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Order-batching methods for an order-picking warehouse with two cross aisles

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Abstract

Order batching is one of the methods used in warehouses to minimize the travel distance of pickers. In this paper, we focus on developing order-batching methods for an order-picking warehouse with two cross aisles and an I/O point at one of its corners. Each of these methods is made up of one seed-order selection rule and one accompanying-order selection rule. Eleven seed-order selection rules and 14 accompanying-order selection rules are studied here. These rules include those newly proposed by us and those by others. Rules proposed by others have been shown to perform well in minimizing the travel distance of pickers. They are included here for the comparison purpose. Unlike previous studies that only focus on developing aisle or location-based rules, this study also develops rules that are distance- or area-based. In addition, two different route-planning methods and two different aisle-picking-frequency distributions are considered in this paper. This study's objective is to investigate not only the performance of seed-order selection rules and accompanying-order selection rules, but also the mutual effects between route-planning methods, aisle-picking-frequency distributions, seed-order selection rules, and accompanying-order selection rules on their performance. The result of this study shows that some of the newly proposed rules outperform those from other studies. It also shows that seed-order selection rules and accompanying-order selection rules significantly affect each other's performance. Lastly, the performance rankings of seed-order selection rules and accompanying-order selection rules are affected by aisle-picking-frequency distributions, but not by route-planning methods.

Keywords: Order batching; Order picking; Seed-order selection; Accompanying-order selection

1. Introduction

The success of Supply Chain Management (SCM) depends much on the efforts, cooperation, and coordination of all facilities along a supply chain. Every facility must optimize its operations so that goods or services can be promptly and reliably delivered to its customers at the least cost. There are many operations in a distribution warehouse, with a large proportion of them being order-picking operations. According to Coyle,

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Bardi, and Langley (1996), order-picking operations can account for roughly 65% of the total operating cost of a warehouse. The study of Tompkins et al. (1996) shows that the travel time accounts for about 50% of all order-picking operations. In other words, the operational efficiency of a distribution warehouse relies much on the efficiency of its order-picking operations. Order picking is often a labor-intensive process, which may consume as much as 60% of all labor activities in a warehouse (Drury, 1988). Making order-picking less laborious is necessary if one wants to enhance order-picking efficiency. Many methods have been devised to achieve this purpose. Some of them resort to methods that can plan good picking routes for order pickers. For example, Ratliff and Rosenthal (1983) developed an efficient algorithm for finding the shortest order-picking route in a warehouse with two cross aisles – one at the front and the other one at the back. Heuristics for warehouses with two cross aisles can also be found in Hall (1993). He developed distance approximation methods for five order-picking strategies, i.e. traversal, midpoint, largest-gap, optimal routing, and minimal. Petersen (1997) investigated the performance of six heuristic routing strategies and compared them to the optimal strategy. He also investigated the impact of warehouse shape and pickup/delivery (P/D) location on the route length. De Koster and Van der Poort (1998) studied the problem of finding efficient order-picking routes for both conventional warehouses (in which pickers had a central depot for picking up and depositing carts and pick lists) and modern warehouses (in which order-picking trucks were allowed to pick up and deposit pallets at the head of every aisle without returning to the central depot). Goetschalckx and Ratliff (1988) investigated the situation where items have to be picked from both sides of an aisle and the picker cannot reach items on both sides without changing positions. Roodbergen and De Koster (2001) investigated route-planning problems in a warehouse with multiple cross aisles. They considered several methods to determine order-picking routes. Hwang, Oh, and Lee (2004) evaluated the performance of three routing policies (i.e. return, traversal, and midpoint policy) in the order process. They assumed that items were assigned to storage locations based on the basis of Cube-Per-Order Index (COI) rule. Petersen and Aase (2004) examined the effect of three process decisions on order picker travel. One of the process decisions was the routing decision. Ho and Chien (2006) compared two route strategies – a static strategy and a dynamic strategy – for visiting different picking zones in a distribution warehouse. Unlike the static strategy whose picking routes are fixed, the dynamic strategy can adjust picking routes according to the current situation of the distribution warehouse. Their study shows that the dynamic strategy performs better in minimizing the total order-picking time.

The travel distance of order pickers is also affected by various design factors, e.g., storage assignment, warehouse shape, and warehouse layout. Jarvis and McDowell (1991) showed that the optimal storage assignment policy was to assign the most frequently picked items to the aisle nearest to the I/O point, and the next most frequently picked items to the next aisle. Gibson and Sharp (1992) and Gray et al. (1992) found that locating high volume items close to the I/O point can significantly improve the picking efficiency. Petersen and Schmenner (1999) examined the interaction of the routing and storage policies under different operating conditions. Their experimental results showed significant differences in the mean route distance for the routing policies, storage policies, and their interactions. Caron, Marchet, and Perego (2000) presented an analytical approach for assessing different layout designs of the picking area in low-level, picker-to-part system using COI (cube-per-order index)-based, and rand storage policies. Petersen, Aase, and Heiser (2004) compared the performance implications of class-based storage to both random and volume-based storage for a manual order-picking warehouse. Petersen and Aase (2004) examined not only the effect of picking and routing decisions, but also the effect of the storage decision on the performance of picker travel. Dekker, De Koster, Roodbergen, and Van Kalleveen (2004) determined a good combination of policies for assigning products to storage locations and for determining the sequence for picking products to meet customer demand for Ankor – a wholesaler of tools and garden equipment. Le-Duc and De Koster (2005) proposed a probabilistic model to estimate the average travel distance of a picking tour. Using the average travel distance as the objective function, they presented a mathematical formulation for the storage zone optimization problem. Hwang and Cho (2006) proposed a performance evaluation model for the design of order-picking warehouses. Important aspects of warehouse designs, e.g., warehouse size, rack size, number of transporters, and the system performance, were included in their study.

