Proceedings of the 10th Annual World Conference of the
Society for Industrial and Systems Engineering,
2021 SISE Virtual Conference
September 23-24, 2021

The Walking Map: A Novel Heuristic for Storage Location Assignment in Warehouse Operations

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Abstract: Warehouse related expenses account for around 25% of the logistics cost in western countries. Logistics, in turn, accounts for about 30% of the final commodity price, making efficient warehouse operations an integral part of any successful business. Delving deeper into the warehouse operations, order picking is the operation to which the majority of the cost (50-75%) is related. Furthermore, the importance of order picking is growing with the rise of e-commerce practices, challenging warehouses with ever-smaller orders needing to be filled ever faster. This could be seen in the order picking share of warehouse operating expenses increasing from 60% in 1996 to 80% in 2007. Order picking planning comprises of four interdependent disciplines: storage location assignment, order batching, zone picking, and picker routing. The "Walking Map" heuristic method devised in this article is a storage location assignment approach that bases its assignment on the picker routing. This method utilizes the historical order picker path and ranks the locations in the warehouse based on their visit frequency. The combinations of different storage and routing approaches are analyzed to establish a benchmark of total distance traveled while addressing the interdependency of disciplines. In addition, a case study was carried out to test and analyze the performance of this heuristic using various cross-aisle and aisle combinations, routing methods, and multiple SKU ranking and clustering approaches. The Walking Map method's significant improvement over the widely used and accepted cube-per-order index in terms of total distance traveled is illustrated and statistically proven through an analysis of variance (ANOVA).

Keywords: Warehouse operations, Storage location assignment, Order picking, Simulation

1. Introduction

Due to the increasing complexity of the markets and globalization, the efficiency of a supply chain is ever more important to business success. This efficiency heavily depends on operational factors such as the warehouses' operations (Prasad & Sounderpandian, 2003). A warehouse is the critical connection point where products and goods are stored for an uncertain amount of time until a customer order generates a need for their movement to another warehouse, distribution center, manufacturing floor, or final customers. When a warehouse does not take advantage of the warehouse management systems (WMS) the process of responding to customer orders can be hugely labor-intensive and time-consuming (Van den Berg and Zijm, 1999). For example, Brynzér and Johansson (1996) and De Koster, Van der Poort, and Wolters (2007) highlight that 60% and 80% of total warehouse operations were associated with manual order picking in their respective warehouses of study. The increase in the magnitude of manual order picking operations seen over the recent decades signifies the importance of implementing efficient order picking systems (OPS). Gu, Goetschalckx, and McGinnis (2007) define OPS operational factors as receiving, storing, picking, and sending products or goods to final destinations. OPS plays a critical role in warehouse operational efficiency for two reasons: first, it accounts for about 50% to 75% of warehouse operations; second, OPS related delays have a ripple effect on the entire supply chain (Coyle, Bardi, & Langley, 1996).

OPS planning problems in turn, can be divided into the following four categories: storage location assignment problem (SLAP), order batching, zone picking, and picker routing (Yu, & De Koster, 2009). Van Gils et al. (2018) and Davarzani and Norrman (2015) discuss the fact that these OPS problems seem to be interdependent, however, the number of publications examining multiple OPS problems concurrently pales in comparison to the ones dealing with one specific OPS problem. For instance, the heuristics designed for the SLAP category of OPS primarily address a single warehouse design and do not accommodate consideration of multiple designs. On the same note, most heuristics designed for the routing category of OPS only accommodate S-shaped or mid-point routings. These examples highlight the fact that most methods are not equipped to handle variability in one OPS category, let alone the interdependencies between them. This research introduces a new heuristic named "Walking Map" that is agnostic to changes in warehouse design and routing method. The Walking Map is more focused on ranking the desirability of different zones within a warehouse based on warehouse parameters. In this paper, the Walking Map is used to test multiple policies of warehouse design for SLAP in junction with multiple routing methods.

The rest of this article is organized as follows. Section two provides a brief review of current literature on the subject, followed by a methodology explanation in Section three. Finally, results and conclusions are discussed in Section four.

