Proceedings of the 29th EurOMA International Annual Conference, 1-6 July 2022, Berlin, Germany
https://www.euroma2022.org/

# Order picking performance improvement through storage location assignment: The case of a hardware wholesaler

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## Abstract

Order picking is the most time-consuming, labour-intensive, and costly activity in picker-to-parts picking systems. The literature frequently minimises picking time but ignores the picking error, which affects picking efficiency and customer satisfaction. This paper to minimise picking time and picking error using multi-objective optimisation. Three storage location assignment policies, i.e., ABC-based, product-popularity-based (PPB) and product-relation-based (PRB), are deployed to minimise the picking time. PPB policy gave both the minimum picking time and picking error, with the trade-off between the two objectives presented in a Pareto frontier. Hence, the managers can determine a storage policy based on the optimisation results.

**Keywords:** Multi-objective optimisation, Picking time and error, Warehouse operations

### Introduction

In the warehouse operation, picking accounts for approximately 60% of the total operation time and 50% of the operation cost. While since 80% of the picking system is manual order picking, i.e., picker-to-parts system (Bartholdi & Hackman, 2019; De Koster et al., 2007; Tompkins et al., 2010), order picking is considered as the most expensive, time-consuming and labour-intensive activity in the warehouse. Meanwhile, as similar products are stored usually in proximity in the warehouse, workers may pick the wrong item due to akin product shape or item number and thus results in rework and return (Battini et al., 2015; Grosse et al., 2015). Hence, the picking time and the picking error are both critical performance indicators that should be considered to improve the order picking performance.

In the case company, since the products are stored randomly in the warehouse, the popular products are not in the close storage locations to the Input/Output (I/O) point (i.e., start and end point of picking), and hence the workers need to travel longer distances to pick orders. While for the probability of making a picking error, based on the conversation with the case warehouse manager, the workers glance at the item ID to identify an item and hence picking error occurs when items with similar IDs are placed in the same storage location. Further, due to the randomness of storage, many similar items can be placed in the same storage location and hence retrieving the wrong items is a frequent mistake for all workers during order picking.

This paper deploys three storage location assignment (SLA) policies, i.e., ABC-based, product-popularity-based (PPB) and product-relation-based (PRB) SLA, to minimise the order picking time. The ABC-based SLA first classifies products to three classes, i.e., class A, B, and C, based on product popularity. Then, the close storage locations are assigned to class A, B and C in sequence. The PPB SLA allocates products based on product popularity, meaning the higher the product popularity, the closer the storage location to the I/O point. The PRB SLA assigns product based on both the product popularity and the sales relationship, meaning the products with higher popularity are assigned to close storage locations to the I/O point while the products that are usually sold together are assigned to the same storage location. Then, the SLA policy with the shortest picking time is further analysed to minimise the probability of making a picking error.

## Literature review

Studies on order picking time minimisation mainly include the picking setup time, search and pick time, and the travelling time. The setup time refers to the time for order picking preparation on activities such as order batching or equipment initiation. The search and pick time is the time needed to identify and retrieve the item from the bins, while the travelling time, which accounts for more than 50% of the total picking time, is the time required to walk from one storage location to another during a picking task (De Koster et al., 2007; Tompkins et al., 2010; Van Gils et al., 2018; Zhang et al., 2017).

This paper use SLA to minimise picking time. Product SLA is to allocate products to different storage locations in the warehouse. The common calculation is to use the distance travelled to calculate the picking travelling time while taking the order setup time, search and pick time as constant values (Van Gils et al., 2018). Since travelling time is a major part of picking time calculation, many studies focus on the picking travelling time. The studies are summarised in Table 1. Dijkstra & Roodbergen (2017) and Ene & Öztürk (2012) only consider the travelling time required under the class-based SLA policy. Similarly, Mantel et al. (2007) and Mirzaei et al. (2021) focus on the travelling time to minimise picking time under product relation-based SLA. Petersen et al. (2005) use Monte-Carlo simulation to analyse both the travelling time and search and pick time under several dedicated SLA policies based on product popularity, turnover, volume, pick density and cube-per-order index, while Kim & Smith (2012) include travelling time, search and pick time, setup time in picking time minimisation using a mixed integer programming (MIP) model. The logic using different SLA policies to minimise picking time is to allocate popular products to storage locations that require less time to visit. In this paper, since the search and pick time is insignificant compared to the travel time and the setup time for the case company's warehouse, it is not considered for picking time minimisation.

