense of lower storage utilization compared to random storage (de Koster et al. 2007). Thereby the items are classified into groups based on a Pareto or ABC-analysis with the objective to minimize travel distance. A popular classification criteria is the picking frequency of the items. A-items represent the share of items with highest demand (for example the 15 % of items that account for 80 % of the picks), B- and C-items then cover the share of the following items regarding picking frequency (de Koster et al. 2007). Each group is assigned a dedicated storage area (A-items are located closest to the depot), but the storage assignment within the groups is random. The within-aisle class based storage arrange the items of each class along the subsequent aisles (so that each aisle contains only items of one class), whereas the across-aisle class based storage distribute the items of each class horizontally over the aisles (each aisle contains items of all three classes, Petersen and Schmenner 1999).

In terms of routing policy research has developed six different heuristic policies and an optimal policy (the policies are applicable for a rectangular layout as shown in Figure 1 that is very frequent in real-world warehouses, Bartholdi and Hackman 2014). The six heuristic policies are as follows: In the return policy the order picker enters each aisle from the same side of the storage area and turns within the aisle. On contrary, in the traversal policy each aisle is traversed completely and the order picker enters the subsequent aisles from alternate sides. When using the midpoint policy the order picker first retrieves all items that are located in the first (upper or lower) half of the storage area and afterwards visits each aisle again from the other half for picking the remaining items. The largest gap policy is very similar to the midpoint policy. As single difference the storage area is not divided by the midline, but by the largest vertical distance between two items in each aisle. In the composite policy the order picker can either traverse an aisle completely or leave it at the same side where s/he entered it, depending on which option reduces the travel distance between the farthest picks in two adjacent aisles. The combined policy works in a similar way like the composite policy, but considers the whole storage area in determining the picking route and not only two adjacent aisles.

The optimal policy guarantees the shortest possible travel distance for each tour by solving a special form of a Traveling Salesman Problem (de Koster et al. 2007). For avoiding confusion the optimal policy is in the following called minimal travel distance policy throughout the paper (when assuming a weight dependent velocity a minimal travel distance does not automatically provide the optimal solution regarding travel time). Especially the three more sophisticated heuristic policies (largest gap, composite, combined) and the optimal policy aim to minimize travel distance by avoiding unnecessary additional travel routes.

The brief overview of literature illustrates that storage assignment and routing policies exclusively focus on the minimization of travel distance, in order to reduce travel times, and thereby assume a constant velocity of the order picker. Particularly storage assignment and routing policies have not been analyzed from this perspective so far.

2.2 Weight Class Based Storage Assignment

Since warehouse operators often prefer easy implementable policies (Petersen and Schmenner 1999), a weight class based storage assignment, as a first approach for reducing the overall weight that must be transported during a tour, is analyzed in the following. The new policies are derived from current class based storage assignment and therefore can be well suited for application in real-world warehouses. Instead of defining classes by picking frequency (demand class based storage) the stored items can be divided in weight classes (weight class based storage) by using the Pareto method. The first weight class (class III) covers a defined share of items with lowest weight, the second weight class (class II) the items with medium weight and the last class (class I) the heaviest items. When taking only the impact of weight on velocity or travel times into account, the classes should be visited by the order picker in ascending order. Therefore, the classes must be assigned to storage areas depending on the routing policy. In case of the return, traversal, combined or composite policy the classes should be distributed across the aisles in the direction of travel of the order picker (when the order picker starts his tours on the left side of the warehouses class III items should be located in the left aisles, class II items in the middle and class I items on the right, see Figure 1, top left). For the midpoint and largest gap policy class III items can be stored in the lower left half, class II items in the upper half and class I items in the lower right half (assuming the order picker starts in the aisle next to the depot and travels clockwise through the storage area, see Figure 1, top right). For the minimal travel distance policy in general a weight class based assignment cannot be derived, since the direction of the order picker can differ in each tour (an individual route with minimal distance is calculated).

