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A SIMPLIFIED LINEAR PROGRAMMING MODEL FOR THE ASSIGNMENT OF DUPLICATE STORAGE LOCATIONS

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Abstract

Research background: In modern warehouses, there is a strong emphasis on ensuring fast and efficient order-picking. Speed is a critical factor, as customers increasingly demand quick delivery times, especially in the e-commerce sector. Warehouse management optimizes the storage of items and picking routes to minimize delays and maximize productivity, ensuring orders are processed and shipped as quickly as possible. Additional benefits in this field can be achieved by the scattered storage of items. In this paper, we propose a new optimization model that minimizes the weighted sum of shortest distances between picking aisles intended for the storage of correlated items. We assume a decentralized pick-up/drop-off and a random storage of items in the assigned picking aisle. Unlike existing proposals based on exact location assignment, the presented MILP model does not need the distance matrix between storage locations (or picking aisles).
Purpose: Optimal storage location assignment for warehouses with scattered storage.
Research methodology: We use mixed integer linear programming (MILP) models (for optimal storage location assignment) and simulations (for verification of the obtained results).
Results: The adopted simplifications reduce the size of the model by over 99% and allow feasible solutions to be found. We show that for the obtained feasible solutions there is a significant reduction in average order picking times. Additionally, we discuss methods of determining the correlation coefficients between the items.
Novelty: Original storage location assignment concept and optimization model.

Keywords: warehouse, storage location assignment, scattered storage, order picking

JEL classification: C44

Introduction

A key aspect of warehouse efficiency is the speed of order fulfilment, as minimizing the time required to pick, pack and ship items directly impacts customer satisfaction and competitiveness. Additionally, efficiency involves controlling operational costs, such as labour expenses and energy usage, while maintaining accuracy and productivity. Striking the right balance between quick order processing and cost management is essential for a warehouse to operate profitably and sustainably. Warehouse management can achieve improved efficiency by organizing work properly to reduce order picking time, and does not involve high financial outlays.

Fast order-picking is playing an increasingly important role in modern e-business. Customers today expect a quick delivery, often within 24–48 hours, thanks to services like same-day or next-day delivery. Meeting these expectations helps businesses stay competitive and retain customers. Faster delivery enhances customer satisfaction, leading to positive reviews, repeat purchases and word-of-mouth recommendations. Fast order fulfilment not only meets customer demands but also drives business growth, fosters loyalty and ensures a competitive edge in the e-commerce landscape. For these reasons, warehouse management tries to organize work in such a way as to make the order picking process as quick as possible.

Although many warehouses are becoming increasingly automated, the order picking process still often relies on manual activities, following the "man-to-goods" principle. There are several reasons why manual picking is still used in warehouses (Bitterling et al., 2022; Roodbergen, Vis, 2009):

- for smaller warehouses or businesses with a lower volume of orders, manual picking can be more cost-effective than investing in automated systems. The upfront costs of automation (e.g., robotics, conveyor systems) can be prohibitive for companies with limited budgets or lower order volumes,
- manual picking offers greater flexibility, especially for complex orders or those requiring customization,
- automated systems often require significant infrastructure, which may need more physical space. In smaller warehouses with limited space, manual picking can be a more practical solution,
- better adaptation to product variety and complexity. Manual picking allows workers to handle different products with varying sizes, shapes and fragility more effectively,

– technology limitations: certain goods may require specific handling or have storage conditions (e.g., temperature-sensitive items) that are not yet suited for automated systems,
– in specific situations, experienced warehouse staff can often pick orders more quickly and accurately than machines,
– the transition to more automated systems requires not only investment but also changes in workflow, training and operational adjustments, which can be a barrier to change.

In summary, while automation is becoming more common, manual "man-to-goods" picking remains in use due to factors such as cost, space limitations, flexibility, the complexity of the tasks involved, and the relatively slow adoption of new technologies.

The aim of our research is to optimize the storage of items in the warehouse in such a way that the average order-picking time is minimized. Since future customer orders are unknown, the problem involves decision-making under conditions of risk and uncertainty. We present a MILP model for minimizing the weighted sum of the shortest distances between picking aisles containing pairs of items that have previously occurred together in fulfilled orders. In our research, we examine whether optimal storage according to the proposed storage policy has a positive impact on the average picking time.