2. Literature Review

Order picking literature comprises of modeling the picking process either with mathematical formulation (usually mixed-integer programming) or indexing methods. The models are then solved with operation research or simulation approaches. Kim and Smith (2012) provide a mixed-integer linear programming for a zone-based storage problem where SKUs are correlated. They have defined each aisle as a zone with a dedicated picker. Then solved the problem using different heuristic methods and reported that simulated annealing delivered the best result. Bindi and Manzini (2007) propose a novel similarity index for all combinations of products (*i,j*) and bundle SKUs together according to it. They also take advantage of the Jaccard similarity index in order to cluster similar items. However, the results do not show significant improvement compared to class-based methods. Bindi and Manzini (2009) Introduce a similarity coefficient to determine level of correlation between different combinations of products. They have created four binary coefficients to assess similarity and have tested the proposed idea with a case study. Peterson and Aase (2004) first provide a novel layered-based approach to warehouse design which comprises of three picking policies, three routing policies, and three storage policies. Then, run a sensitivity analysis with different order sizes from small to large size problems and assess the quality of different permutations of picking, routing, and storage policies. Second, they introduce warehouse shape, location of input/output (I/O) point, and distribution of SKUs into the analysis to provide a thorough analysis of their idea. Xiao and Zheng (2010) develop a mathematical programming for the storage assignment problem where the orders are known in advance. They provide a heuristic solution to the problem of assigning SKUs to a multi-warehouse single block. Zhang (2016) clusters SKUs into different classes with regard to their associate correlation with other SKUs. The author proposes two distinct class-based priority methods; a) sum-seed clustering where SKUs are sorted according to descending order of their correlation frequency with other SKUs, then locations are assigned according to this priority rule; b) static-seed clustering where correlation is always calculated to the highest priority SKU. Rouwenhorst, Reuter, and Stockrahm (2000) provide a thorough framework for warehouse design. They envision a warehouse comprised of processes, resources, and organization. Their process section focuses on receiving, storing, order picking, and shipping goods and items. Van Gils, Ramaekers, Braekers, Depaire (2018) develop a full factorial ANOVA analysis for all the factors that might affect order picking. Authors have studied random, within-aisle, across-aisle, diagonal, and perimeter LAP methods in conjunction with FCFS, SEED, and saving for batching policy while having a zone picking policy such as strict, two-zone customer type/pick frequency, and four-zone customer type/pick frequency. Finally, they add a policy from a pool of aisle-by-aisle, traversal, return, largest gap, and optimal routing methods to provide a comprehensive factorial ANOVA for order picking. Finally, they test different combinations of small to large size problems and utilize a paired t-test to compare the results. Chuang, Lee, Lai (2012) mathematically formulate a correlated SLAP. SKUs are then clustered into *k* mutually exclusive clusters. They solve the problem for a *k* that yields the minimum distance traveled for picking all the products. Accorsi, Manzini, Bortolini (2012) focus on the inventory level for each SKU to find the optimal location of storage. Ansari, Smith (2020) introduced an SKU sorting method called Gravity Clustering, which proves to be more efficient under certain circumstances.

3. Methodology

The Walking Map heuristic proposed in this paper aims to find the best storage location assignment in warehouses with the two following objectives: a) maximizing space utilization and b) minimizing material handling efforts.

To do so, a new warehouse location ranking is devised which sorts the locations not based on their distance from I/O point but based on their visitation frequency by the order picker. This is achieved by following the picker throughout the warehouse and mapping the most frequently visited locations. The locations visited by the picker are either a pick location or the locations on the path to the picking location. To illustrate this, let's consider the following graph representation of a warehouse in Figure 1 where the I/O point is marked red and the two SKUs that need to be picked are represented by purple points and numbered "1" and "2". In this simple picking scenario and assuming that the picker is currently stationed at the I/O point, the color highlighted path in Figure 2 is an example of optimal picking route where multiple locations highlighted in blue represent the visited locations that do not involve a picking operation. Let's assume that the example path illustrated in Figure 2 is one of the most popular paths in the warehouse. Therefore, assigning materials closer to this path helps the picker maximize the number of orders picked when he/she is passing through this path. The parameters which play a role in determining the picker path include but are not limited to warehouse design, , items needing to be picked, the location of the SKUs, and the routing method. To illustrate the effect of these factors , figure 3 depicts a 3D representation of the picker walk

