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Article

Investigation of factors and consequences in the evaluation process for storage location assignment optimization

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Abstract: Optimizing Storage Location Assignment (SLA) is essential for improving warehouse operations, reducing operational costs, travel distances and picking times. The effectiveness of the optimization process should be evaluated. This study introduces a novel, generalized objective function tailored to optimize SLA through integration with a Genetic Algorithm. The method incorporates key parameters such as item order frequency, storage grouping, and proximity of items frequently ordered together. Using simulation tools, this research models a picker-to-part system in a warehouse environment characterized by complex storage constraints, varying item demands and family-grouping criteria. The study explores four scenarios with distinct parameter weightings to analyze their impact on SLA. Contrary to other research that focuses on frequency-based assignment, this article presents a novel framework for designing SLA using key parameters. The study proves that it is advantageous to deviate from a frequency-based assignment, as considering other key parameters to determine the layout can lead to more favorable operations. The findings reveal that adjusting the parameter weightings enables effective SLA customization based on warehouse operational characteristics. Scenario-based analyses demonstrated significant reductions in travel distances during order picking tasks, particularly in scenarios prioritizing ordered-together proximity and group storage. Visual layouts and picking route evaluations highlighted the benefits of balancing frequency-based arrangements with grouping strategies. The study validates the utility of a tailored generalized objective function for SLA optimization. Scenario-based evaluations underscore the importance of fine-tuning SLA strategies to align with specific operational demands, paving the way for more efficient order picking and overall warehouse management.

Keywords: storage location assignment; objective function; evaluation method; parameterization; optimization

1. Introduction

Order picking is the most time- and cost-consuming operation within a warehouse (Le-Duc and De Koster, 2005). In the interest of fostering efficient warehouse operations, it is essential to review processes and intervene at the right time to optimize them. The optimization process, particularly in a picker-to-part system, is geared towards supporting order picking activities. According to the literature, various research efforts focus on optimizing picking routes, while others concentrate on optimizing Storage Location Assignment (SLA) or a combination of both to increase efficiency, reduce travel distances and picking time (Le-Duc and De Koster, 2005; Xu et al., 2024; Xu and Ren, 2022; Zhang, 2016). By enhancing the SLA and picking routes, warehouses can significantly improve their throughput and response times to customer orders.

The concept of SLA is fundamental to efficient warehouse management, focusing on the strategic assignment of inventory to optimize space utilization and enhance operational efficiency. SLA involves the careful allocation of various items—each differing in size, weight and turnover rates—to specific locations, a practice crucial for improving picking efficiency. For instance, high-demand items are often positioned near preparation areas to minimize travel time and costs. Dynamic demand in industries such as fast-moving consumer goods (FMCG) and e-commerce introduces complexity into the SLA process. Factors like seasonal fluctuations and promotional activities necessitate frequent adjustments to SLA to maintain optimal efficiency. Advancements in technology, including warehouse management systems (WMS) and machine learning, further aid in refining SLA by predicting optimal item placements based on historical data and anticipated trends. Effective SLA is vital not only for reducing operational costs but also for improving customer satisfaction through faster order fulfilment, thereby boosting a warehouse's competitive edge. Optimizing SLA is crucial at various stages of a warehouse's lifecycle. It is particularly critical when establishing or reorganizing a warehouse to ensure space is used efficiently from the start. Adjustments to SLA are also essential during significant inventory changes like the introduction of new products or during peak seasons to adapt to new demand patterns. Periodic reviews and updates are necessary, especially in rapidly evolving sectors like FMCG or e-commerce, to keep the SLA aligned with current operational demands and market conditions. Scheduled regular optimizations can pre-empt potential inefficiencies and maintain ongoing operational excellence, ensuring that warehouses operate at their optimal capacity continuously.