This paper analyses the storage assignment problem in a manual picking warehouse with scattered storage, where each item can be stored in many non-adjacent locations. The remainder of the paper is organized as follows. Section 1 presents a literature review and highlights the research gaps. Section 2 describes mixed integer linear programming (MILP) models for the storage of items in a scattered storage warehouse, taking into account the correlation between Stock Keeping Units (SKUs). We use a popular concept known from the literature to introduce the original MILP model based on slightly simplified assumptions: assignment to picking aisles instead of particular locations, and different indices of decision variables. We discuss the advantages and drawbacks of the adopted simplifications. Section 3 reports the results of experiments that were conducted to evaluate the optimization model. Finally, Section 4 concludes the paper.

1. Literature review

A key element in evaluating the performance of a warehouse is the order picking time. In facilities where people are responsible for picking items, the order picking time can be reduced by, among others, planning the picking zone, storing fast-moving items in locations that are easily accessible to pickers, and choosing (and matching) the heuristic for determining picker routes (De Koster et al., 2007).

Proper planning of the picking zone includes determining the number and length of picking aisles, the layout of cross aisles, the form and location of the place of Pick-up/ Drop-off (PD), and where pickers start and finish their routes. The PD can be compact and it is usually located in the corner of the warehouse. The benefits of locating the PD point opposite the central picking aisle have also been investigated. A significant reduction in the distance covered by pickers (and therefore the average order picking time) can be achieved by choosing a decentralized PD. The decentralized variant means that a conveyor is placed in the warehouse (usually along the main cross aisle), on which picked items are left.

Another key issue that influences the efficiency of the order-picking process is determining the layout of picking aisles and cross aisles. One-block rectangular warehouses (with two cross aisles located at the ends of the picking aisles) are often used in practice and are well-researched scientifically (De Koster, Van Der Poort, 1998). In practice, heuristics are mainly used to determine picker routes. For popular rectangular one-block warehouses, a return and s-shape heuristics are utilized in practice. In theoretical studies for this type of warehouse, other routing methods have also been analysed: combined, midpoint and largest gap. There are also existing algorithms that allow for the quick determination of the shortest possible route (Ratliff, Rosenthal, 1983; De Koster, Van Der Poort, 1998), although for various reasons they are rarely used in practice.

Significant benefits can be obtained in particular thanks to the scattered storage of items, mainly with a fast-rotating ratio. The routing issue in warehouses with many locations for the same item was defined by Daniels et al. (1998). The authors proposed the MILP model, which assigns particular locations with items to the route and optimizes the distance travelled by the picker. As the problem is NP-hard, a tabu search algorithm for the approximate criterion value was also introduced. Weidinger (2018) presented a very fast routing algorithm for scattered storage with an average optimality gap of 0.5%. Similarly, Weidinger et al. (2019) precisely defined the problem of picker routing in warehouses with scattered storage and prescribed a solution procedure.

A separate issue that indicates the possibility of significant improvement in warehouse efficiency is the scattered version of storage location assignment for items. Jiang et al. (2020) and Weidinger and Boysen (2018) proposed the MILP models, which minimize the weighted minimal distance between locations with correlated items. Their proposals are based on a distance matrix between storage locations and generate large problems that are difficult to solve, even for small instances. For this reason, Jiang et al. (2020) presented a faster heuristic based on a genetic algorithm and particle swarm optimization algorithm. However, the problem can be simplified by omitting the calculation of the minimal distance between correlated items in the objective criterion. Albán et al. (2023, 2024) optimized the value of average distance instead of minimal distance. Additionally, Albán et al. (2024) developed a variable neighbourhood search metaheuristic.

Another approach (based on a multi-criteria analysis) to the problem of optimizing the order-picking time in warehouses with the scattered storage of items was presented in papers by Dmytrów (2018a, 2018b, 2018c, 2020).

2. Optimization models for scattered storage location assignment

2.1. Problem description

The problem we address is assigning items to storage locations in a warehouse. We consider a picker-to-parts warehousing system. Although we analyse a one-block rectangular warehouse, the MILP model we propose can be easily adapted to other layouts. In a one-block rectangular warehouse (Figure 1), picking aisles are located parallelly and the picker can enter each picking aisle depending on the implemented routing heuristic (Figure 2) from a front cross aisle (return heuristic) or from both cross aisles (s-shape heuristic). We analyse a decentralized PD in which the conveyor is located across the main cross aisle.