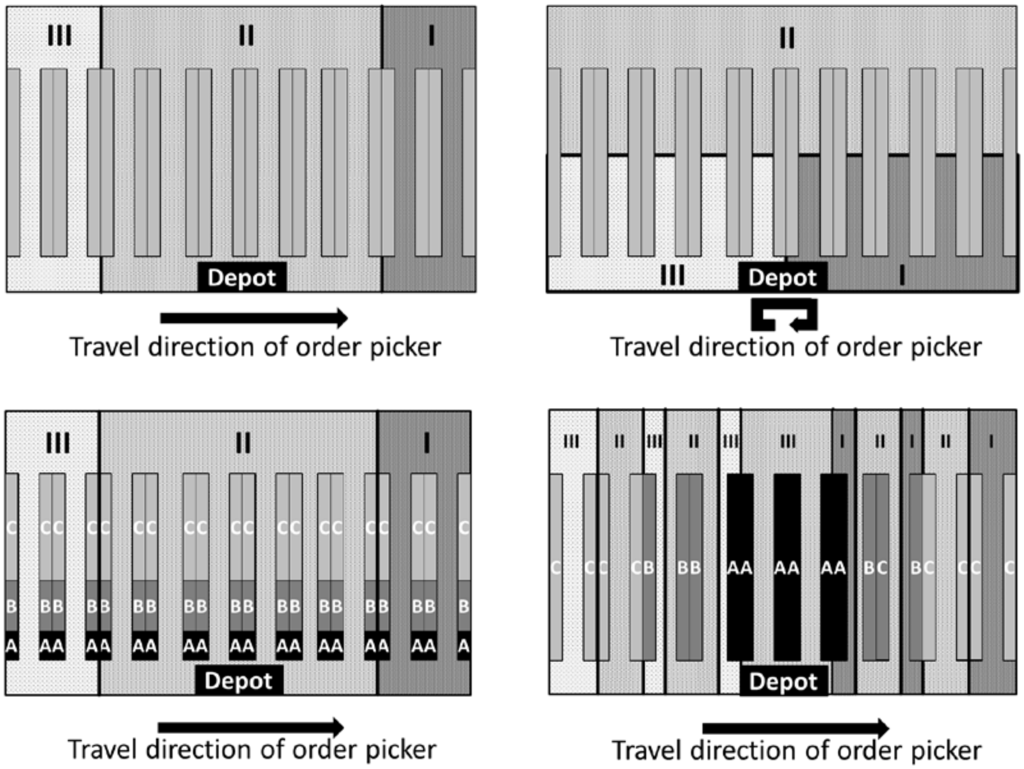

Figure 1: Weight class based storage assignment policies.

When demand is not considered in storage assignment (warehouses with random storage assignment), the items can easily be sorted into the respective weight classes. However, a combination of demand and weight class based storage is also possible so that both the influence of travel distance/picking frequency and item weight can be considered. When using ABC across-aisle storage the items in each demand class can be assigned by weight class in the direction of travel of the order picker in a second step (for example from left to right so that the left part of the storage area only contains class III items, but in the three demand classes, see Figure 1, bottom left). For ABC within-aisle storage this policy results in a split of the weight classes over the storage area (for example from left to right: the order picker visits class C/class III items first, then class C/class II items, then class B/class III items, then class B/class II items and so on, see Figure 1, bottom right). However, this policy could still reduce travel times compared to a pure random storage assignment within the demand classes. A prerequisite for a combination of demand and weight class based storage is the non-correlation of item demand and item weight, which in the following is assumed throughout the paper.

In order to operationalize the two RQs and to analyze the influence of item weight/weight class based storage assignment, in the next step the following research propositions (P) are derived:

RQ 1 (comparison of travel times with constant and weight dependent velocity):

P 1.1: Travel times significantly depends on overall transported item weight during a tour. Therefore, travel times increase with increasing item weights.

Furthermore it is assumed that travel times with weight dependent velocity significantly differ from travel times with constant velocity independent of item weight. The difference depends on the deviation of the item weights in the warehouse compared to an average item weight when the constant velocity should represent the speed of an order picker moving such average item weights. Therefore the next proposition is as follows:

P 1.2: The difference of travel times with weight dependent velocity, compared to constant velocity, increases with the deviation of the item weights in the warehouse, compared to an average item weight that is reflected by the constant velocity.

RQ 2 (travel time reduction due to consideration of item weight in storage assignment):

For an analysis of travel time reduction, due to consideration of item weight in storage assignment, the respective pairs of storage assignment policies without and with weight class based storage must be compared (random storage without and with weight classes, ABC within-aisle storage without and with weight classes, ABC across-aisle storage without and with weight classes). The proposition to evaluate is then:

P 2.1: Travel times are significantly lower for storage assignment with weight classes compared to the respective storage assignment policy without weight classes.