The travel distance of a picker can also be reduced through zoning, in which a picker picks items that are in his or her assigned zone. Petersen (2002) examined the configuration or shape of picking zones by simulating a bin-shelving warehouse to measure picker travel where Stock-Keeping Units (SKUs) were assigned to storage locations either using random or volume-based storage. Ho and Liu (2005) studied the problem of converting a regular warehouse into a zone-picking warehouse. They proposed different design methods and examined their performance. Different routing strategies and storage assignment methods were also investigated by them. Jane and Laih (2005) developed a heuristic algorithm to balance the workload among pickers in a synchronized zone order-picking system. The objectives are to improve the utilization of the order-picking system and to reduce the time needed for fulfilling each order.

Another way to minimize the travel distance of order pickers is order batching. Order batching can significantly reduce the travel distance of order pickers if orders with similar picking locations are batched together and picked in the same picking trip. Some order-batching studies are reviewed as follows. Gibson and Sharp (1992) compared the performance of two order-batching procedures using computer simulation. They considered various factors, e.g., travel metric, warehouse representation, item location assignments, number of items per order, and the total number of orders. Rosenwein (1996) compared several heuristics for order batching. One important component of his study was comparing various metrics that approximated the relative 'closeness' between orders and provided a quantifiable basis for batching orders. De Koster, Van der Poort, and Wolters (1999) compared two groups of order-batching algorithms – the Seed algorithms (CPU time saving) and Time Savings algorithms (CPU time consuming) – using two different routing strategies (i.e. S-shape and Largest-gap strategies). Gademann, Van Den Berg, and Van Der Hoff (2001) addressed the order-batching problem in a parallel-aisle warehouse with the objective of minimizing the maximum lead time of any of the batches. They presented a branch-and-bound algorithm to solve the problem exactly. Gademann and Van De Velde (2005) addressed the order-batching problem in a parallel-aisle warehouse with the objective of minimizing the total traveling time needed to pick all items. Hwang and Kim (2005) studied the order-batching problem in a low-level picker-to-part warehouse system. They developed an efficient order-batching algorithm based on a cluster analysis for each of the three routing policies – traversal, return, and midpoint routing policy. Won and Olafsson (2005) reconsidered the traditional warehousing problems of batching and picking orders with respect not only to improving efficiency, as measured by low picking time and effective use of vehicles, but also to optimizing customer response time. Chen and Wu (2005) proposed an order-batching method that was based on data-mining and integer programming. Hsu, Chen, and Chen (2005) proposed a GA (Genetic Algorithms)-based order-batching method. Ho and Tseng (2006) proposed many batching methods that were made up of seed-order selection rules and accompanying-order selection rules. The rules proposed by them were mainly aisle or location-based. Le-Duc and De Koster (2007) considered the order-batching problem for a 2-block rectangular warehouse with the assumptions that orders arrives according to a Poisson process and the method used for routing the order-pickers is the S-shape heuristic.

Order-batching problems have also been studied under different environments. Elsayed and Stern (1983) proposed several algorithms for processing a set of orders in automated warehousing systems. They proposed four seed-order selection rules, three order-addition rules, and two seeding rules. They came up with 24 batching algorithms from these rules and studied their performance. Elsayed and Unal (1989) presented heuristics and analytical models for the order-batching problem in an Automated Storage/Retrieval System (AS/RS). They developed four methods that were based on the time-saving criterion of combining two or more orders in one single tour. An analytical model was developed to estimate the S/R machine's travel time. Hwang, Baek, and Lee (1988) adopted cluster-analysis techniques to solve the order-batching problem in an AS/RS and studied their performance through computer simulation. Hwang and Lee (1988) investigated the order-batching problem for a man-on-board AS/RS. Their algorithms batched orders according to similarity coefficients defined in terms of orders' attribute vectors. Pan and Liu (1995) also studied the order-batching problem in an AS/RS system. They considered four seed-order selection rules and four order-addition rules. Together, these rules make up 16 order-batching algorithms.

In this paper, we continue the study of Ho and Tseng (2006) by investigating more order-batching methods. Similar to the order-batching methods proposed by Ho and Tseng (2006), each of the order-batching methods studied here is also made up of a seed-order selection rule and an accompanying-order selection rule. In all, 11 seed-order selection rules and 14 accompanying-order selection rules are studied. Some of these rules are from Ho and Tseng (2006) and some of them are newly proposed by us. Rules adopted from Ho and Tseng (2006) have been proven by them to perform superiorly in minimizing the travel distance of pickers. These rules are included here in order to serve as performance benchmarks for rules newly proposed by us. As for the newly proposed rules, they are based on attributes or measurements not considered in previous studies. Simulations will be conducted to test the performance of these 11 seed-order selection rules and 14 accompanying-order selection rules. Furthermore, we will study the performance of these rules under two different route-planning methods and two different aisle-picking-frequency distributions, so that the effects of route-planning methods and aisle-picking-frequency distributions can be examined. It is hoped that the knowledge learned from this study can assist practitioners in choosing good order-batching methods for their ordering batching operations. It is also hoped that the result of this study can benefit other researchers in developing even better order-batching methods.

The remainder of this paper is organized as follows. Section 2 presents the problem environment and assumptions of this paper. Section 3 introduces the order-batching process of the proposed order-batching methods. The seed-order selection rules and the accompanying-order selections rules that make up different order-batching methods are also introduced here. Experiments were conducted to test the performance of seed-order selection rules and accompanying-order selection rules under two different route-planning methods and two different aisle-picking-frequency distributions. The experiments are described in Section 4. In Section 5, the experimental results are analyzed and discussed. Finally, Section 6 summarizes and concludes the results of this study. A discussion on some future research possibilities is also presented here.