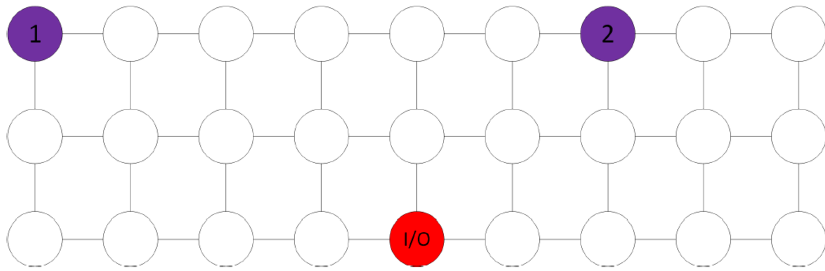

Figure 1. An example representation of a warehouse

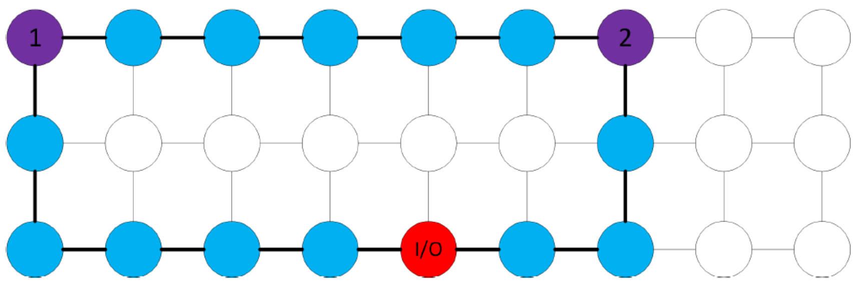

Figure 2. A picker path illustrated in the graph representation of the warehouse

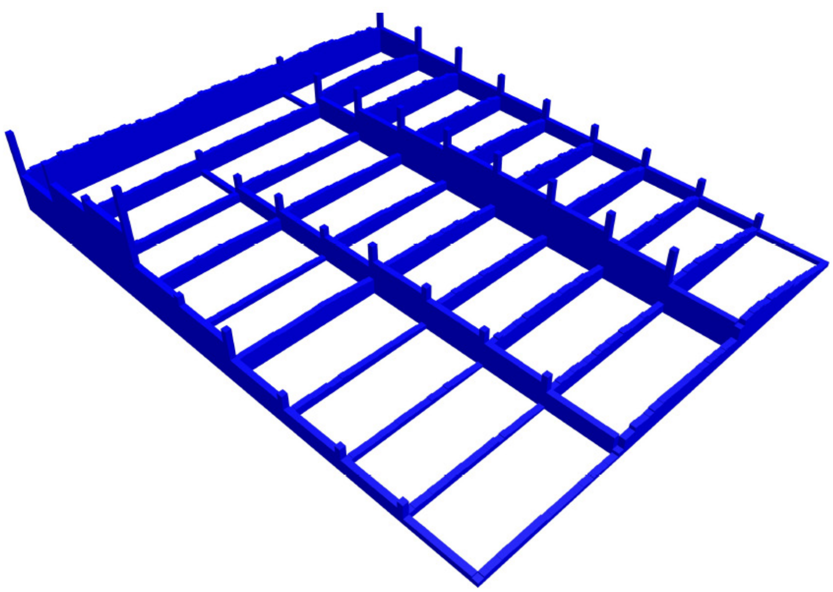

Figure 3. 3D representation of picker walk map while using S-Shaped routing method

map if the picker follows the S-Shaped routing algorithm, in a warehouse with ten aisles, 4 cross-aisles, and Random SLAP. Each bar hight represents the visit frequency for that location in the warehouse.

ISBN: 97819384962-1-9

The parameters and their possible qualitative/quantitative values considered in our design of experiment (DOE) to compare their effect on the amount of time it takes to fulfill a batch of orders are shown in Table 1.