The optimization of SLAs has been studied from several angles and several authors published articles on solving SLA. The Storage Location Assignment Problem (SLAP) is addressed within the literature on this topic. There are several SLA policies to assign the items - like random storage, full turnover storage, class-based (de Koster et al., 2007). In the state-of-the-art research, it is clearly visible that solving SLA has been investigated by combining different storage and order picking logics (van Gils et al., 2018; Xu and Ren, 2022). In many cases, the batching of order picking (Ardjmand et al., 2019; Kübler et al., 2020) and class-based storage (Wang et al., 2020; Yerlikaya and Arıkan, 2024) are used for picking inspections to ensure efficient picking. SLA policies require a complex solution. Based on the number of combinations when hundreds of items need to be assigned to hundreds of locations, SLAP is a huge combinatorial problem. The solution of SLAP is being studied by many researchers and the most researched direction is the application of heuristics (Liu and Poh, 2023; Quintanilla et al., 2015; Xie et al., 2015) and algorithms based on different approaches. Based on our literature review, SLA optimization has been successfully applied with Particle Swarm Optimization (PSO) (He et al., 2019), Discrete Evolutionary Particle Swarm Optimization (DEPSO) (Kübler et al., 2020) and evolutionary algorithms, like differential evolution algorithm (Wisittipanich and Kasemset, 2015; Wisittipanich and Meesuk, 2015); Genetic Algorithm (GA) (Pawar et al., 2024; Peng et al., 2021; Saleet, 2020; Xu and Ren, 2020; Zhou et al., 2020) and Bacterial Memetic Algorithm (BMA) (Udvardy et al., 2024).

The optimization process and algorithms require evaluation. During the research, the literature primarily focuses on reducing the total picking time or decreasing picking distances. Picking lists were utilized for evaluation of SLA, with the goal of shortening the picking route to complete picking tasks more effectively (Dijkstra and Roodbergen, 2017; Li et al., 2016; Li et al., 2021; Silva et al., 2020; Zhang et al., 2019; Zhang, 2016). When checking against the various lists, only a partial allocation of items can be known by comparing the lists. The authors of the article were curious about how the entire SLA changed during the optimization process, which was not an example during the state-of-the-art research. A new, generalized evaluation method and objective function have been formulated that comprehensively assesses the entire SLA. Since managing items ordered together and compliance with storage together rules are important factors in warehouse operations, the evaluation method takes this into account in addition to order frequency, allowing for a comprehensive examination of warehouses. In the operation of FMCG warehouses, the order frequency value of items is important, but there may also be regulations that certain items must be stored together, so it is crucial during optimization that the algorithm places them together in SLA. Such as in the electronics sector, certain products are commonly stored together due to their complementary nature. Laptops are frequently stored alongside laptop bags and accessories, while smartphones are often paired with chargers, cases and screen protectors to facilitate convenient order fulfillment. Considering commercial aspects, it can be demonstrated which items are frequently ordered together, even if their frequency values vary greatly. A commonly cited example is the joint ordering of ketchup and mustard, particularly from the perspective of restaurant or household consumption. Typically, ketchup appears on order lists more frequently due to its higher demand compared to mustard. However, it is also common that when mustard is ordered, ketchup is purchased alongside it. Based on this example similar co-ordered patterns can be observed across various product categories. In the food and beverage sector—like ketchup and mustard—coffee is often ordered together with sugar or cream. In the realm of electronics, items like computers are frequently purchased together with accessories such as computer monitors. Office supplies also exhibit such patterns, with notebooks and pens, or printers and ink cartridges being common ordered together. In the automotive sector, motor oil and oil filters or car wax and microfiber cloths are typical complements. Lastly, seasonal items, such as barbecue grills with charcoal or wrapping paper with tape, also highlight these co-ordering trends. It may be advisable to place these products close to each other during the optimization of SLA to minimize travel distances, improve picking efficiency, and streamline order fulfillment processes. In many warehouses, not every item is assigned a picking position. After the optimization of SLA and during the examination of replenishment processes, a product that justifies its frequency value should be placed in a picking location. The discussed factors may not be relevant for every warehouse, or to the same extent. To manage and examine this, the objective function is equipped with weight parameters. This article presents the generalized objective function and the specifics of its parameterization. Through an analytical example, the effects of weight parameter settings according to different scenarios on SLA are presented. For the examination, the objective function uses the

GA algorithm, which is most applied for SLA optimization. The validation of the objective function and the efficiency of the optimization are investigated by means of the picking lists.

The article aims to highlight the benefits of deviating from solely frequency-based SLA planning, emphasizing the importance and utility of considering various factors within the framework of more complex evaluations to refine SLA optimization and enhance operational efficiency.

2. Applying a generalized objective function in the evaluation and optimization of storage location assignment

This section provides a detailed exploration of the generalized objective function used for evaluating the SLA optimization process. It discusses various factors considered during assignment process such as frequency-based arrangement, storing together criteria, and family-grouping, where products frequently ordered together are stored in close proximity. Furthermore, the adaptability of the objective function is demonstrated through its application across various logistic scenarios, using the Genetic Algorithm to validate its effectiveness. The goal of the objective function is to determine a favorable SLA during the optimization process by weighting the described aspects, thus supporting shorter picking distances and efficient warehouse operations.