2. The problem environment, assumptions, and the proposed order-batching process

Several of the studies reviewed above are for AS/RS systems. Unlike the AS/RS environment of these studies, the problem environment of ours is similar to the one in Ho and Tseng (2006), i.e. an order-picking warehouse of a distribution center with two cross aisles – one front cross aisle and one back cross aisle. The warehouse has one I/O point at one of its corners. The I/O point is not only the place where pickers receive order-picking instructions, but also the place where pickers deposit the items they have picked from the warehouse. In our warehouse, order-picking operations are performed by human pickers. Human pickers push picking carts to visit different storage locations and pick items that are required in the order batches. Fig. 1 gives a model warehouse. The warehouse has 12 picking aisles indexed from one to 12. And, each aisle has 32 picking locations. The warehouse in Fig. 1 will also be used in the experiments in Section 4. The other important assumptions of this study are summarized as follows.

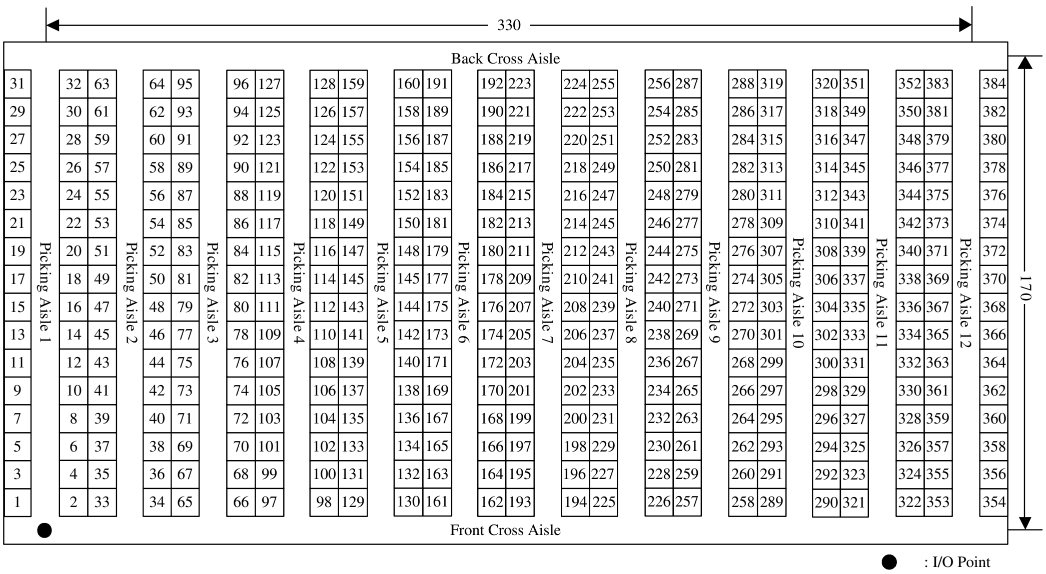

Fig. 1. The illustration of the warehouse studied in this paper (Ho & Tseng, 2006).

- Many order-picking shifts are performed in the warehouse.
- At the beginning of an order-picking shift, the set of orders to be picked in this shift is known. One will refer to this set of orders as an order pool. Please note that the content of an order pool cannot be changed once an order-picking shift has begun.
- If an order pool contains orders with cart-capacity demands greater than the picking cart's capacity, these orders will be split into two or more smaller orders, so that no orders' cart-capacity demands are greater than the picking cart's capacity.

Since this study is the continuation of Ho and Tseng (2006), the order-batching process used by them is also adopted here. Fig. 2 gives the flow chart of the order-batching process. As shown, to form an order batch, a seed order is selected first from the order pool using a seed-order selection rule. The selected seed order is the first order added to the order batch. Then updates are made on the remaining capacity of the picking cart. After that, an accompanying-order selection rule is adopted to select another order from the order pool and add it to the order batch. It should be noted that the selected order's required cart capacity cannot exceed the remaining capacity of the picking cart. After that, the remaining capacity of the picking cart is updated again. The accompanying-order selection process (i.e. step 5 to step 8) is then repeated until the picking cart does not have enough capacity for any more orders. It needs to be noted that the cumulative-seed mode is used in the batching process. Under this mode, when selecting an accompanying order from the order pool, one needs to compare every order in the order pool with orders that have already been added to the order batch. It has been proven by De Koster et al. (1999) that the cumulative-seed mode is better than the single-seed mode.

3. Seed-order selection rules

In this paper, 11 seed-order selection rules are studied. Three of them are from Ho and Tseng (2006). These rules have been shown by Ho and Tseng (2006) to perform well in minimizing the total travel distance of pickers. They will be compared with the rules newly proposed by us. In addition, unlike Ho and Tseng (2006) that