In our study, we consider a scattered storage of items, which means that each item can be stored in several separate locations. The number of locations with the same item can be determined based on item turnover factors: frequently ordered items are stored in more locations. In our empirical study, the results of which are presented in Chapter 4, in some experiments we also assume a constant number of locations for all items.

According to the concept proposed by Jiang et al. (2020), locations are allocated to items in such a way as to minimize the sum of the distances between the closest locations assigned to all pairs of items. These values are additionally weighted by the correlation coefficients between these items, where correlation means the frequency of the co-occurrence of items in historical orders (this issue will be discussed later in the paper).

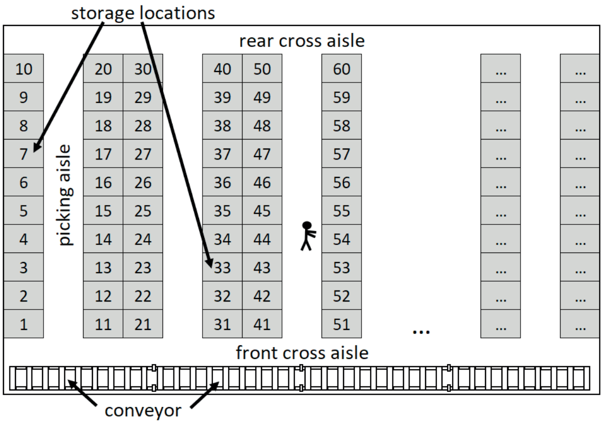

Figure 1. A one-block rectangular warehouse with a decentralized depot

Source: own elaboration.

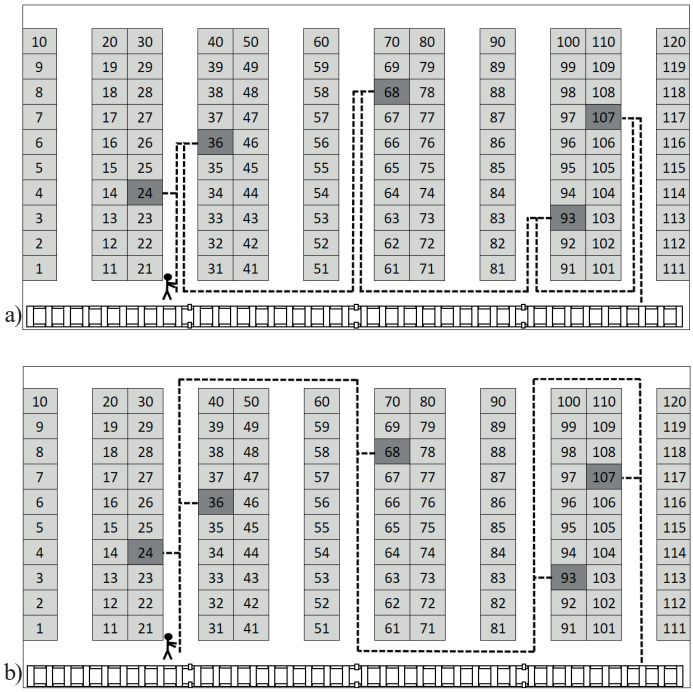

Figure 2. Two popular routing heuristics easily adopted in practice: a) return, b) s-shape

Source: own elaboration.

2.2. Model for a centralized PD and an exact distance value proposed by Jiang et al. (2020)

Jiang et al. (2020) proposed a model that minimizes the sum of the distances between the locations with all pairs of items weighted by correlation coefficients. In the case of many locations with the same item, only the shortest distances between both items are considered.

The goal is to assign each item to many locations in a way that will minimize the distances covered by the picker in the future. Additionally, the authors assume that the number of storage locations is more than the number of items, so the model also determines the number of separate locations with each item. It is also worth noting that in the pre-processing stage, the distance matrix between all storage locations needs to be calculated.

2.2.1. The MILP model

Indexes:

i, j – indexes of items, $i, j \in \{1, 2, \ldots, I\}$,

k, l – indexes of storage locations, $k, l \in \{1, 2, \ldots, K\}$.

Parameters:

I – total number of items,

K – total number of storage locations,

$K_{\max}$ – maximum allowable number of storage locations for each item,

r_{ij} – correlation of items i and j,

d_{kl} – distance between storage location k and storage location l.