Table 1. Different parameters and methods checked for the experiment

Parameter	Values
Location ranking	Diagonal, within-aisle, across-aisle, walking map
SKU ranking	COI, random
Routing method	S-shaped, Mid-point, optimal, random
(Aisle)*(cross-aisle)	10*2, 10*3, 10*4, 15*2, 15*3, 15*4

We ran all the DOE simulations in the AnyLogic environment. Although other programming software such as Python can be used to model warehouse operations (Ansari and Smith, 2007), Anylogic's vast library in warehouses modeling and experiment options make it an excellent choice for this purpose. For each run, a random sample from the data set was taken, and a specific combination of methods was used to fulfill the order. The optimal value of the routing method parameter is obtained using the Guroubi® solver to solve the routing problem. For the Walking Map value of the location ranking parameter, the slot-distance to I/O point method is used to map the initial picker route which is then used in the Walking Map method as described above. There are 192 different combinations of Table 1 parameter values, and each combination's simulation is replicated ten times resulting in 1920 of total runs for the whole experiment. In the end, we used full ANOVA to compare the results which will be discussed in the next section.

4. Results and Conclusion

To compare the performance of the Walking Map with other methods, we used this combination of factors as the baseline: random SLAP, random routing method, two cross aisles, and ten aisles. Then we calculated the improvement percentage (reduction in order picking time) in comparison to the baseline. For each method we used the average order picking time of the 10 runs. To be concise, we just presented a few selected instances of the 192 results in Table 2 where heat mapping is used to show the differences between methods. The green cells show significant improvement; the yellow ones mean a moderate improvement; and the red cells show deterioration in performance compared to the baseline. Table 2 highlights that the Walking Map outperforms the across-aisle method for most combinations of parameters; for diagonal and within aisle methods, it outperforms the original ranking methods in some cases (e.g., COI SLAP method, Random Routing method, three cross-aisles, and ten aisles). However, for some combinations of parameters (e.g. COI SLAP method, S-shaped Routing method, four cross-aisles and 10 aisles) other methods yield better results. In general, the improvement percentage reaches up to 99% for some combination of parameters.

Table 2. Comparing Walking Map method performance with other location ranking methods

SLAP method	Routing method	Number of cross-aisles	Number of Aisles	Diagonal	Within-aisle	Across-aisle	Walking map
COI	Mid-Point	3	15	39.90%	44.64%	-8.37%	38.35%
COI	Mid-Point	4	10	54.86%	54.83%	9.28%	26.43%
COI	Optimal	3	15	39.38%	43.84%	-15.07%	36.57%
COI	S-shaped	4	15	48.64%	49.86%	-15.36%	40.06%
COI	Random	3	10	-10.66%	-0.60%	-29.16%	29.19%
COI	S-shaped	3	10	54.01%	56.36%	22.18%	60.96%
COI	S-shaped	4	10	57.28%	57.32%	23.88%	57.54%
COI	Optimal	4	15	55.25%	56.79%	17.03%	50.02%

The results of a full factorial ANOVA test are presented in Table 3. As it can be seen, the p-values for all the factors are zero. Therefore, all the factors, as well as their interactions, are significant. This indicates the importance of the factors analyzed in this paper.

Table 3. Full factorial ANOVA for order-picker total travel time (alpha=0.01)