2.1. The generalized objective function

Based on the factors considered, the objective function is defined and published previously by the authors as follows, that designed to examine the entire SLA (Görbe and Bódis, 2023). The objective function's parameters include the number of picking of the item on the p picking location (f_{pt}), the summarized item order lines (F_t), the distance between picking location and the depot (l_p), the number of picking of non-assigned items (j_t), the distance between items within a group ($lg_{i1,i2}$), the number of items within a group (Ig_n), the order frequency of two ordered together items (o_{i_1,i_2}), the distance between of two items (l_{i_1,i_2}), and the weights of the components (ω_n) (Equation (1)). Equation (2) gives frequency value of the items based on the order characteristics. Equation (3) evaluates non-assigned items and gives the value for objective function. These components are addressed jointly in the objective function since they influence one another. Warehouses frequently adopt the logic of storing together, in which identical items or items categorized based on specific criteria are stored together. Equation (4) evaluates the range of these items. During the optimization process, it is could be important in warehouses to store regularly co-ordered items close together so that they may be picked quickly. This is the family grouping method. Equation (5) evaluates the ordered together items.

$$\min\left(\frac{\omega_1 * \sum_p\left(\frac{f_{pt}}{F_t} * l_p\right)}{\omega_2 * \frac{1}{\sum_i \frac{j_t}{F_t}}} + \omega_3 * \sum_g \frac{\sum lg_{i1,i2}}{Ig_n} + \omega_4 * \sum_i \left(\frac{o_{i1i2}}{\sum_i o_{i1i2}} * l_{i1i2}\right)\right) \tag{1}$$

$$\sum_{p}(\frac{f_{pt}}{F_t}\cdot l_p) \tag{2}$$

$$\frac{1}{\sum_i \frac{j_t}{F_t}} \tag{3}$$

$$\sum_{g}\frac{\sum lg_n}{Ig_n} \tag{4}$$

$$\sum_{i}(\frac{o_{i_1,i_2}}{\sum_i o_{i_1,i_2}}\cdot l_{i_1,i_2}) \tag{5}$$

Each term in the objective function has a weighting parameter. These weights allow for the customization of the evaluation of the warehouses under study, enabling adjustments on how much each factor influences the operation of a specific warehouse. Additionally, by modifying and fine-tuning the weights, the assignment can be supported to achieve more efficient operations.

In certain warehouses where the stored together factor is not relevant, the weighting is set at a lower proportion; however, if the product portfolio indicates that numerous products are regularly ordered together, it may be advisable to set this weighting parameter at a higher proportion. In the case of products ordered together, the frequency parameter may vary, but by applying the family-grouping logic and storing these products closer to each other—deviating from strict frequency-based storage—a more favorable picking route length can be achieved.

Thus, information can be provided to the optimization algorithm on where to direct the SLA through the parameterization of the weights.

2.2. Parameterization of the objective function

Logistical case study formulated based on industrial experiences were employed to examine the operation of the evaluation method and the objective function. Within this context, a warehouse environment was defined, which utilizes single-deep racking storage method which is commonly used in the picker-to-parts systems. The stored products are characterized by rapidly changing demands, a wide range of products, and seasonality, typical of the FMCG sector. The products possess varying ordering frequencies. An important factor of the storage strategy is the adherence to storing together rules and the consideration of items often ordered together, known as 'family grouping,' which facilitates operational efficiency but presents a challenge in the optimization process. Furthermore, during the allocation of storage locations, only one item per picking location is permitted. In the test case, the specified warehouse had 1332 picking locations. The use of buffer locations was necessary for real warehouse operations. In our case, we defined 10% of the total picking locations, which were 133 buffer locations. Based on this, it was necessary to assign 1199 picking locations to the items stored. The model considered 1466 items that needed to be handled in the warehouse. Since we allowed one item per location, some items were not assigned to picking locations. These items were non-assigned items that were physically collected but were assigned to a storage location that was not a low-level picking location. The items had a picking frequency value, which categorized the items as A, B and C. Due to the storing together criteria, four groups were defined for the study. Each group contains a different quantity of products. In relation to products ordered together, 146 combinations were designated for the study, involving 255 products. **Table 1** summarizes the specifications for the modelled case study.

Table 1. Specifications of the modelled case study.