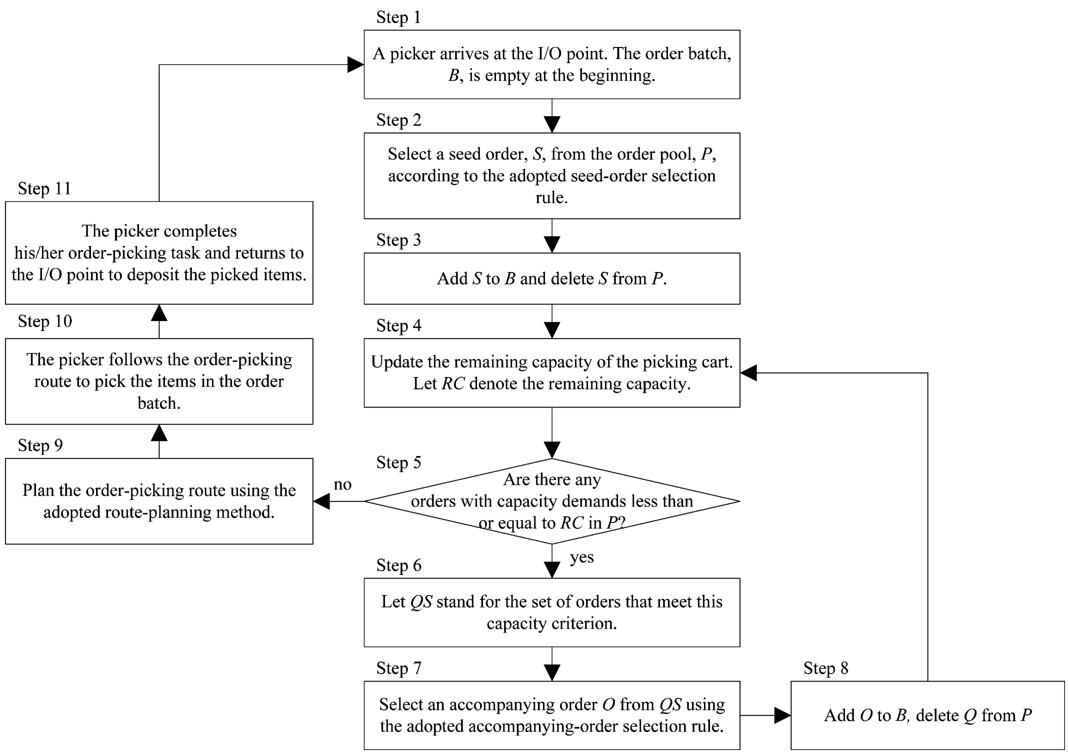

Fig. 2. The flow chart of order-batching process (Ho & Tseng, 2006).

only focuses on aisle-based and location-based rules, we also focus on area-based and distance-based rules. In the following, each of the seed-order selection rules studied here will be introduced.

- RanDom Seed-order selection (RDS) Rule
  If the RDS rule is used, one randomly selects an order from the order pool as the seed order. The RDS rule is included in the study, since it can serve as a performance benchmark for other rules. It is apparent that rules performing worse than the RDS rule are not worth adopting.
- Smallest Number of Picking Locations (SNPL) Rule
  The SNPL rule is one of the three seed-order selection rules adopted from Ho and Tseng (2006). It is a location-based rule. Detailed steps of the SNPL rule are as follows. First, one calculates the PL(R) (i.e. the number of picking locations that a picker needs to visit in order to pick the items required by an order R) of every order R in P (i.e. the order pool as defined in Fig. 2). Second, from P, one selects the order R^* that has the smallest PL(R^*) as the seed order.
- Smallest Number of Picking Aisles (SNPA) Rule
  The SNPA rule is adopted from Ho and Tseng (2006). It is an aisled-based rule. Under this rule, one first calculates the PA(R) (i.e. the number of picking aisles that a picker needs to visit in order to pick the items required by an order R) of every order R in the order pool P. After that, from P, one selects the order R^* that has the smallest PA(R^*) as the seed order.
- Smallest Aisle-Exponential-Weight Sum (SAEWS) Rule
  The SAEWS rule is also proposed by Ho and Tseng (2006). It is based on the weights assigned to aisles. To use the SAEWS rule, one first applies Eq. (1) to calculate the AEWS(R) (i.e. the Aisle-Exponential-Weight Sum of an order R) of every order R in the order pool P. In Eq. (1), $\mathrm{AEW}_i = 2^i$, i.e. the exponential weight of aisle i. After that, from P, one selects the order R^* that has the smallest AEWS(R) as the seed order.

  $$\mathrm{AEWS}(R) = \sum_{i \in \mathrm{AS}(R)} \mathrm{AEW}_i \tag{1}$$

  where,
  i aisle index
  AS(R) the set of aisles that a picker needs to visit in order to pick the items required by an order R
  AEW_i the exponential weight of aisle i, $\mathrm{AEW}_i = 2^i$

  As mentioned before, the aisles of the warehouse have been indexed from one to NoOfAisles (the total number of aisles in the warehouse). The closer an aisle to the I/O point, the smaller its index. As defined above, the exponential weight of an aisle with an index i is equal to 2^i. With this weight definition, an aisle's weight increases exponentially with its index.
- Smallest Aisle-Simple-Weight Sum (SASWS) Rule
  Similar to the SAEWS rule, the SASWS rule is also based on the weights of aisles but with a different weight definition. In the SASWS rule, the weight of an aisle is equal to its index. To use the SASWS rule, one first applies Eq. (2) to calculate the ASWS(R) (i.e. the Aisle-Simple-Weight Sum of an order R) of every order R in the order pool P. After that, from P, one selects the order R^* with the smallest ASWS(R) as the seed order.

  $$\mathrm{ASWS}(R) = \sum_{i \in \mathrm{AS}(R)} \mathrm{ASW}_i \tag{2}$$

  where,
  i aisle index
  AS(R) the set of aisles that a picker needs to visit in order to pick the items required by an order R
  ASW_i the simple weight of aisle i, $\mathrm{ASW}_i = i$

- Greatest Aisle-Simple-Weight Sum (GASWS) Rule
  The GASWS rule is the opposite of the SASWS rule. To use this rule, Eq. (2) is also used to calculate the ASWS(R) of every order R in the order pool P. After that, from P, the order R^* with the greatest ASWS(R) is selected as the seed order.