*Table 1 – Overview of papers deploying SLA to minimise picking time*

| Paper | Model | SLA policy | Travel time | Search and pick time | Setup time |
|---|---|---|---|---|---|
| Dijkstra & Roodbergen (2017) | Dynamic Programming | Class-based | ✓ | | |
| Ene & Öztürk (2012) | Integer Programming | Class-based | ✓ | | |
| Kim & Smith (2012) | Mixed Integer Programming | Product-relation based | ✓ | ✓ | ✓ |
| Mantel et al. (2007) | Integer Programming | Product-relation based | ✓ | | |
| Mirzaei et al. (2021) | Integer Programming | Product-relation based | ✓ | | |
| Petersen et al. (2005) | Monte-Carlo Simulation | Several dedicated storage policies | ✓ | ✓ | |
| This paper | Multi-objective Optimisation | Product popularity based & Product-relation based | ✓ | | ✓ |

Studies on picking error are mostly qualitative. A picking error occurs when a wrong item or the wrong quantity of an item is retrieved from the storage locations. Manual order picking error occurs due to the storage methods, picking methods and other factors such as the picking environment (e.g., light and noise in the warehouse), the design of the picking list and the coordination among pickers (Burinskiene, 2010). Brynzer & Johansson (1995) identify that the picker reading error is the most common error in manual picking systems, while Grosse et al. (2015) study the impact of human factors in picking operation and also conclude the picking error is mainly resulted from the pickers' cognitive errors, meaning the pickers read or process the wrong information and thus pick the wrong item. Hence, in general, human cognitive error is the most significant reason for picking errors in picker-to-parts storage systems.

The use of technology to reduce picking errors is a popular research topic. Battini et al. (2015) compare five paperless picking systems, i.e., barcodes handheld, RFID tags handheld, voice picking, traditional pick-to-light and RFID pick-to-light system and conclude that paperless picking technology can help reduce the picking error while different systems perform better or worse under different warehouse storage policies. They conclude that the RFID and barcodes handheld devices and the voice picking system are more suitable for low-level picking while the RFID pick-to-light system is best for multilevel picking. Similarly, some scholars also study the RFID-based picking systems and smart trolleys to reduce the picking error (Poon et al., 2009; Sham et al., 2018). The logic of using the technology in picking is to facilitate workers in correctly identifying and picking the items required and hence reduce the chance of committing an error. Lee et al. (2018) study the picking error under different picking policies. They find that using the strict order picking policy, where each picker handles one order at a time, will result in less picking error, whereas batch zone picking, where orders are picked in multiple zones simultaneously, and wave picking, where orders are separated into waves based on time or quantity, will increase the picking error.

In general, studies on the picking error are mostly focused on the impact of human factors and the use of technology to reduce the error. As most picking error studies are qualitative, the mathematical model to incorporate the picking error into order picking optimisation is rarely constructed.

**Methodology**

Three SLA policies, namely, ABC-based, PPB, and PRB SLA policies, are deployed in one of the warehouses of the case company to minimise the picking time. Then, a multi-objective optimisation on the picking time and the picking error score minimisation is conducted for the storage scenario with the shortest picking time.

A 3D matrix is created where the number of rows and number of columns are the warehouse length and width (147 feet X 155 feet) while the number of layers is the maximum number of levels for a storage shelf i.e., nine layers. Hence, the matrix is 147 x 155 x 9 in rows, columns, and layers. The matrix is binary where 0s are the aisles and the 1s are the storage racks.

Next, four SLA models, i.e., base case storage, ABC-based storage, PPB storage and PRB storage are formulated and the horizontal and vertical travelling time to pick an order is calculated. The ABC-based SLA first categorise products based on the product hits and thus the space required by each class of SKUs are determined. Class A accounts for 60% of hits and 13% of SKUs, the next 25% hits with approximately 20% of SKUs are Class B and the rest SKUs are class C. Then, the storage locations are assigned to each class one at a time from the closest storage location to the farthest to the I/O point.