Number of items		1466
Number of picking locations		1332
Buffer locations		133
Number of stored together items	Group 1	165
	Group 2	55
	Group 3	92
	Group 4	55
Number of combinations of items ordered together		146
	Involved items	255
Number of non-assigned items		267

As mentioned, the defined warehouse incorporates strategies including the storing together criteria and rules for storing frequently ordered products together, beyond just frequency values. We examined the characteristics that warehouses might have regarding storage strategies to determine different weightings for the objective function. For modelling real warehouse operations, we defined and utilized four scenarios in the case study, which provide the weighting parameters for the objective function to investigate its behavior during algorithm execution. During the study, we will modify the weighting parameters of the 1st, 3rd and 4th components, which are the item frequency value (ω_1), stored together items (ω_3) and ordered together items (ω_4). The examination of non-assigned items is not emphasized in the article but is part of the frequency-based assignment, and previous experience suggests that even minimal value assignment supports the objective function to direct products to guaranteed locations for items that are rarely ordered. Functionally, for the objective function (Equation (1)), it is mandatory to assign a minimal value to the non-assigned component and give it a fixed parameter during the study. The scenarios were defined with different weighting ratios. Each scenario represents a real operation. We examine the changes in assignment through the described case study by altering the ratios of these factors. The scenarios are summarized in **Table 2**. To examine the operation of the objective function, the first scenario uses only the frequency-based assignment, where the other weights do not receive any value. In the settings of the other three scenarios, it is observable that frequency receives a significant weight initially, and gradually, the other factors become more important.

Table 2. Weights of scenarios.

Scenario	ω_1	ω_2	ω_3	ω_4
1	100 %	-	-	-
2	90 %	-	5 %	5 %
3	70 %	-	20 %	10 %
4	50 %	-	30 %	20 %

3. Results and discussion

For the empirical research, modelling scenarios, we utilized the Tecnomatix Plant Simulation 2201.0010 software developed by Siemens. We implemented a genetic algorithm for the optimization task, which, as the literature shows, is the most effective solution for solving the SLAP. The genetic algorithm was programmed in the software, inserting our defined objective function into its evaluation component. At the end of the optimization process, the software allows us to visually represent the assignments on the layout. During the analytical examination, we analyse the impact of the objective function on the optimizing algorithm by comparing these arrangements. The SLA optimization in the study begins with a random arrangement, which is the initial state shown in **Figure 1**. Different colors indicate different categories based on the frequency values. Red indicates category A, green category B and blue category C. Our decision was based on the fact that we found it absolutely necessary to investigate the ability of the objective function to support the layout from a rule-free initial state based on parameters.

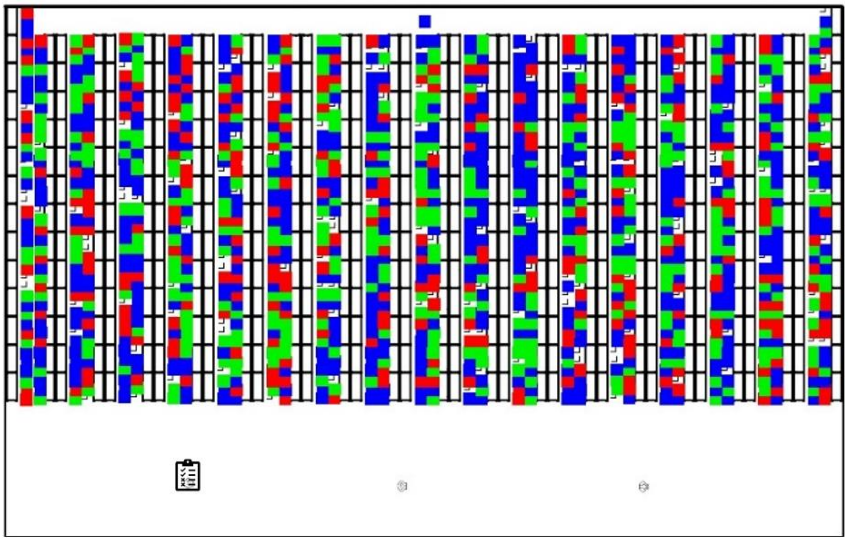


Figure 1. Random assignment.

The results of running the optimization algorithm with the objective functions parameterized by the four scenarios are shown in the layout in **Figure 2**. In image (a), the assignment according to Scenario 1 clearly shows that the items are organized based on frequency values into A, B and C categories. The algorithm aligns the assignment with the bottom left depot point, considering distance data.