For further analysis the following two propositions can be derived:

P 2.2: The decrease in travel time when applying weight class based storage assignment increases with increasing item weights.

P 2.3: The decrease in travel time is higher for random storage and ABC across-aisle storage than for ABC within-aisle storage, because in the latter case the weight classes are split over the storage area.

Regarding routing policies, when applying one of the six heuristic policies the travel direction of the order picker is clearly defined. For the minimal travel distance policy the travel direction depends on the specific position of the items in each tour (since a travelling salesman problem is solved every time) and therefore assigning fixed weight classes can be not that efficient. This results in the next proposition:

P 2.4: The decrease in travel time is higher when applying one of the six heuristic routing policies than using the minimal travel distance policy.

Furthermore, it is possible that the increase in velocity of the order picker due to weight class based storage assignment outweighs higher travel distances of heuristic routing policies. Therefore the last proposition is as follows:

P 2.5: The combination of weight class based storage assignment with a heuristic routing policy can result in lower travel times, than using a minimal travel distance policy without consideration of item weight in storage assignment.

3 SIMULATION STUDY

For answering the RQs and testing the propositions P 1.1-2.5 an agent-based simulation study of a picker-to-parts-system with rectangular warehouse layout is conducted. Agent-based simulation is well suited to investigate complex, weakly structured systems, where agents interact with their environment (Bonabeau 2002). In this context, single tours of the order pickers (agents) are simulated, whose travel velocity depends on the current item weight in their cart (interaction with environment). A rectangular layout is chosen, because it is very frequent in real-world warehouses (Bartholdi and Hackman, 2014). The process of order picking is modelled as follows: The order picker starts its tour at the depot and picks the items according to their sequence on his pick list. For retrieving the item out of the storage a constant picking time is assumed.

After each pick i of a tour the cumulated item weight in the cart W_i (in kg) is updated and a constant velocity v_i (in m/s) for the following travel is determined, based on the following functional relationship:

$$v_i = v_{\max} \cdot \left(1 - v_1 \cdot W_i^{v_2}\right) \quad (1)$$

The equation is introduced in Battini et al. (2015) and based on empirical observations of the authors and simplifying equations developed in literature. The parameter $v_{\max}$ represents the maximum velocity without items in the cart and is set to 1 m/s. The dimensionless parameters v_1 and v_2 define the decrease in velocity, dependent on the cart load, and are set to 0.08 and 0.4 according to Battini et al. (2015). In particular case all three parameters depend on design factors of the cart (e.g. handle height) and environment factors (e.g. floor material) and can therefore differ for each warehouse (Jung et al. 2005).

Regarding routing and storage assignment a full-factorial design is used for analyzing all possible combinations of policies that are introduced in this paper. The combination of seven routing policies with six storage assignment policies are analyzed. In terms of routing policies, the six heuristic policies (return, traversal, midpoint, largest gap, composite, combined) and the minimal travel distance policy, as introduced in section two, are considered. For storage assignment random storage, ABC within-aisle and ABC across-aisle storage without and with weight classes are included Overall, this results in 42 combinations, whereas for each combinations 1000 tours are simulated.

Each pick list contains a constant amount of 20 items. The location and weight of the items are calculated by using a random generator. In the first step, the location is determined by drawing a random number from an uniform distribution between 0 and 1 for each item. For random storage (without and with weight classes) this number directly correspondents to a storage location. For ABC within-aisle and ABC across-aisle storage (without and with weight classes) the number is compared to the assumed share of A, B and C items of picking frequency. According to the range in which the number lies, a random location inside the assigned storage area of the respective class is specified. It is assumed that 20 % of the items are class A (accounting for 80 % of the picks), 30 % of the items are class B (accounting for 15 % of the picks and 50 % of the items are class C (accounting for 5 % of the picks). It follows that, if the random number is less or equal to 0.8, the location lies in the storage area for A items and so on.

After the storage location is identified, the item weight is calculated in the second step. A fixed weight class (I-III) is assigned to each location dependent on the storage assignment policy in use. The thresholds for the weight classes are assumed to be 20 % for class III (meaning that class III contains the 20 % share of items with lowest weight) and 80 % for class I (meaning that class I contains the 20 % share of items with highest weight; in consequence class II contains the 60 % of items with medium weight). The exact item weight is drawn from a truncated normal distribution. Based on predefined thresholds for the weight classes a respective value is drawn from the distribution according to the weight class of the storage location. For storage assignment without weight classes the item weight is drawn randomly from the distribution.