The PPB SLA model assigns products based on the product hits, meaning the higher the product hits, the closer the products to the I/O point. The products are allocated to the sorted storage locations, ensuring the popular products are assigned to closer storage locations to the I/O point. Under this policy, each product has an exact storage location. Hence, the routing distances and travelling time between any two products and between a product to or from the I/O point are obtained.

The PRB SLA model identifies the product pairwise sales relationship through analysing customer order data and then assigns the SKUs using a similar logic to Integrated Cluster Assignment (ICA) proposed by Mirzaei et al. (2021), where product sales affinity and product popularity are considered simultaneously for SLA. The logic is as follows. First, count the number of orders between two products and on a product and thus the number of supports i.e., number of evidence selling a pair of products together and the confidence i.e., number of supports divided by the number of orders on an item in the pair are calculated. The assignment starts from the product with the highest hits and then search the product sales relationship for the SKU that have sales relationship with the pair and assign the pair of products together when there is enough space in a storage location. Otherwise, assign the next product with the highest hits and follow the same logic described above. Hence, the products with high hits are assigned to closer storage location to the I/O point and the products that are usually sold together are arranged in the same storage location.

The horizontal travelling distance to pick an order for all SLA models are calculated using the same routing logic as follows. The picker starts and ends each order picking at the I/O point. The items are picked in sequence according to the horizontal travelling distance to the I/O point, meaning items stored in nearer storage locations are picked first and vice versa for items stored in farther storage locations to the I/O point.

The distance between any two points in the matrix is calculated using the Breadth-first search (BFS) algorithm, a graph searching algorithm starting from the end node and exploring all neighbouring nodes one step at a time, providing a guaranteed best solution (Rakhee & Srinivas, 2016). The algorithm ensures the pickers cannot walk through the storage racks and can only travel in the aisle space, i.e., the 0s in the matrix.

Then, based on the company's expert judgment on the horizontal and vertical walking speed, the horizontal and vertical travelling time is calculated by dividing the horizontal and vertical distance by the walking speed respectively. Then, the picking time results are calculated and compared with the base case using historical data. Finally, the SLA policy with the shortest picking time is selected to minimise the probability of making a picking error. The rest of this section presents the math model with the notations in Table 2.

*Table 2 – Notations of the mathematical model*

| | | | |
|---|---|---|---|
| $K$ | The set of storage locations in the warehouse | $ID_i$ | SKU $i$ ID number |
| $I$ | The set of SKUs stored in the warehouse | $r_i$ | The total storage space required by SKU $i$ |
| $O$ | The set of customer orders | $TS_k$ | The picking setup time for storage $k$ |
| $k$ | The storage location indexes ($k \in K$) | $TV_k$ | The vertical travelling time to storage $k$ Decision Variables |
| $i, j$ | The SKU indexes ($i, j \in I$) | $x_{i,k}$ | = 1 if SKU $i$ is assigned to storage k and 0 otherwise |
| $o$ | The order serial number ($o \in O$) | $y_{o,k}$ | = 1 if order $o$ require picking in storage $k$ and 0 otherwise |
| $Ca_k$ | The maximum space capacity of storage $k$ | $S_i$ | The item similarity score of SKU $i$ calculated after $x_{i,k}$ are found |
| $c_{o,i}$ | Parameter equal to 1 if SKU $i$ is in order $o$ and 0 otherwise | $TH_o$ | The horizontal routing time to finish picking order $o$ |

The mathematical model is formulated as follows.