The changes in assignment based on different scenario settings can be seen in images (b), (c) and (d). In each scenario, the heaviest weight is given to assigning items according to their frequency. This well-established criterion was not intended to be underweight at all during the optimization of the assignment. As the storage groups receive greater weight, they become more pronounced in the assignment. The groupings are framed in the **Figure 2b–d**. Within the groups, there are mixed items based on frequency categories, which affect the placement of individual groups. Based on frequency data, some items are placed in less frequented locations, but thanks to the groupings, the picking route may be reduced in the long term. The proximity of items that are ordered together is also visible in the assignment, showing up in mixed colors compared to the clear assignment from Scenario 1. In these cases, a trade-off may occur where an A-category product can be placed further away in the assignment, or a B or C category product ordered with it can be placed closer to the A-category items. By examining and weighting both stored together and ordered together items, the length of the picking route can be further reduced. The scenarios are weighted as follows. Scenario 2 introduces a modest consideration for grouping and co-ordering, assigning 5% weight to each while retaining a strong emphasis (90%) on frequency. In Scenario 3, the weights shift further, with 20% assigned to grouping and 10% to co-ordering, reducing the frequency factor to 70%. Scenario 4 places a strong emphasis on grouping (30%) and co-ordering (20%), with frequency reduced to 50%.