Decision variables:

x_{ik} – assignment of item i to storage location k,

$$x_{ik} = \begin{cases} 1 & \text{if item } i \text{ is assigned to storage location } k \\ 0 & \text{otherwise} \end{cases},$$

y_{ijkl} – marker of the shortest distance between items i and j,

$$y_{ijkl} = \begin{cases} 1 & \begin{array}{l} \text{if item } i \text{ is assigned to storage location } k, \\ \text{item } j \text{ is assigned to storage location } l, \\ \text{and the distance between } k \text{ and } l \\ \text{is the shortest among items } i \text{ and } j \end{array} \\ 0 & \text{otherwise.} \end{cases}$$

Model:

$$\min \sum_{i=1}^{I} \sum_{\substack{j=1 \\ j \neq i}}^{I} \sum_{k=1}^{K} \sum_{l=1}^{K} r_{ij} d_{kl} y_{ijkl} \tag{1}$$

$$\sum_{i=1}^{I} x_{ik} = 1 \quad \forall k = 1, \ldots, K \tag{2}$$

$$\sum_{k=1}^{K} x_{ik} \geq 1 \quad \forall i = 1, \ldots, I \tag{3}$$

$$\sum_{k=1}^{K} x_{ik} \leq K_{max} \quad \forall i = 1, \ldots, I \tag{4}$$

$$y_{ijkl} \leq x_{ik} \quad \forall i, j = 1, \ldots, I;\ j \neq i;\ \forall k, l = 1, \ldots, K \tag{5}$$

$$y_{ijkl} \leq x_{jl} \quad \forall i, j = 1, \ldots, I;\ j \neq i;\ \forall k, l = 1, \ldots, K \tag{6}$$

$$\sum_{k=1}^{K} \sum_{l=1}^{K} y_{ijkl} = 1 \quad \forall i, j = 1, \ldots, I;\ j \neq i \tag{7}$$

$$x_{ik} \in \{0,1\} \quad \forall i = 1, \ldots, I; \forall k = 1, \ldots, K \tag{8}$$

$$y_{ijkl} \in \{0,1\} \quad \forall i, j = 1, \ldots, I;\ j \neq i;\ \forall k, l = 1, \ldots, K \tag{9}$$

In the model by Jiang et al. (2020), the objective criterion minimizes the sum of the distances of all pair items weighted by correlation coefficients r_{ij} calculated by the use of equation (10) recommended for a centralized PD. Constraints (2) guarantee that each location can store only one item. Constraints (3) and (4) ensure that the number of locations storing each item is from 1 to $K_{\max}$. Constraints (5) and (6) connect decision variables y_{ijkl} and x_{ik} ($y_{ijkl} = 1$ only if $x_{ik} = 1$ and $x_{jl} = 1$). Constraints (7) in connection with objective criterion (1) guarantee that decision variables y_{ijkl} indicate the shortest distance between locations with items i and j, and there is only one such value. Finally, constraints (8) and (9) define the types and ranges of the decision variables.

2.2.2. Similarity measure of items useful for a centralized PD

In the model by Jiang et al. (2020), the correlation between items is calculated as follows:

$$r_{ij} = \frac{G_{ij}}{G} \tag{10}$$

where:

G – total number of historical orders,

G_{ij} – number of historical orders containing both i and j items.

Using equation (10) one can obtain higher correlation values for a pair of items that are more often ordered together, regardless of how often these items appeared in orders in a configuration with other items. The obtained values do not reflect the relative relationship between the items. Two items that are rarely ordered but always together may be less correlated than items that are very often ordered but only occasionally in a set. The correlation coefficients determined in accordance with equation (10) can therefore be used to store fast-moving items in locations closer to the PD. However, this requires modifying the objective function (1) in such a way that the minimized expression also includes the distance between the PD and the locations with items.

For the model presented above, it is difficult to obtain solutions, even for small instances (for this reason, the authors also proposed a heuristic that allows approximate solutions to be found). The main reason for the difficulty is the number of binary decision variables y_{ijkl}. Four indexes with a large value domain (two indicating the item number and two indicating the location number) cause the tasks that require solving to become huge. Examples of the model sizes for different values of the number of items and storage locations are presented in Table 1.