- Smallest Rectangular-Covering Area (SRCA) Rule
  The SRCA rule is an area-based rule. Its steps are as follows. First, for every order R in the order pool P, identify the smallest rectangle that can cover the storage locations of the items required by R and calculate the smallest rectangle's area. Second, from P, the order with the smallest rectangular-covering area is selected as the seed order. An example is given in Fig. 3 to help readers understand this rule. Fig. 3a shows the storage locations of an order's items, while Fig. 3b gives the smallest rectangle (i.e. the shadowed area) that can cover these storage locations. The greater the area of an order's smallest covering rectangle, the more widespread the order's items are in the warehouse.
- Greatest Rectangular-Covering Area (GRCA) Rule
  The GRCA rule is the opposite of the SRCA rule. This rule's first step is identical to the first step of the SRCA rule. In the second step, the order with the greatest rectangular-covering area is selected as the seed order.
- Shortest Average Rectangular Distance to the I/O point (SARD) Rule
  The SARD rule is based on an order's average rectangular distance to the I/O point. To use this rule, one first applies Eq. (3) to calculate ARD(R) (i.e. an order R's average rectangular distance to the I/O point) for every order R in the order pool P. After that, from P, one selects the order R^* with the shortest ARD(R^*) as the seed order. In Eq. (3), RD(T) (which stands for an item T's rectangular distance to the I/O point) can be understood with the illustration in Fig. 4. In the figure, the triangle denotes the storage location of T, while the hexagon the pickup location at which pickers stop to pick up T. As shown, RD(T) = DisX(T) + DisY(T), in which DisX(T) is the distance between T's storage location and the I/O point in the x-axis, and DisY(T) the distance between T's picking location and the I/O point in the y-axis.

$$\mathrm{ARD}(R) = \frac{\sum_{T\in \mathrm{IS}(R)} \mathrm{RD}(T)}{\mathrm{NofItems}(R)} \tag{3}$$

where,

IS(R) the set of items in an order R
T item T
RD(T) the rectangular distance from the storage location of T to the I/O point
NofItems(R) the number of items in an order R

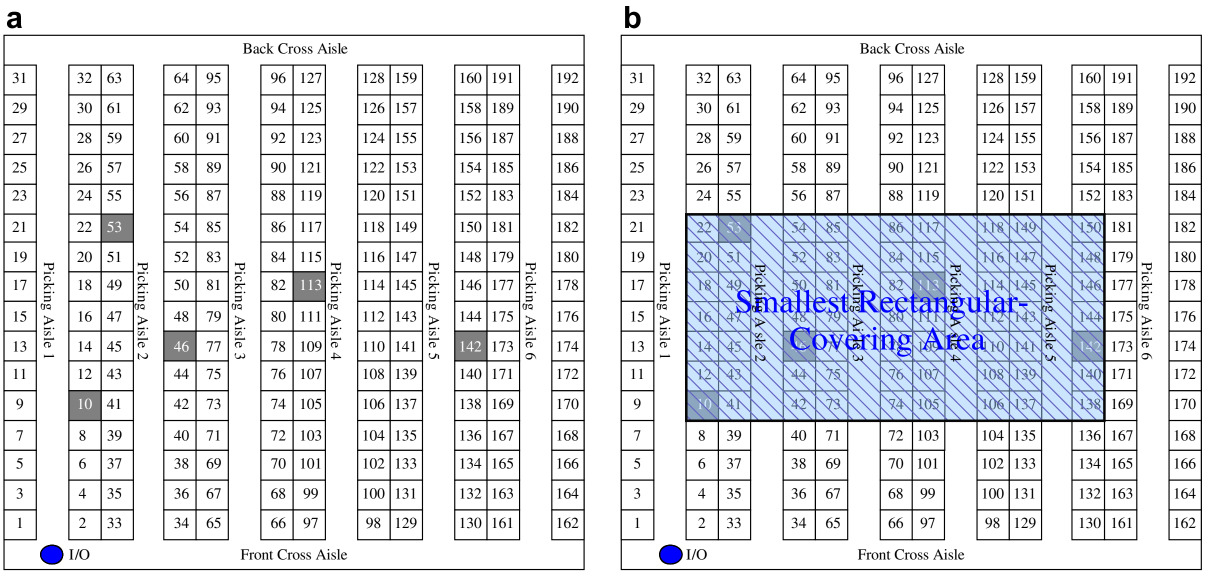

Fig. 3. An illustration of the smallest rectangular-covering area.

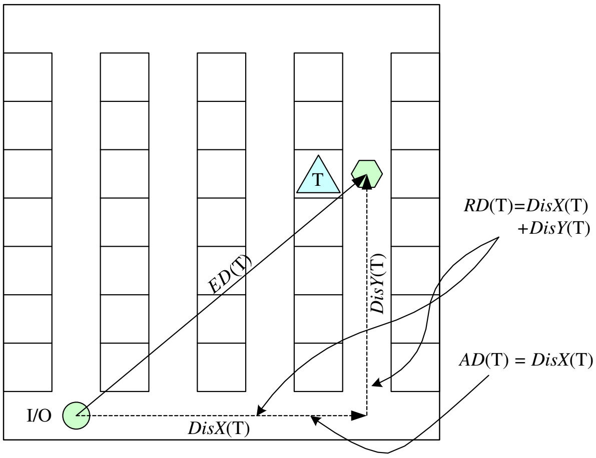

Fig. 4. An illustration of different distance measures.