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Location sorting	3	3.86E+13	1.28E+13	253540.68	0.00
SLAP	1	3.15E+13	3.15E+13	619398.15	0.00
Routing	3	1.86E+14	6.21E+13	1221535.55	0.00
# of cross-aisles	2	3.76E+13	1.88E+13	369776.14	0.00
# of Aisles	1	6.08E+12	6.08E+12	119638.44	0.00
Location sorting *SLAP	3	3.86E+13	1.28E+13	253383.24	0.00
Location sorting *Routing	9	5.06E+12	5.63E+11	11071.30	0.00
Location sorting *# of cross-aisles	6	4.22E+12	7.03E+11	13838.38	0.00
Location sorting *# of Aisles	3	9.00E+11	3.00E+11	5901.66	0.00
SLAP *Routing	3	2.19E+13	7.32E+12	143976.57	0.00
SLAP *# of cross-aisles	2	7.25E+12	3.62E+12	71323.65	0.00
SLAP *# of Aisles	1	2.98E+11	2.98E+11	5870.25	0.00
Routing *# of cross-aisles	6	1.19E+13	1.99E+12	39155.42	0.00
Routing *# of Aisles	3	5.87E+11	1.95E+11	3849.72	0.00
# of cross-aisles*# of Aisles	2	3.18E+11	1.59E+11	3129.47	0.00
Location sorting *SLAP *Routing	9	5.07E+12	5.63E+11	11085.57	0.00
Location sorting *SLAP *# of cross-aisles	6	4.21E+12	7.02E+11	13811.74	0.00
Location sorting *SLAP method*# of Aisles	3	9.06E+11	3.02E+11	5939.60	0.00
Location sorting *Routing method*# of cross-aisles	18	8.80E+11	4.88E+10	961.44	0.00
Location sorting *Routing *# of Aisles	9	2.49E+12	2.76E+11	5443.13	0.00
Location sorting *# of cross-aisles*# of Aisles	6	1.22E+11	2.04E+8	401.63	0.00
SLAP *Routing *# of cross-aisles	6	1.69E+12	2.82E+11	5544.73	0.00
SLAP *Routing *# of Aisles	3	1.28E+12	4.27E+11	8413.84	0.00
SLAP *# of cross-aisles*# of Aisles	2	7.21E+11	3.60E+11	7091.86	0.00
Routing *# of cross-aisles*# of Aisles	6	1.07E+11	1.79E+10	353.45	0.00
Location sorting *SLAP *Routing *# of cross-aisles	18	8.84E+11	4.91E+10	965.64	0.00
Location sorting *SLAP *Routing *# of Aisles	9	2.48E+12	2.76E+11	5429.32	0.00
Location sorting *SLAP *# of cross-aisles*# of Aisles	6	1.21E+11	2.03E+10	399.55	0.00
Location sorting *Routing *# of cross-aisles*# of Aisles	18	2.04E+11	1.13E+10	223.78	0.00
SLAP *Routing *# of cross-aisles*# of Aisles	6	2.97E+11	4.95E+10	974.47	0.00
Location sorting *SLAP *Routing *# of cross-aisles *# of Aisles	18	2.04E+11	1.13E+10	223.84	0.00
Error	1728	8.78E+10	5.08E+7		
Total	1919	4.13E+14			

In this paper, we first analyzed the current research in warehousing and pinpointed some of the areas in which more research is needed. In order to fill the gap, we introduced a heuristic storage location assigning method named Walking Map. Our novel method utilizes the picker's path to pick multiple items of an order, ranks the locations based on their visit frequency, and assigns the SKUs to these locations based on their priority. Later, we analyzed the performance of our suggested method under various warehouse designs and routing methods and compared it to other storage location assigning approaches. As our analysis indicated, our method outperforms the COI method under various configurations. Usually the proposed method provides its best performance under the S-Shaped routing approach. This is because of the predictable nature of the path used in this routing method which can be followed by a picker with no need for Warehouse Management Systems (WMS). The Walking Map approach utilizes the predictability feature of the S-Shaped routing which results in overperformance in various configurations of the warehouse that use the S-Shaped routing. Finally, a full ANOVA test is performed to assess the significance of improvements statistically. The performed ANOVA presented in Table 3 illustrates that all the factors that we studied in this research significantly affect the performance of the picker in a warehouse. Hence, the introduced Walking Map method has been studied under various combinations and levels of these factors.

The introduced Walking Map location sorting method is still in its infancy. Although the performance of the method has been studied with various warehouse configurations, more complex configurations still need to be investigated. Future works in this area include using the new Walking Map method alongside other SLAP methods, such as correlation-based and zone-based storage location assigning methods, and other routing methods, such as Combined and Combined+ (Roodbergen and Koster, 2001). Also, the performance of the suggested method needs to be investigated using different warehouse designs such as Chevron and Flying-V (Öztürkoğlu, Gue, Meller, 2012)

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