2.3. The MILP model for a decentralized PD and item assignment to picking aisles

The model proposed by Jiang et al. (2020) can be simplified by several procedures. First, we assign items to picking aisles instead of specific storage locations. This reduces the number of decision variables, but also allows for easier practical implementation (instead of a dedicated storage policy, we get a random one inside the picking aisles which allows for more flexibility). To determine the pickers' route in a one-block rectangular warehouse, one of the heuristics is usually used: s-shape or return, for which (with some exceptions) precise placement of the item in a specific location in the aisle is not very important. Second, the model will be reduced if the indices of decision variable y do not refer to specific warehouse locations or picking aisles. Instead, we propose indices referring to the location number dedicated for a specific item. Additionally, we abandon the distance matrix, and calculate the distance between items co-occurring on orders directly in the model. For the presented simplified approach, this distance is calculated as the minimum distance between the indices of the aisles to which these products have been assigned.

2.3.1. The MILP model

Indexes:

i, j – indices of item, $i, j \in \{1, 2, \ldots, I\}$,

m, n – indices of picking aisle, $m, n \in \{1, 2, \ldots, N\}$,

a, b – indices of locations with the same item, $a, b \in \{1, 2, \ldots, A_i\}$.

Parameters:

I – total number of items,

N – number of picking aisles,

K_{aisl} – number of storage locations in one picking aisle,

A_i – number of scattered storage locations intended for item i,

r_{ij} – correlation of items i and j,

M – a sufficiently large number, $M \geq N - 1$.

Decision variables:

x_{ima} – assignment of item i to picking aisle m (as a-th location of this item),

$$x_{ima} = \begin{cases} 1 & \text{if item } i \text{ is assigned to picking aisle } m \\ 0 & \text{otherwise} \end{cases},$$

y_{ijab} – the indicator of minimal distance between items,

$$y_{ijab} = \begin{cases} & \text{if the shortest distance between items } i \text{ and } j \\ 1 & \text{is for the } a-\text{th location of item } i \\ & \text{and the } b-\text{th location of item } j, \\ 0 & \text{otherwise} \end{cases},$$

u_{ij} – minimal distance between picking aisles with items i and j.

Model:

$$\min \sum_{i=1}^{I} \sum_{j=1}^{I} r_{ij} u_{ij} \tag{11}$$

$$\sum_{i=1}^{I} \sum_{a=1}^{A_i} x_{ima} \leq K_{aisle} \quad \forall m = 1, \ldots, N, \tag{12}$$

$$\sum_{m=1}^{N} x_{ima} = 1 \quad \forall i = 1, \ldots, I; \forall a = 1, \ldots, A_i \tag{13}$$

$$u_{ij} \geq \sum_{m=1}^{N} m x_{ima} - \sum_{n=1}^{N} n x_{jnb} - \left(1 - y_{ijab}\right) M \quad \forall i = 1, \ldots, I; \forall j = 1, \ldots, I; \\ \forall a = 1, \ldots, A_i; \forall b = 1, \ldots, A_j \tag{14}$$

$$u_{ij} \geq \sum_{n=1}^{N} nx_{jnb} - \sum_{m=1}^{N} mx_{ima} - \left(1 - y_{ijab}\right)M \quad \forall i = 1,\ldots,I; \forall j = 1,\ldots,I;$$
$$\forall a = 1,\ldots,A_i; \forall b = 1,\ldots,A_j \tag{15}$$

$$\sum_{a=1}^{A_i}\sum_{b=1}^{A_j} y_{ijab} = 1 \quad \forall i, j = 1,\ldots,I; j \neq i \tag{16}$$

$$x_{ima} \in \{0,1\} \quad \forall i = 1,\ldots,I; \forall m = 1,\ldots,N; \forall a = 1,\ldots,A_i \tag{17}$$

$$y_{ijab} \in \{0,1\} \quad \forall i, j = 1,\ldots,I; j \neq i; \forall a = 1,\ldots,A_i; \forall b = 1,\ldots,A_j \tag{18}$$

$$u_{ij} \geq 0 \quad \forall i = 1,\ldots,I; \forall j = 1,\ldots,I \tag{19}$$

In our model, the objective criterion (11) minimizes the sum of weighted values of the shortest distances between picking aisles with all pairs of items. The weights are the correlations between items. This concept is similar to the one in Jiang et al. (2020), but as we assume a decentralized PD, the similarity between items is measured in a slightly different way (equations 20–21). Constraints (12) ensure that the number of locations storing items in each picking aisle does not exceed $K_{\max}$. Constraints (13) guarantee that exactly one picking aisle will be assigned for each fixed location intended for an item. Constraints (14) and (15) are active only for the shortest distance between picking aisles with items *i* and *j* and assign that distance to decision variables u_{ij}. For both mentioned sets of constraints, in only one constraint can the right-hand side factor be nonnegative. The weighted sum of u_{ij} is minimized by objective criterion (11), so u_{ij} is exactly equal to that nonnegative value. Constraints (16) guarantee that decision variables y_{ijab} indicate only the one shortest distance between picking aisles containing items *i* and *j*. Finally, constraints (17–19) define the types and ranges of the decision variables.