- Shortest Average Euclidean Distance to the I/O point (SAED) Rule
  Similar to the SARD rule, the SAED rule is also a distance-based rule, except it is based on an order's average Euclidean distance to the I/O point. When using the SAED rule, Eq. (4) is first used to calculate AED(R) (i.e. an order R's average Euclidean distance to the I/O point) for every order R in the order pool P. In Eq. (4), ED(T) – an item T's Euclidean distance to the I/O point – is equal to $\sqrt{\mathrm{DisX}(T)^2 + \mathrm{DisY}(T)^2}$ (see Fig. 4). After that, from P, the order R^* with the smallest AED(R^*) is selected as the seed order.

$$\mathrm{AED}(R) = \frac{\sum_{T\in \mathrm{IS}(R)} ED(T)}{\mathrm{NofItems}(R)} \tag{4}$$

  where,
  ED(T) the Euclidean distance from the pickup location of T to the I/O point

- Shortest Average Aisle Distance to the I/O point (SAAD) Rule
  The SAAD rule is based on an order's average aisle distance to the I/O point. If the SAAD rule is used, Eq. (5) is used to calculate AAD(R) (i.e. an order R's average aisle distance to the I/O point) for every order R in the order pool P. In Eq. (5), AD(T) – an item T's aisle distance to the I/O point – is equal to DisX(T) (see Fig. 4). After that, from P, one selects the order R^* with the smallest AAD(R^*) as the seed order.

$$\mathrm{AAD}(R) = \frac{\sum_{T\in \mathrm{IS}(R)} \mathrm{AD}(T)}{\mathrm{NofItems}(R)} \tag{5}$$

  where,
  AD(T) the aisle distance from the pickup location of T to the I/O point

4. Accompanying-order selection rules

Fourteen accompanying-order selection rules are studied here. One of them is from Ho and Tseng (2006). According to Ho and Tseng (2006), this rule is the best (among the 10 accompanying-order selection rules investigated by them) in minimizing the total travel distance of pickers. This rule is included here for the comparison purpose. The following introduces the accompanying-order selection rules investigated in this study. As described in Fig. 2, one uses an accompanying-order selection rule to select an accompanying order from QS, which (as defined in Fig. 2) is the set of orders that can satisfy the cart-capacity criterion.

- RanDom Accompanying-order selection (RDA) Rule
If the RDA rule is used, one randomly selects an order from QS as the accompanying order. The performance of the RDA rule can serve as the performance benchmark for other rules. An accompanying-order selection rule is not worth adopting if it performs worse than the RDA rule.
- Smallest Number of Additional Picking Aisles (SNAPA) Rule
The SNAPA rule is an aisle-based rule proposed by Ho and Tseng (2006). It has been shown by Ho and Tseng (2006) to perform well in minimizing the total travel distance of pickers. If the SNAPA rule is used, one first calculates the NAPA(R, B) (i.e. the number of additional picking aisles that a picker needs to visit if an order R is added to the order batch B) of every order R in QS (see Fig. 2). After that, from QS the SNAPA rule selects the order R^* with the smallest NAPA(R^*, B) as the accompanying order.
- Greatest Overlapping covering-Area (GOA) Rule
The GOA rule is an area-based rule. To apply this rule, one first calculates the OA(R, B) (i.e. the overlapping area between the smallest covering rectangle of the order batch B and the smallest covering rectangle of an order R) of every order R in QS. After that, from QS, the GOA rule selects the order R^* with the greatest OA(R^*, B) as the accompanying order. The greater the OA(R, B) between an order R and an order batch B, the greater the chance their items are close to each other. Fig. 5 illustrates the OA(R, B) between the smallest covering rectangle of an order R (whose items are at locations 10, 46, 53, 113, and 142) and the smallest covering rectangle of an order batch B (whose items are at locations 16, 30, 49, 60, 81, 86, 87, and 94). The smallest covering rectangle of the order R has already been shown in Fig. 3. Fig. 5a shows the smallest covering rectangle of B, while Fig. 5b gives the overlapping area of the smallest covering rectangles of R and B.
- Smallest Overlapping covering Area (SOA) Rule
The SOA rule is opposite to the GOA rule. Under this rule, the OA(R, B) between the smallest covering rectangle of B and the smallest covering rectangle of every order, R, in QS is calculated. After that, from QS, the SOA rule selects the order R^* with the smallest OA(R^*, B) as the accompanying order.
- Greatest Overlapping-area to Total-covering-area Ratio (GOTR) Rule
The GOTR rule is also an area-based rule. To use this rule, one first calculates OTR(R, B) (i.e. the overlapping-area to total-covering-area ratio between the order batch B and an order, R) for every order R in QS. After that, the order R^* with the greatest OTR(R^*, B) is selected from QS as the accompanying order. Eq. (6) shows the calculation of OTR(R, B). Using the same R and B in Figs. 3 and 5, Fig. 6 shows the total area covered by either the smallest covering rectangle of R or the smallest covering rectangle of B. The