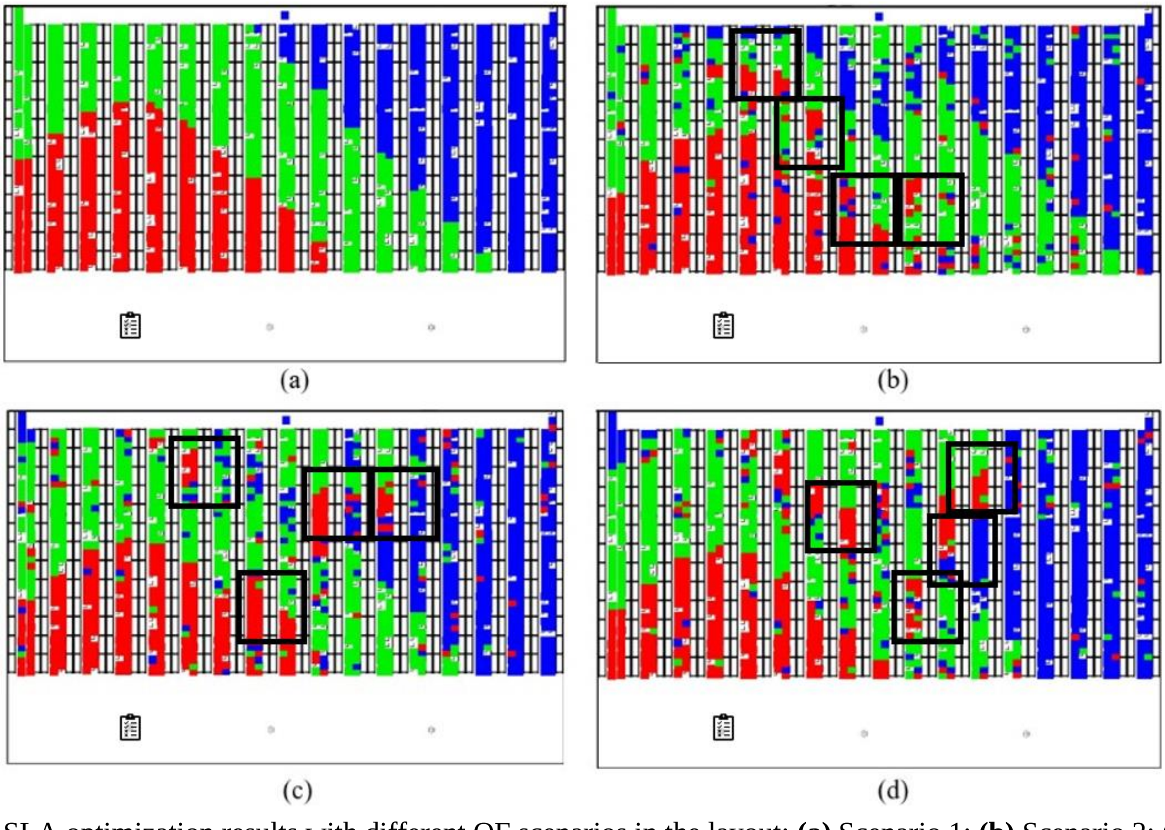


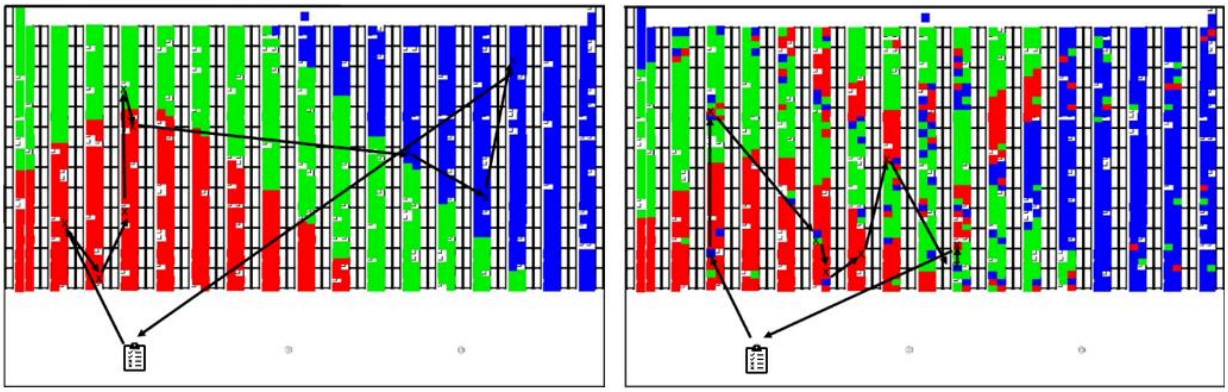
Figure 2. SLA optimization results with different OF scenarios in the layout; **(a)** Scenario 1; **(b)** Scenario 2; **(c)** Scenario 3; **(d)** Scenario 4.

We employed picking lists to assess the impact and efficiency of the layouts provided by the scenarios on the picking processes. Various lengths and compositions of picking lists were defined for the examination, these are summarized in **Table 3**. The lists contain different item types in different numbers. The quantity to be picked per item and the picking time of the picking task are not included in the scope of the inspection. It focuses on the location of items and examines to reduce the length of the picking route. As presented, the test warehouse was designated with grouping and ordered-together characteristics. Taking these characteristics into account, the picking lists were randomly assembled to simulate the diverse, real-world operation of the warehouses. Items in the lists were allocated mixed, taking into account groups and the often ordered together items. **Figure 3** displays the storage locations that need to be visited according to the first picking list. According to the list, it is necessary to pick 8 items, so 8 locations must be visited during the picking task. The layout in **Figure 3a** shows the assignment of Scenario 1, where items were assigned based on their frequency values. List_1 contains items, most of which belong to the items that are ordered together regularly. **Table 3** shows how the length of the picking route varies based on the assignment of items in the different scenarios.

Table 3. Length of picking routes for different scenarios.

Picking list	Num. of items/list	Total distance [m]			
		Scenario 1	Scenario 2	Scenario 3	Scenario 4
List_1	8	319,41411	371,91478	263,76883	214,0851
List_2	9	327,16729	326,29419	328,81717	351,34246
List_3	5	261,79623	295,07863	254,39032	264,08967
List_4	10	357,00598	313,31405	381,81356	347,38195
List_5	4	189,96299	157,65299	101,14847	151,2133
Total distance [m]/scenario		1455	1464	1330	1328

In Scenario 1, which relies solely on frequency-based assignment, items with high turnover rates (Category A) are assigned closest to the depot to minimize travel distances for frequently picked items. While this approach works well for simple operations with a narrow focus on item turnover, it fails to account for the benefits of grouping or co-ordering. As a result, travel distances remain longer in cases where frequently ordered together items are stored far apart, making this scenario less effective for warehouses with complex order patterns. In scenario 2 the slight adjustment improves picking efficiency in scenarios involving ordered together items, but the improvements are limited. The scenario represents a transitional approach, providing incremental gains but not fully capitalizing on the benefits of grouping and proximity-based storage. Scenario 3 leads to significant reductions in travel distances, particularly when items that are frequently ordered together are stored near each other. However, some trade-offs arise when less frequently ordered items are moved closer to meet grouping requirements. Overall, this scenario strikes a balance between improving efficiency and maintaining practicality, making it a more robust option for warehouses with moderate complexity. Scenario 4 achieves the most favorable outcomes, with the shortest overall travel distances and the highest picking efficiency. Frequently co-ordered items are consistently stored in close proximity, optimizing the picking process for diverse and interdependent product assortments. While this approach may involve compromises for items with lower turnover rates, it is particularly well-suited for warehouses where grouping and co-ordering patterns significantly influence operational efficiency and the picking lead time. In summary, scenario 1 is ideal for simple setups, while Scenario 4 offers maximum efficiency for complex and diverse order patterns. Scenarios 2 and 3 provide intermediate solutions, with Scenario 3 standing out as a balanced approach for operations requiring some level of grouping and co-ordering.