A truncated normal distribution allows to parametrize different possible distributions of item weight. By specifying the minimum and maximum item weight $w_{\min}$ and $w_{\max}$ (in kg) of the truncated normal distribution, lower and upper bounds for item weight in the warehouse can be defined. The mean item weight w_{mean} is calculated by

$$w_{mean} = \frac{w_{\max} + w_{\min}}{2} \quad (2)$$

assuming a symmetric distribution. The standard deviation w_σ parametrizes the spread of item weights. Besides $w_{\min}$ and $w_{\max}$ this value allows to analyze warehouses with different importance of item weight regarding travel time. With increasing values of w_σ and increasing difference between $w_{\min}$ and $w_{\max}$ item weight is of higher relevance, since the weights vary more and the sequence of picking items with different weights gains a stronger influence. For taking this aspect into account each of the 42 combinations of storage assignment and routing policy is analyzed for three different warehouse types regarding the distribution of item weight. For warehouses with low item weight (type l) the parameters are set to $w_{\min} = 0.05\,\text{kg}$, $w_{\max} = 5\,\text{kg}$ and $w_{\sigma} = 2.5\,\text{kg}$ (it follows that $w_{mean} = 2.525\,\text{kg}$). For warehouses with medium item weight (type m) the values are $w_{\min} = 0.1$ kg, $w_{\max} = 10$ kg and $w_{\sigma} = 5$ kg ($w_{mean} = 5.05$ kg) and for warehouses with high item weight (type h) the values are $w_{\min} = 0.2$ kg, $w_{\max} = 20\,\text{kg}$ and $w_{\sigma} = 10\,\text{kg}$ ($w_{mean} = 10.1\,\text{kg}$).

The assumption of a normal distribution as well as the parameter values for the three warehouse types are determined based on a large empirical study regarding manual material handling task parameters conducted by Ciriello et al. (1999). The authors identify a wide spread of item weights with a concentration in the range of medium weights. For carrying tasks the weights range from values below 2 kg up to values higher than 45 kg. When considering the fact that 20 items are loaded in the cart after the last pick, a maximum weight of 20 kg seems more adequate. This assumption also reflects ergonomically acceptable maximum cart loads, which are in the range of 225 kg (Resnick and Chaffin 1995) and are reached in the warehouse type high when the mean item weight is taking as basis. However, the determination of empirical-based weight distributions that can represent real-world warehouses appropriately is a matter for further empirical investigation. The aim of this analysis is rather to provide insights about the general impact of weight distribution on travel time by the means of a parameter study.

4 RESULTS

For each combination of storage assignment policy, routing policy and warehouse type regarding item weight distribution, the mean travel time with weight dependent velocity (wdv) $\bar{t}_{travel,wdv}$ for the respective 1000 simulated tours is evaluated. The travel time consist of all time periods in which the order picker moves through the warehouse (movement from the depot to the location of the first item on the pick list, movements between the storage locations, and movement from the last storage location to the depot). Besides mean travel times the mean of the average velocities $\bar{v}_{wdv}$ are calculated as well (defined as overall travel distance of the tour divided by travel time).

For evaluating P 1.2 (differences in travel time for weight dependent and constant velocity) the values for $\bar{t}_{travel,wdv}$ are compared to mean travel times with constant velocity (cv) $\bar{t}_{travel,cv}$. For calculating $\bar{t}_{travel,cv}$ the travel distances of the simulated tours are divided by an unitary value for the constant velocity v_{cv}. The value for v_{cv} is determined based on the average velocities of the tours when assuming a weight dependent velocity. Concretely, v_{cv} is defined by the mean of those average velocities over all simulated tours. Through this calculation method v_{cv} reflects an average constant velocity independent of the specific item weights in the warehouse, as it is assumed in current literature as standard so far. For the comparison the differences between $\bar{t}_{travel,wdv}$ and $\bar{t}_{travel,cv}$ as well as for $\bar{v}_{wdv}$ and v_{cv} are tested for each combination of storage assignment and routing by the means of paired t-tests with the software SPSS 23.0. Since the same tours are compared (same travel distances, same item weights), statistically significant differences can only result from the different calculation methods for the velocity.