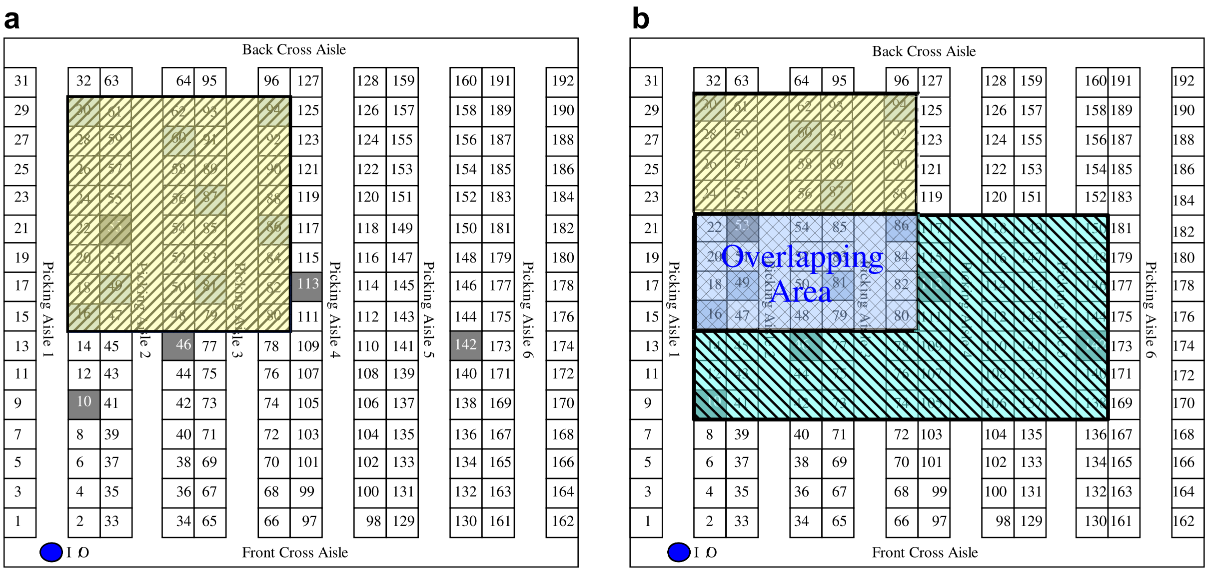

Fig. 5. An illustration of OA (Overlapping covering Area).

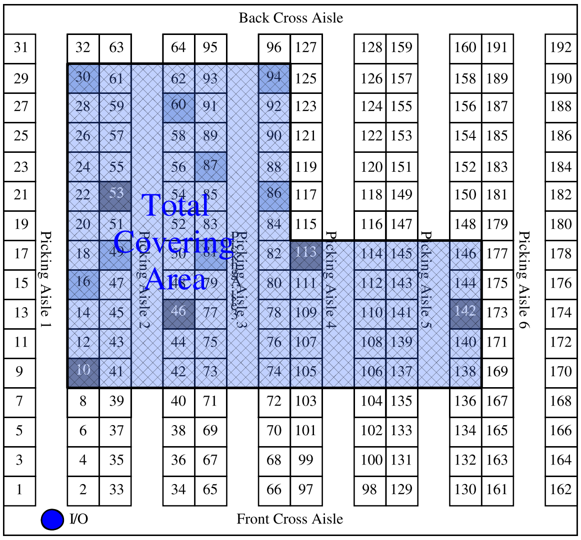

Fig. 6. An illustration of total covering area.

OTR(R, B) between R and B can be obtained by dividing the overlapping area in Fig. 5b with the total covering area in Fig. 6. It is obvious that the greater the OTR(R, B) between R and B, the closer their items are to each other.

$$\mathrm{OTR}(R,B) = \frac{\mathrm{OA}(R,B)}{\mathrm{TCA}(R,B)} \tag{6}$$

where,

OA(R, B) the overlapping area between the smallest covering rectangles of R and B

TCA(R, B) the total area covered by either the smallest covering rectangle of R or the smallest covering rectangle of B

- Smallest Overlapping-area to Total-covering-area Ratio (SOTR) Rule
  The SOTR rule is the opposite of the GOTR rule. Under this rule, the OTR(R, B) between B and every order R in QS is calculated. After that, from QS, the order R^* with the smallest OTR(R^*, B) is selected as the accompanying order.
- Smallest Additional Covering Area (SACA) Rule
  The SACA rule is also an area-based rule. To apply this rule, the additional covering area, ACA(R, B), between B and every order R in QS is calculated, after which the order R^* with the smallest ACA(R^*, B) is selected as the accompanying order. The ACA(R, B) between an order batch B and an order R can be calculated using Eq. (7). One can interpret ACA(R, B) as the additional area needed by the smallest covering rectangle of B in order to cover the items of R. Using the same R and B shown in previous figures, Fig. 7 shows the additional covering area between R and B. It is apparent that the smaller the ACA(R, B) between R and B, the closer their items are to each other.

$$\mathrm{ACA}(R,B) = \mathrm{TCA}(R,B) - \mathrm{RCA}(B) \tag{7}$$

where,

RCA(B) the area of the smallest covering rectangle of B

TCA(R, B) the total area covered by either the smallest covering rectangle of R or the smallest covering rectangle of B

- Greatest Additional Covering Area (GACA) Rule
  The GACA rule is the opposite of the SACA rule. In using this rule, the ACA(R, B) between B and every order R in QS is calculated. After that, the order R^* with the greatest ACA(R^*, B) is selected as the accompanying order.

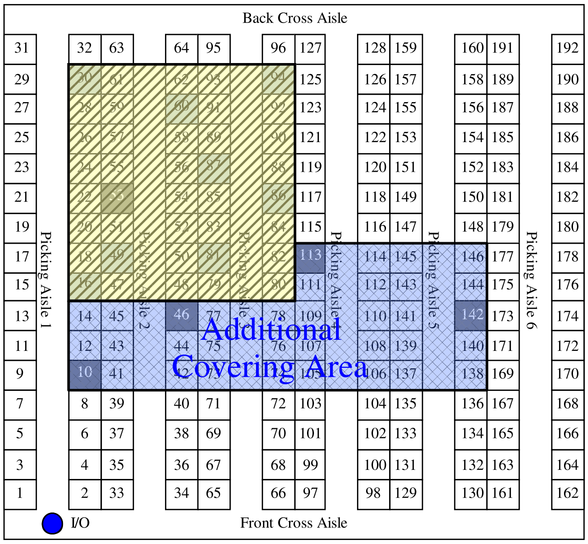

Fig. 7. An illustration of ACA (Additional Covering Area).