(a) (b)

Figure 3. List_1 picking route comparison for scenario 1 and scenario 4.

The experience of comparing picking lists demonstrates that it is necessary to define the weighting parameters of the evaluation method through the examination of specific warehouse operations and picking lists. Proper analysis, uncovering characteristics and examining ordering characteristics are essential for parameterizing the objective function before the optimization process to achieve the most favorable results. The limitation of the method, as shown by the results of picking lists created through sampling, is that in some cases, based on the composition of the list, the travel route is not always optimal in the given arrangement when each list is examined separately. Not every order and picking list is composed in such a way that it involves all the characteristics. However, optimizing the SLA according to individual factors limits the achievement of more favorable picking routes. Based on the study, it can be stated that in warehouse operations with mixed ordering characteristics, where groupings and the proximity storage of items ordered together are important, more favorable results can be achieved after optimization. This is represented by Scenario 4, where the weighting of the factors is higher and shows the most favorable result for the entire picking route during the simulation study.

Periodic review and re-optimization of SLA, combined with the integration of the evaluation method, provides an opportunity for warehouses to respond more quickly to changing demands and become more flexible in their operations. During periodic reviews, the use of identical weight parameters in the objective function allows for tracking how SLA have evolved. In the redesign phase, the ideal SLA value derived from the objective function can serve as a benchmark, in addition to evaluating against picking lists. Thanks to the parameterizable of the objective function, the SLA can be fine-tuned to maintain and enhance efficiency. The described objective function enables achieving an SLA during optimization that reduces picking routes and lead times. This can yield favorable results for warehouse operations in multiple ways. Shorter picking times per picking list allow for the completion of more orders, improving efficiency and saving human resources.

4. Conclusion

During the optimization of SLA, the primary goal is to find an assignment that reduces travel distances during picking and enables efficient warehouse operations. While most research in this process focuses on distances and analyses outcomes based on specific tasks, this study concentrates on evaluating the entire SLA. The article presented a novel generalized objective function for optimizing Storage Location Assignment (SLA) in warehouses, addressing efficiency challenges in order picking processes. By integrating parameters such as item order frequency, storing-together rules and ordered-together proximity, the study demonstrated improved operational outcomes. The methodology incorporated a simulated warehouse setup with specific storage constraints, product characteristics and operational requirements, ensuring the robustness of the analysis. The defined objective function was successfully integrated into a genetic algorithm applied for SLA optimization. The impact of the objective function on the algorithm and thus on SLA was examined through the parameterization of the function’s weights. In addition to visual and quantitative evaluations, the achieved results were also verified using picking lists. Optimizing the SLA based solely on individual factors can restrict the potential to achieve more favorable picking routes. The study indicates that in warehouse operations with mixed ordering characteristics, where we consider the priority of storing frequently ordered items and groupings in close proximity, optimization tends to yield more favorable outcomes. Scenario-based analysis revealed that balancing frequency-based arrangements with grouping strategies significantly reduced picking route distances. Examining warehouse characteristics and order patterns is crucial for parameterizing the objective function. By testing the parameter settings, the SLA optimization can be fine-tuned to achieve efficient operation. The research highlights the utility of tailored generalized objective function and factor-based SLA optimization for enhancing warehouse efficiency and operational adaptability.

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References

Ardjmand, E., Sanei Bajgiran, O., & Youssef, E. (2019). Using list-based simulated annealing and genetic algorithm for order batching and picker routing in put wall based picking systems. Applied Soft Computing, 75, 106–119. https://doi.org/10.1016/j.asoc.2018.11.019

de Koster, R., Le-Duc, T., & Roodbergen, K. J. (2007). Design and control of warehouse order picking: A literature review. European Journal of Operational Research, 182(2), 481–501. https://doi.org/10.1016/j.ejor.2006.07.009

Dijkstra, A. S., & Roodbergen, K. J. (2017). Exact route-length formulas and a storage location assignment heuristic for picker-to-parts warehouses. Transportation Research Part E: Logistics and Transportation Review, 102, 38–59. https://doi.org/10.1016/j.tre.2017.04.003