Table 1 provides an overview of the results. The table shows the mean travel time when assuming a constant velocity $\bar{t}_{travel,cv}$ and the mean travel times when assuming a weight dependent velocity $\bar{t}_{travel,wdv}$ for each combination of storage assignment and routing policy. The values for $\bar{t}_{travel,wdv}$ are further differentiated by warehouse type regarding item weight (low, medium, high item weights). Additionally, the mean average velocities $\bar{v}_{wdv}$ are shown in dependence of storage assignment, routing and warehouse type. Finally, the significance levels of the paired t-tests are also presented.

The mean travel times for constant velocity $\bar{t}_{travel,cv}$ reflect the differences in travel distance that exist between different combinations of storage assignment and routing. In this case the minimal travel distance routing policy ensures the lowest travel times for each storage assignment policy. Furthermore, the ABC within-aisle storage assignment provides the lowest travel times overall. A combination of ABC within-aisle storage with the minimal travel distance policy results in a mean travel time $\bar{t}_{travel,cv}$ of 418 seconds, which is 18 % lower than combining the minimal travel distance policy with ABC across-aisle storage and 42 % lower than combining it with random storage.

The results for $\bar{t}_{travel,wdv}$ confirm P 1.1 (travel times increase with item weight). The mean travel times for weight dependent velocity $\bar{t}_{travel,wdv}$ increase with higher item weights in the warehouse due to decreasing mean average velocities $\bar{v}_{wdv}$. Throughout all combinations of storage assignment and routing the values for $\bar{t}_{travel,wdv}$ are on average 15 % higher for warehouse type medium compared to warehouse type low and even 27 % higher for warehouse type high compared to medium (the values for $\bar{v}_{wdv}$ decrease by 12 % and 21 % respectively).

When comparing $\bar{t}_{travel,wdv}$ with $\bar{t}_{travel,cv}$ for evaluating P 1.2 the travel times differ at the 0.1 % significance level throughout all combinations of storage assignment and routing in warehouses with low and high item weight. The same holds for the difference between mean average (weight dependent) velocity $\bar{v}_{wdv}$ and constant velocity v_{cv}. The travel times for the warehouse type high are on average 25 % higher for weight dependent velocity (the mean velocity $\bar{v}_{wdv}$ is 19 % lower). For warehouse type low they are 14 % less ($\bar{v}_{wdv}$ is 17 % higher). Only for the medium warehouse type the travel times reach a comparable level because of almost equal mean velocities (v_{cv} is calculated to 0.63 m/s, $\bar{t}_{travel,wdv}$ is on average 2 % lower, $\bar{v}_{wdv}$ is 2 % higher). In this case some combinations of storage assignment and routing do not show significant differences regarding the travel times. However, even in most of those combinations the mean average velocity is significantly different (only for ABC within-aisle storage without weight classes and composite or combined routing there exists no significant deviation).

In summary P 1.1 and P 1.2 are confirmed by the simulation results. An increase in item weight results in increasing travel times by 15 % (for medium compared to low item weights) or 27 % (for high compared to medium item weights), respectively. Significant differences between travel times assuming weight dependent or constant velocity occur especially for low and high item weights.

Regarding P 2.1 (weight class based storage assignment can reduce travel times) a one-way ANOVA was conducted with the software SPSS 23.0 for testing the statistical significance of weight class based storage assignment on travel times (normal distribution of the tested data and variance homogeneity of the tested classes was evaluated by Shapiro-Wilk-tests and Levene-test, respectively). In the tests the travel times for a specific routing policy and a specific warehouse type are compared between the respective pairs of storage assignment policies (without and with weight classes as presented in P 2.1).

The results are also shown in Table 1 (for example the shown significance levels in the cells of random storage with weight classes and return routing represent that those travel times are significantly lower than for random storage without weight classes and return routing for the respective warehouse type). The comparability of the travel times is ensured by additional one-way ANOVA for the mean overall item weight as well as for the mean travel distances. The test results show that in most cases significant reductions of travel time are reached and therefore P 2.1 is backed by the simulation experiments.