$$\text{Min} \sum_{o \in O} \sum_{k \in K} (TS_k + TV_k) y_{o,k} + \sum_{o \in O} TH_o \quad (1)$$

$$\text{Min} \sum_{o \in O} \sum_{i \in I} c_{o,i} S_i \quad (2)$$

Subject to:

$$y_{o,k} = min\left(\sum_{i \in I} c_{o,i} x_{i,k}, 1\right), \forall o \in O, \forall k \in K \tag{3}$$

$$\sum_{i \in I} x_{i,k} r_i \leq Ca_k, \forall k \in K \tag{4}$$

$$\sum_{i \in I} r_i \leq \sum_{k \in K} Ca_k \tag{5}$$

$$\sum_{k \in K} x_{i,k} = 1, \forall i \in I \tag{6}$$

$$S_i = h\left(x_{i,k}, ID_i, ID_j\right), \forall k \in K, \forall i, j \in I \tag{7}$$

$$TH_o = f\left(x_{i,k}, c_{o,i}\right), \forall o \in O, \forall k \in K, \forall i \in I \tag{8}$$

$$S_i \in Z^*, TH_o > 0, x_{i,k}, y_{o,k} \in \{0,1\}, \forall o \in O, \forall k \in K, \forall i \in I \tag{9}$$

The Objective statement in Equation 1 minimises the total picking time including picking setup time, vertical travelling time, and horizontal travelling time. The picking setup time and vertical travelling time are multiplied by the 0-1 variable $y_{o,k}$ denoting whether order $o$ requires a visit to storage location $k$.

The Objective statement in Equation 2 minimises the probability of making a picking error. The $S_i$ is the number of similar items to SKU $i$ while $c_{o,i}$ denotes whether the SKU $i$ is picked in order $o$. The total picking error score is the summation of all items from all orders on unit picking error score. Hence, the higher the popularity of an SKU and the higher the number of similar items to an SKU in a storage location, the higher the picking error score.

Constraint 3 means if SKU $i$ is not assigned to storage $k$ ($x_{i,k}$= 0) or if order $o$ does not require SKU $i$ ($c_{o,i}$ = 0), the picker will not visit the storage $k$ ($y_{o,k}$= 0). Constraint 4 means the storage capacity of storage location $k$ should not be exceeded. Constraint 5 means the total storage space in the warehouse should be able to accommodate the total space required by all the SKUs. Constraint 6 ensures each SKU can only be assigned to one storage location. Constraint 7 and Constraint 8 denotes the item similarity score $S_i$ and the horizontal routing time $TH_o$ are functions of decision variable $x_{i,k}$ respectively. The functions are case specific and depend on the method to calculate the probability of making picking error and the horizontal routing time.

**Findings and discussions**

The order picking time for all SLA models are calculated (Figure 1). The base case annual picking time is 1729 hours while the ABC-based, PPB and PRB SLA annual picking time are 1059, 726 and 925 hours respectively.

The red bars represent the ABC-based SLA. Overall, the ABC-based SLA shows roughly 39% of picking time reduction compared to the base case. The logic of picking time reduction is to first classify items based on the product hits and hence the popular products are stored in closer storage area to the I/O point while also allowing the items to be stored randomly inside a class, better utilising the storage space compared to the product PPB SLA policy. Though the ABC-based storage generally requires more time to finish picking an order, the storage space utilisation is higher than that of the PPB and PRB storage. This is because the products have the flexibility to be stored in any open storage locations under random storage or in their corresponding classes under ABC-storage.

The green bars are the PPB SLA monthly order picking times. This SLA policy demonstrates approximately 58% of time reduction compared to the base case. It places popular items to close storage locations to the I/O point, reducing the walking distance to retrieve popular products and thus reduce the picking time.

The grey bars demonstrate the PRB SLA picking time. It has approximately 46% of time reduction compared to the base case. This SLA policy considers the product hits while it also takes the product sales relationship into account (i.e., assigning products to the same storage location if they frequently appear together in the orders). Hence, product with high hits will be placed at closer storage locations to the I/O point and the product usually sold together will be placed in the same storage locations, reducing the time to retrieve popular items and the routing distance to pick an order.