Görbe, P., Bódis, T. (2023). Generalized objective function to ensure robust evaluation for evolutionary storage location assignment algorithms. Communications in Computer and Information Science, 1864, 546–559. https://doi.org/10.1007/978-3-031-41774-0_43

He, Y., Wang, A., Su, H., et al. (2019). Particle Swarm Optimization Using Neighborhood-Based Mutation Operator and Intermediate Disturbance Strategy for Outbound Container Storage Location Assignment Problem. Mathematical Problems in Engineering, 2019(1). Portico. https://doi.org/10.1155/2019/9132315

Kübler, P., Glock, C. H., & Bauernhansl, T. (2020). A new iterative method for solving the joint dynamic storage location assignment, order batching and picker routing problem in manual picker-to-parts warehouses. Computers & Industrial Engineering, 147, 106645. https://doi.org/10.1016/j.cie.2020.106645

Le-Duc *, T., & De Koster, R. (M.)B. M. (2005). Travel distance estimation and storage zone optimization in a 2-block class-based storage strategy warehouse. International Journal of Production Research, 43(17), 3561–3581. https://doi.org/10.1080/00207540500142894

Li, J., Moghaddam, M., & Nof, S. Y. (2016). Dynamic storage assignment with product affinity and ABC classification—a case study. The International Journal of Advanced Manufacturing Technology, 84(9–12), 2179–2194. https://doi.org/10.1007/s00170-015-7806-7

Li, Y., Méndez-Mediavilla, F. A., Temponi, C., et al. (2021). A Heuristic Storage Location Assignment Based on Frequent Itemset Classes to Improve Order Picking Operations. Applied Sciences, 11(4), 1839. https://doi.org/10.3390/app11041839

Liu, M., & Poh, K. L. (2023). E-commerce warehousing: An efficient scattered storage assignment algorithm with bulky locations. Computers & Industrial Engineering, 181, 109236. https://doi.org/10.1016/j.cie.2023.109236

Pawar, N. S., Rao, S. S., & Adil, G. K. (2024). Scattered storage for retail e-commerce fulfillment warehouses with consideration for product turnover. Computers & Industrial Engineering, 197, 110551. https://doi.org/10.1016/j.cie.2024.110551

Peng, G., Wu, Y., Zhang, C., et al. (2021). Integrated optimization of storage location assignment and crane scheduling in an unmanned slab yard. Computers & Industrial Engineering, 161, 107623. https://doi.org/10.1016/j.cie.2021.107623

Quintanilla, S., Pérez, Á., Ballestín, F., et al. (2015). Heuristic algorithms for a storage location assignment problem in a chaotic warehouse. Engineering Optimization, 47(10), 1405–1422. https://doi.org/10.1080/0305215x.2014.969727

Saleet, H. (2020). Smart Solution For Enhancing Storage Location Assignments In WMS Using Genetic Algorithm. International Journal of Engineering Research and Technology, 13(11), 3456. https://doi.org/10.37624/ijert/13.11.2020.3456-3463

Silva, A., Coelho, L. C., Darvish, M., et al. (2020). Integrating storage location and order picking problems in warehouse planning. Transportation Research Part E: Logistics and Transportation Review, 140, 102003. https://doi.org/10.1016/j.tre.2020.102003

Udvardy, K., Görbe, P., Bódis, T., et al. (2024). Conceptual Framework for Adaptive Bacterial Memetic Algorithm Parameterization in Storage Location Assignment Problem. Mathematics, 12(23), 3688. https://doi.org/10.3390/math12233688

van Gils, T., Caris, A., Ramaekers, K., et al. (2019). Designing efficient order picking systems: The effect of real-life features on the relationship among planning problems. Transportation Research Part E: Logistics and Transportation Review, 125, 47–73. https://doi.org/10.1016/j.tre.2019.02.010

van Gils, T., Ramaekers, K., Caris, A., et al. (2018). Designing efficient order picking systems by combining planning problems: State-of-the-art classification and review. European Journal of Operational Research, 267(1), 1–15. https://doi.org/10.1016/j.ejor.2017.09.002

Wang, M., Zhang, R. Q., & Fan, K. (2020). Improving order-picking operation through efficient storage location assignment: A new approach. Computers & Industrial Engineering, 139, 106186. https://doi.org/10.1016/j.cie.2019.106186