For a further understanding P 2.2-2.4 are evaluated. When analyzing the reductions with regard to item weight (P 2.2) the travel times decrease by 3 % for warehouse type low, by 3 % for warehouse type medium and by 5 % for warehouse type high. Hence, especially for high item weights the new storage assignment policies can be worthwhile for warehouse operators. Regarding P 2.3 random storage with weight classes and ABC across-aisle storage weight classes can be most beneficial for warehouse operators. In this case travel times decrease, compared to the same storage assignment without weight classes, on average by 5 % and 4 % respectively. As assumed in the proposition ABC within-aisle storage with weight classes leads only to a reduction of 2 %, because weight classes are partially mixed and not strictly sorted according to the travel direction of the order picker (from lowest to highest weight class).

As further influence factor the travel time reductions also vary in relation to the routing policy, as stated in P 2.4. For all compared storage assignment policies and warehouse types the highest decreases are realized for the traversal policy (on average 6 %), followed by the combined policy (5 %), the return policy (5 %) and the composite policy (5 %). For high item weights the reductions can be in the range up to 10 % (for traversal, composite or combined policy and random storage or ABC across-aisle storage with weight classes).

Table 1: Travel time and mean velocity in dependence of storage assignment and routing policies.

Storage assignment policy	**Routing policy**	**Travel time constant velocity** $\bar{t}_{travel,cv}$ **[s]**	**Travel time weight dependent velocity** $\bar{t}_{travel,wdv}$ **[s]**			**Mean average velocity** $\bar{v}_{wdv}$ **[m/s]**		
			l	**m**	**h**	**l**	**m**	**h**
Random without weight classes	Return	1082	953 a	1110 a	1361 a	0.72 a	0.62 a	0.49 a
	Traversal	892	778 a	897 a	1156 a	0.72 a	0.63 b	0.49 a
	Midpoint	854	743 a	851	1092 a	0.73 a	0.63 c	0.49 a
	Largest gap	812	705 a	808 a	1030 a	0.73 a	0.63 a	0.50 a
	Composite	827	722 a	831 a	1077 a	0.72 a	0.62 a	0.49 a
	Combined	792	688 a	796 c	1020 a	0.72 a	0.63 c	0.49 a
	Minimal travel distance	717	629 a	728 a	931 a	0.72 a	0.62 a	0.49 a
Random with weight classes	Return	1091	916 a/d	1039 a/d	1276 a/d	0.75 a	0.66 a	0.54 a
	Traversal	893	745 a/d	847 a/d	1053 a/d	0.75 a	0.66 a	0.53 a
	Midpoint	850	713 a/d	803 a/d	1003 a/d	0.75 a	0.66 a	0.54 a
	Largest gap	812	683 a/d	779 a/d	966 a/d	0.75 a	0.66 a	0.53 a
	Composite	826	688 a/d	784 a/d	978 a/d	0.75 a	0.66 a	0.53 a
	Combined	792	658 a/d	752 a/d	932 a/d	0.75 a	0.66 a	0.54 a
	Minimal travel distance	719	637 a/e	742 a/d	964 a/d	0.71 a	0.61 a	0.47 a
ABC within-aisle without weight classes	Return	644	565 a	666 a	854 a	0.71 a	0.62 a	0.47 a
	Traversal	510	444 a	506	663 a	0.73 a	0.63 b	0.49 a
	Midpoint	558	475 a	543 a	687 a	0.74 a	0.64 a	0.51 a
	Largest gap	526	449 a	509 a	655 a	0.74 a	0.64 a	0.51 a
	Composite	482	421 a	477	630 a	0.73 a	0.63	0.48 a
	Combined	459	395 a	459	597 a	0.73 a	0.63	0.49 a
	Minimal travel distance	418	374 a	426 a	554 a	0.71 a	0.62 a	0.48 a
ABC within-aisle with weight classes	Return	646	554 a/f	642 a/d	825 a/e	0.73 a	0.64 a	0.49 a
	Traversal	507	428 a/d	492 a/e	645 a/f	0.74 a	0.65 a	0.51 a
	Midpoint	557	474 a	550 a	681 a	0.74 a	0.65 a	0.51 a
	Largest gap	521	437 a/e	503 a	650 a	0.74 a	0.65 a	0.51 a
	Composite	487	413 a	480 a	606 a/d	0.74 a	0.64 a	0.50 a
	Combined	460	390 a	447 a/f	573 a/d	0.75 a	0.65 a	0.51 a
	Minimal travel distance	420	364 a/f	420	541 a/f	0.73 a	0.63 b	0.50 a
ABC across-aisle without weight classes	Return	549	483 a	558 a	718 a	0.72 a	0.62 a	0.48 a
	Traversal	865	750 a	865	1110 a	0.72 a	0.63 c	0.49 a
	Midpoint	639	536 a	600 a	747 a	0.75 a	0.67 a	0.54 a
	Largest gap	632	527 a	596 a	741 a	0.75 a	0.67 a	0.54 a
	Composite	532	465 a	535 a	697 a	0.72 a	0.62 a	0.49 a
	Combined	531	463 a	539 a	692 a	0.72 a	0.62 a	0.48 a
	Minimal travel distance	511	454 a	525 a	688 a	0.71 a	0.61 a	0.47 a
ABC across-aisle with weight classes	Return	550	461 a/d	524 a/d	662 a/d	0.75 a	0.66 a	0.53 a
	Traversal	862	716 a/d	806 a/d	992 a/d	0.76 a	0.67 a	0.55 a
	Midpoint	640	525 a/d	591 a/e	717 a/d	0.77 a	0.68 a	0.56 a
	Largest gap	638	526 a	589 a/f	716 a/d	0.76 a	0.68 a	0.56 a
	Composite	534	449 a/d	508 a/d	635 a/d	0.75 a	0.66 a	0.53 a
	Combined	533	447 a/d	507 a/d	633 a/d	0.75 a	0.66 a	0.53 a
	Minimal travel distance	512	455 a	528 a	678 a/f	0.71 a	0.61 a	0.48 a