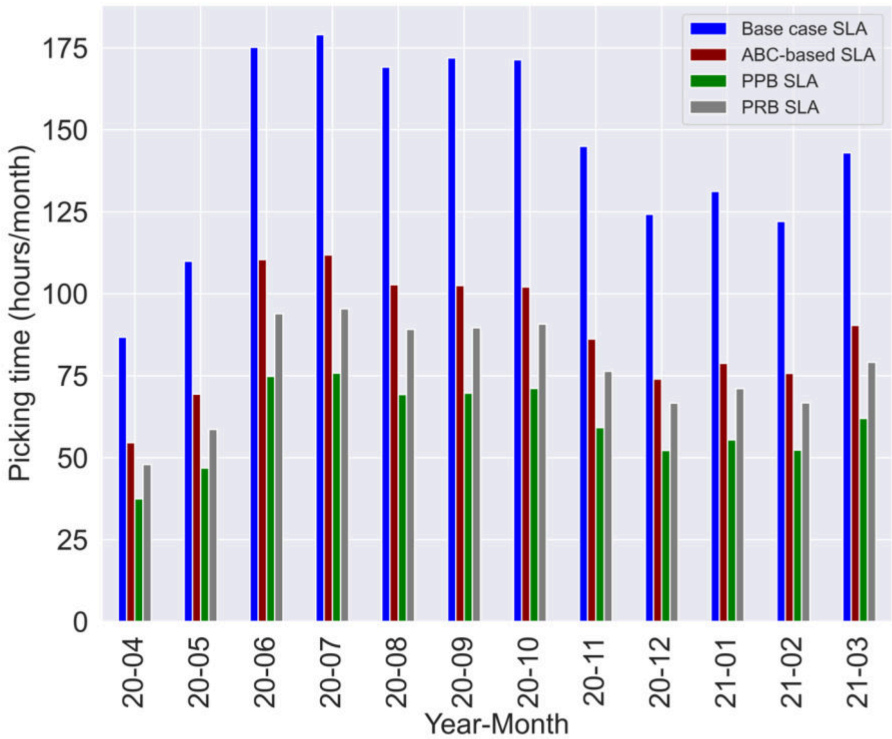


*Figure 1 - Picking time comparison*

Overall, PPB SLA performs the best, i.e., 58% of time reduction in the case warehouse. It arranges the products based on the product popularity and hence, the higher the hits a product has, the closer the storage location to the I/O point. Based on picking time minimisation results, the PPB SLA has the highest picking time reduction percentage compared to the other SLA polices for the case company's warehouse and hence this policy is further studied for the picking error score minimisation.

In the case warehouse, the PPB and PRB SLA demonstrate 58% and 46% of picking time reduction compared to the base case respectively. This is because the product sales relationship is not strong for the case company, for instance, the most supported product pair has 369 orders requesting the item pair together while the two SKUs are requested 564 and 447 times individually. Hence, the PRB SLA is not performing better than the

PPB SLA in terms of picking time. The PRB SLA logic is based on the integrated cluster assignment (ICA) proposed by (Mirzaei et al., 2021), where the proposed SLA model shows a higher time reduction percentage i.e., up to 40% compared to the class-based SLA and FTB SLA. They explain this is because the product affinity is high in their case study while in case of low product affinity and low turnover of SKUs, the PRB SLA will not demonstrate any advantages in picking time over other SLA policies, implying the product affinity in order data has a significant impact on the PRB SLA order picking time. Generally, the higher the product affinity, the more benefit the PRB SLA will demonstrate over other SLA policies (Li et al., 2016).

Figure 2 demonstrates the Pareto front of the picking time and picking error score minimisation. The top left point is the PPB SLA picking error score minimisation starting point i.e., the picking time minimisation results using PPB SLA policy. The starting point annual picking time is 726 hours, and the annual picking error score is 17,873. Then, the picking error is minimised in a sequence from the SKU with the highest annual bin hits. The big gap between the starting point and the next point is due to moving a top 3 popular item to another storage location and hence the picking time increases around 6 hours to 732 hours and the picking error score is reduced to 14959. This process is repeated one item at a time until the total picking error score is 0, i.e., the ending point in Figure 2 where the picking time is 755 hours.