2.3.2. Similarity measure of items useful for a decentralized PD

The correlation between items can be calculated according to the formula introduced by Bindi at al. (2007):

$$r_{ij} = \frac{G_{ij}}{G_{ij} + G_{i\sim j} + G_{\sim ij}} \tag{20}$$

where:

G_{ij} – number of historical orders containing both items *i* and *j*,

$G\sim_{ij}$ – number of historical orders containing item *j* but not containing item *i* ,

$G_{i\sim j}$ – number of historical orders containing item *i* but not containing item *j*.

SKUs appear in orders with different frequencies. Items that are rarely ordered may often (or even always) be accompanied by another item that also appears in different configurations. In such a situation, the correlation coefficients can be calculated in a different way. The Bindi at al. (2007) formula can be simplified by eliminating the last factor in the denominator:

$$r_{ij} = \frac{G_{ij}}{G_{ij} + G_{i\sim j}} \tag{21}$$

Now the correlation coefficients are not symmetrical, but they better reflect the relationships between the ordered items.

Table 1 presents the basic differences between the presented models, and the advantages and disadvantages of the proposed simplifications in the second model. The basic advantage of the model allocating items to picking aisles is a much smaller number of generated decision variables and constraints. For example, Table 2 presents the values of warehouse parameters, the number of decision variables and the constraints for both models. For all the analysed examples, the model of allocating items to picking aisles reduced the number of both decision variables and constraints by over 99.9%.

Table 1. Differences between the optimization models

	Picker's route	Storage assignment	Correlation between items	Pick-up/Drop-off
Storage using a location assignment model	Searching for the shortest routes between storage locations	Assignment of items to particular locations	The quotient of the number of orders containing both items and the number of all orders; a symmetrical relation	Centralized PD (PD is usually located next to the first picking aisle)
Storage using a picking aisle assignment model	Suitable for s-shape or return routing heuristics	Assignment of items to picking aisles (random storage inside a picking aisle)	The quotient of the number of orders containing both items and the number of orders containing the first of them; an asymmetric relationship	A decentralized PD (a conveyor located along the picking aisles)
Benefits of the model of storage using a picking aisle	No distance matrix	A smaller number of decision variables and constraints in the optimization models	Standardized value, better reflecting the relationship between items	Shorter picker routes and average order picking time
Deficiencies of the model using storage to a picking aisle	Potentially longer routes	The optimization process is less accurate	The picking frequency of items is omitted; high-frequency items can be stored in all picking aisles (not recommended for a centralized PD)	Higher implementation costs

Source: own elaboration.

Table 2. Examples of the size of a small problem-solving

Problem description				
No. picking aisles	10	15	25	30
No. locations in one picking aisle	2 × 10	2 × 20	2 × 25	2 × 100
Total no. locations in warehouse	200	600	1,250	6,000
No. items	100	300	625	3,000
No. locations with the same item	2	2	2	2
Storage using a location assignment model				
No. decision variables	~400 million	~32 billion	~610 billion	~324 trillion
No. integer decision variables	~400 million	~32 billion	~610 billion	~324 trillion
No. constraints	~800 million	~64 billion	~1.2 trillion	~648 trillion
Storage using a picking aisle assignment model				
No. decision variables	52,000	459,000	1,984,375	~45 million
No. integer decision variables	42,000	369,000	1,593,750	~36 million
Variable reduction (%)	99.98700	99.99858	99.99967	99.99999
No. constraints	89,910	809,715	3,515,025	80,997,030
Constraint reduction (%)	99.98876	99.99875	99.99971	99.99999

Source: own elaboration.

3. Experiment results

In order to verify how the solutions generated by the model allocating items to picking aisles affect the length of the picker's route, several experiments were conducted. Unfortunately, none of the experiments confirmed the optimality of the obtained solution admissible for the given maximum computation time. Nevertheless, the solutions allowed for an allocation of items to picking aisles that caused a significant reduction in the distance covered by the picker.