Test for difference $\bar{t}_{travel,wdv}$ and $\bar{t}_{travel,cv}$ a: $p < 0.001$, b: $p < 0.01$, c: $p < 0.1$

Test for differences in $\bar{t}_{travel,wdv}$ for storage assignment without/with weight classes d: $p < 0.001$, e: $p < 0.01$, f: $p < 0.1$

As proposed the minimal travel distance policy is the only routing policy for which a weight class based storage assignment does not provide reductions of travel time (on average the travel time increases by 0.01 %), because of varying travel direction of the order picker throughout the tours.

Finally also P 2.5 is supported by the results. For ABC across-aisle storage with weight classes the travel times for the combined policy are on average 4 % lower than for the minimal travel distance policy in ABC across aisle-storage without weight classes. The highest reduction is reached for warehouse type high (8 %), followed by warehouse type medium (4 %) and warehouse type low (1 %). It follows that, especially for high item weights, combining weight class based and demand class based storage can be more preferable for warehouse operators than applying a minimal travel distance policy and neglecting the item weight in storage assignment.

In conclusion also P 2.1-2.5 can be confirmed by the simulation results. A substantial reduction of travel times is especially possible for random and ABC across-aisle storage with weight classes, for high item weights and for the traversal, composite or combined routing policy.

5 CONCLUSION

For answering RQ 1 travel times for low and high item weights differ up to 25 % when a weight dependent velocity is considered. Only for medium item weights the travel times are in the same range compared to assuming a constant velocity. Regarding RQ 2, a possible reduction of travel times ranges up to 10 % for high item weights and for the traversal, composite or combined policy, respectively.

In summary, the simulation results support the importance of taking item weight and a weight dependent velocity into account for travel time calculation. Assuming a constant velocity can especially lead to large deviations in travel time calculation when the constant velocity is determined by assuming average item weights, whereas item weights in the warehouse are substantially higher or lower. Regarding managerial implications the consideration of item weight in storage assignment could bear a potential for travel time reductions. For ABC across-aisle storage this can result in even lower travel times than applying a minimal travel distance policy.

Research limitation is the lack of empirical data regarding velocity functions and item weight distributions. Therefore, the results should be interpreted as first study that gives reason for further empirical investigations in this research field. Furthermore, the simulation experiments do not consider a range of additional influencing factors regarding velocity that can be present in real-world warehouses. More experienced workers may travel faster than new workers, which can be of high relevance because of high staff turnovers in warehouses. Additionally, maximum velocities can decrease in time periods with high demand due to congestion or picker blocking (order pickers block each other in the warehouse aisles).

In the next step more sophisticated planning approaches can be analyzed (for example new routing policies that consider both item weight and travel distance or a combination of such routing policies with weight based storage assignment). Furthermore a probable increasing storage space that is necessary when using weight class based storage, should be considered, too. Since additional restrictions are applied regarding storage locations the storage area cannot be that efficiently exploited as in random storage.

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