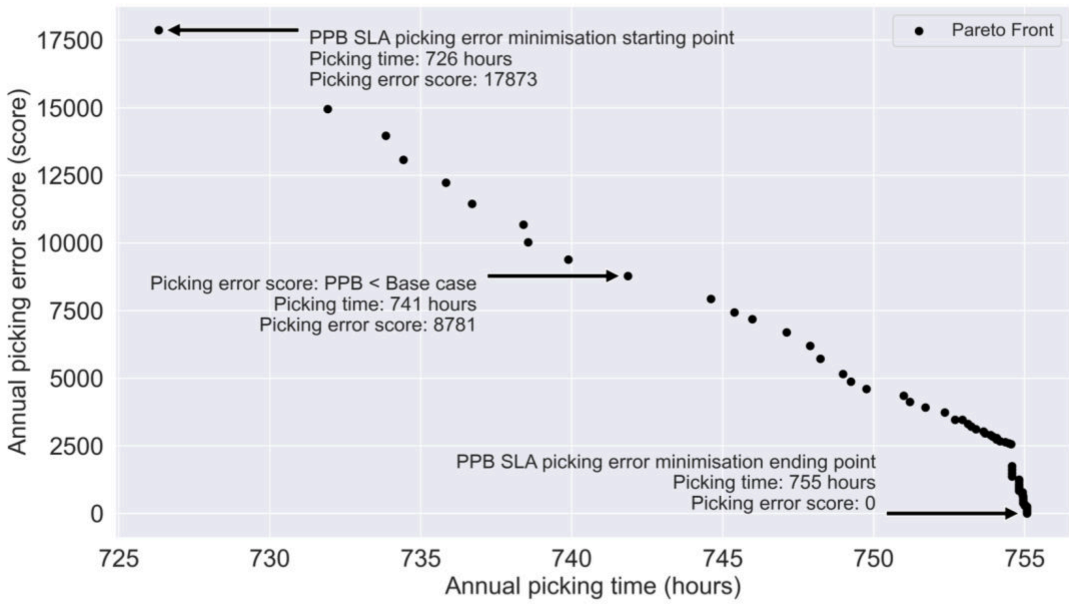


*Figure 2 - Pareto front of picking time and picking error minimisation*

In the case warehouse, if picking error score minimisation is not implemented, the PPB picking error score will be higher than that of the base case. While if we move from the starting point to the 10th point in Figure 2, meaning ten SKUs are moved to their upper storage locations, the PPB picking error score (8,781) will be lower than that of the base case (9,034). Hence, the trade-off here is the increment of picking time and the reduction of the picking error score for PPB SLA. Based on the Pareto front graph (Figure 2), it is implied that the time increment is not as significant as the picking error decrement under PPB SLA, meaning a 4% increase in total picking time can eliminate the similarity-based picking error probability entirely under the PPB SLA.

The picking error score is only measured when items with similar IDs are placed in the same storage location and the popular SKUs i.e., SKUs with higher hits will have higher picking error score compared to the less popular SKUs when the number of similar items in a storage location are the same for these two SKUs. Since the picking error minimisation is conducted by moving one item in the similar item pair to the storage location one level above, moving popular items will reduce more picking error score compared to the less popular items. In this case, the first point of the Pareto front (Figure 4.5) have higher impact on picking time increment compared to the following points. The picking error score is minimised one at a time from the SKU with the highest bin hits to the SKU with the lowest bin hits. Since the first SKU is more frequently ordered by customers, the picking time increment moving a popular item is higher than that of the less popular items.

## Conclusion

This paper aims at minimising the picking time and the probability of making a picking error to improve the order picking performance. Three SLA policies, i.e., ABC-based, PPB and PRB SLA, are deployed to minimise the order picking time, and the results are compared with the base case picking time. Then, the SLA policy with the shortest picking time, i.e., PPB SLA in the case study, is studied to minimise the picking error score. Overall, this paper fills the literature gap by proposing a multi-objective optimisation model to minimise both the picking time and the probability of making a picking error in multilevel order picking systems.

This paper measures the picking performance based on picking time and the probability of making a picking error. Future research can include other metrics such as ergonomic factors, storage utilisation rate, or the flexibility of the storage system. Moreover, for product affinity analysis, the product relationships are mainly concluded from the customer order data. However, assigning products usually ordered together may not be feasible in practice. Hence, using data-driven methods considering criteria such as product size, shape, weight, and mechanical property to classify and assign products to storage locations in a warehouse is a promising future research avenue.

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