The research was conducted using three artificially generated data sets and one real data set. For generated data, it was assumed that the picking frequency of items follows the 80–20 Pareto rule. The datasets were generated using an exponential distribution according to the procedure presented by Caron et al. (1998).

The number of items in orders ranged from two to four. The orders were initially divided into a training set and a test set. The training set was used to determine the correlation coefficients between the items, and the distances covered by the picker were later calculated based on the orders from the test set. It was assumed that the number of locations with the same item was 2 for all items, or from 1 to 4 (in one experiment from 2 to 3) depending on the turnover coefficient determined based on the training set (the most frequently ordered items were assigned to a larger number of locations).

The problems were solved using Python and the Gurobi solver. The maximum computation time was set at 3,600 seconds for smaller problems (artificial data) and 10800 seconds for problems based on a set of real data. Gurobi did not find an optimal solution for any task within the allotted time (in fact, we do not even have confirmation of the potential optimality of the obtained solutions), but very quickly (within a dozen or so seconds) it found acceptable solutions, which were then improved. The computation progress for sample problems generated for the artificial data is shown below in Figure 3. The thicker points on the graph indicate a change in the value of the objective function.

The most feasible solutions obtained after reaching the time limit were used to allocate items to picking aisles and made it possible to determine the average distances covered by the picker. The picker's route was determined for a decentralized PD (the picker started the route at the beginning of the picking aisle where they finished the previous order) and the return heuristic (Figure 2a). For almost all experiments, the distance was reduced compared to both random scattered storage and storage in single locations according to the popular heuristic based on the ABC classification: across aisle. Only in one experiment conducted for real data (number of locations with the same item: 1–4) was the picker's route extended. The feasible solution determined within the designated time limit of 3 hours was of too poor quality. Calculations in the Gurobi solver for this example were performed again with an increased calculation time limit of 190,800 seconds. Figure 4 below shows the progress of results for examples generated on the basis of the real data set. For the analysed problem, the best solution was obtained after about 48,000 seconds, and further calculations did not improve it. Table 3 presents both the distance value determined based on the result obtained in the time limit of 10,800 seconds and 190,800 seconds (marked with an asterisk). Increasing the calculation time reduced the value of the objective function value by 25.9%, which in consequence caused the average distance of the picker to be shortened by 6.1% (from 47.90 to 44.94).

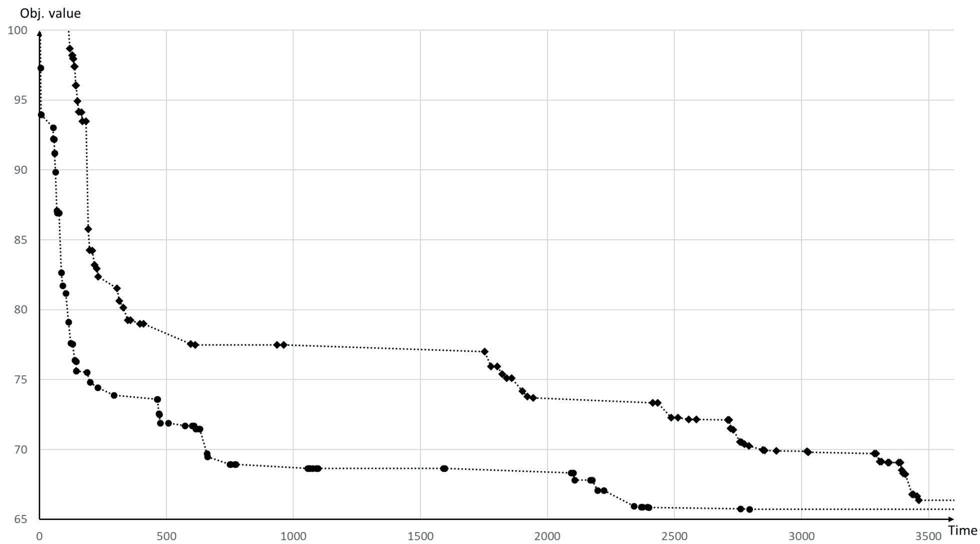

Figure 3. Changes in the objective function value during the optimization process for problems generated for artificial data

Source: own elaboration.

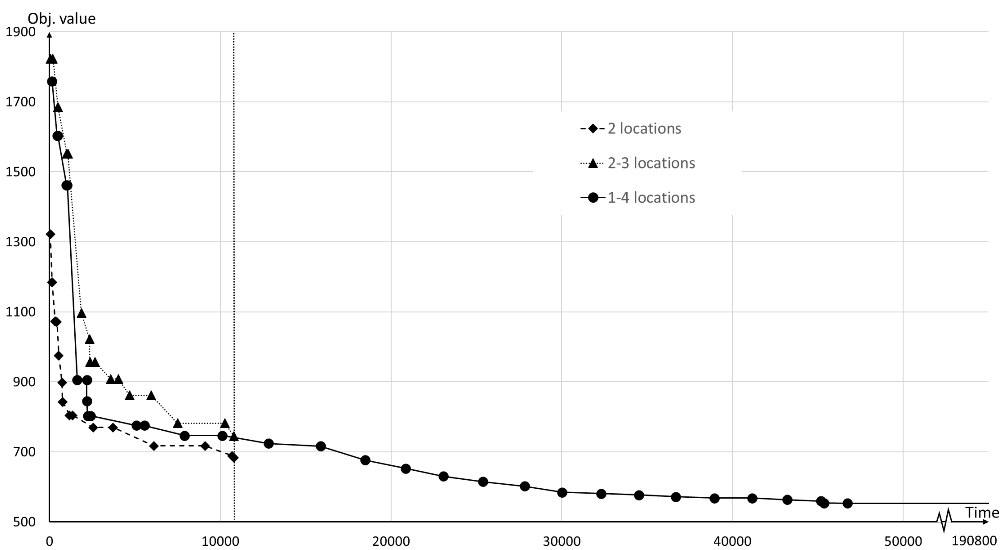

Figure 4. Changes in the objective function value during the optimization process for problems generated for real data

Source: own elaboration.

Table 3. Comparison of the average distance travelled by the picker for conventional ABC storage (one location of each item according to a within aisle policy), random scattered storage, and optimized scattered storage

Dataset	No. items on one pick list	No. locations with the same item	No. picking aisles	No. locations in a picking aisle	Storage method		
					one location ABC within aisle	scattered random	scattered optimized
Artificial DS1	2	2	15	20	23.94	24.71	17.49
Artificial DS1	2	1–4	15	20	29.08	26.13	19.77
Artificial DS2	3	2	15	20	26.74	34.18	22.31
Artificial DS2	3	1–4	15	20	34.30	33.65	31.23
Artificial DS3	4	2	20	20	31.26	41.23	30.96
Artificial DS3	4	1–4	20	20	40.53	42.57	33.79
Real dataset	2–4	2	15	60	46.20	44.89	42.66
Real dataset	2–4	2–3	15	60	49.46	46.91	44.25
Real dataset	2–4	1–4	15	60	49.88	45.78	47.90 (44.94*)

* Obtained for longer solver calculation time.

Source: own elaboration.

Based on the research, it is difficult to state unequivocally whether differentiating the number of locations designated for an item based on its turnover rate has a positive effect on the length of the picking route. This issue should be thoroughly investigated in further research.

Conclusions

In this paper, we introduce and analyse the problem of scattered storage assignment into picking aisles instead of exact locations. The aim of the proposed MILP model is to assign items to picking aisles in such a way that minimizes the weighted sum of closest distances between picking aisles containing a pair of items that occurred together on previously fulfilled orders. In the research, we analyse a one-block rectangular warehouse with a decentralized PD, and present a formula for determining the correlation between items appropriate for such a warehouse layout. Thanks to the adopted simplifications, the size of the model has been drastically reduced compared to the model that was the starting point of our research.

The results of the empirical study indicate that obtaining acceptable solutions is possible in a short time, and the distances covered by the picker can be shortened compared to random scattered storage (the reduction was on average 17%, and in one case even by over 34% compared to random storage). The problem that we tried to investigate initially, but for which we were unable to reach key conclusions, is determining the number of locations designated for a given item and linking this number with the turnover coefficient of this item. This issue requires further detailed research. Another issue that may constitute a basis for future study is the simplification of the optimization criterion. Minimizing the sum of weighted average distances between picking aisles with items, instead of the closest distances, may make the model easier to solve and could result in finding an optimal solution.

Applying the proposed method carries certain risks related to demand volatility. Certain challenges in practical implementation may also require periodic verification and modification of the adopted solutions.

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