- Greatest identical-pickup-Locations to additional-covering Area Ratio (GLAR) Rule
The GLAR rule considers two factors – the number of identical pickup locations between R and B, and the additional covering area of R and B. To use this rule, the "identical-pickup-Locations to additional-covering Area Ratio", i.e. $\mathrm{LAR}(R,B)$, between B and every order R in QS is first calculated, following which the order R^* with the greatest $\mathrm{LAR}(R^*,B)$ in QS is selected as the accompanying order. Eq. (8) shows how $\mathrm{LAR}(R,B)$ is calculated. As shown, a greater $\mathrm{NIPL}(R,B)$ or a smaller $\mathrm{ACA}(R,B)$ can lead to a greater $\mathrm{LAR}(R,B)$.

$$\mathrm{LAR}(R,B)=\frac{\mathrm{NIPL}(R,B)}{\mathrm{ACA}(R,B)} \tag{8}$$

where, $\mathrm{NIPL}(R,B)$ the number of identical pickup locations between R and B
$\mathrm{ACA}(R,B)$ the additional covering area between R and B

- Smallest identical-pickup-Locations to additional-covering Area Ratio (SLAR) Rule
The SLAR rule is opposite to the GLAR rule. Under this rule, a calculation is performed to attain the $\mathrm{LAR}(R,B)$ between B and every order R in QS. After that, from QS the SLAR rule selects the order R^* with the smallest $\mathrm{LAR}(R^*,B)$ as the accompanying order.
- Shortest Average Mutual-nearest-Rectangular Distance (SAMRD) Rule
The SAMRD rule is a distance-based rule. Its detailed steps are as follows. First, for every order R in QS, calculate its $\mathrm{AMRD}(R,B)$, i.e. the average mutual-nearest-rectangular distance between R's items and B's items. Eqs. (8)–(10) show how $\mathrm{AMRD}(R,B)$ can be calculated. Second, the order R^* with the smallest $\mathrm{AMRD}(R^*,B)$ is selected from QS as the accompanying order. The smaller the $\mathrm{AMRD}(R,B)$ between R and B, the closer their items are to each other.

$$\mathrm{ANRD}_{R\to B}=\frac{\sum_{T\in \mathrm{IS}(R)}\mathrm{SRD}(T,B)}{\mathrm{NofItems}(R)} \tag{8}$$

$$\mathrm{ANRD}_{B\to R}=\frac{\sum_{T\in \mathrm{IS}(B)}\mathrm{SRD}(T,R)}{\mathrm{NofItems}(B)} \tag{9}$$

$$\mathrm{AMRD}(R,B)=(\mathrm{ANRD}_{R\to B}+\mathrm{ANRD}_{B\to R})/2 \tag{10}$$

where,
$\mathrm{ANRD}_{R\to B}$ the average nearest rectangular distance of the items in R to their nearest respective items in B

$\text{SRD}(T, B)$ the rectangular distance from the pickup location of an item T to the nearest item in B
$\text{AMRD}(R, B)$ the average mutual-nearest-rectangular distance between R's items and B's items

- Shortest Average Mutual-nearest-Euclidean Distance (SAMED) Rule
The SAMED rule is similar to the SAMRD rule, except it is based on Euclidean distance. Its detailed steps are also similar to those of the SAMRD rule, except at the first step one calculates $\text{AMED}(R, B)$ (i.e. the average mutual-nearest-rectangular distance between R's items and B's items) for every order R in QS. Eqs. (11)–(13) show how $\text{AMED}(R, B)$ can be calculated. After that, from QS the SAMED rule selects the order R^* with the smallest $\text{AMED}(R^*, B)$ as the accompanying order.

$$\text{ANED}_{R\to B} = \frac{\sum_{T\in \text{IS}(R)} \text{SED}(T, B)}{\text{NofItems}(R)} \tag{11}$$

$$\text{ANED}_{B\to R} = \frac{\sum_{T\in \text{IS}(B)} \text{SED}(T, R)}{\text{NofItems}(B)} \tag{12}$$

$$\text{AMED}(R, B) = (\text{ANED}_{R\to B} + \text{ANED}_{B\to R})/2 \tag{13}$$

where,
$\text{ANED}_{R \to B}$ the average nearest Euclidean distance of the items in R to their nearest respective items in B
$\text{SED}(T, B)$ the Euclidean distance from the pickup location of an item T to the nearest item in B
$\text{AMED}(R, B)$ the average mutual-nearest-Euclidean distance between R's items and B's items

- Shortest Average Mutual-nearest-Aisle Distance (SAMAD) Rule
The SAMAD rule is similar to the previous two distance-based rules, except it is based on aisle distance. The first step calculates $\text{AMAD}(R, B)$ – the average mutual-nearest-aisle distance between R's items and B's items – for every order, R, in QS. Eqs. (14)–(16) show how $\text{AMAD}(R, B)$ can be calculated. After that, the order, R^*, with the smallest $\text{AMAD}(R^*, B)$ is selected from QS as the accompanying order.

$$\text{ANAD}_{R\to B} = \frac{\sum_{T\in \text{IS}(R)} \text{SAD}(T, B)}{\text{NofItems}(R)} \tag{14}$$

$$\text{ANAD}_{B\to R} = \frac{\sum_{T\in \text{IS}(B)} \text{SAD}(T, R)}{\text{NofItems}(B)} \tag{15}$$

$$\text{AMAD}(R, B) = (\text{ANAD}_{R\to B} + \text{ANAD}_{B\to R})/2 \tag{16}$$

where,
$\text{ANAD}_{R \to B}$ the average nearest aisle distance of the items in R to their nearest respective items in B
$\text{SAD}(T, B)$ the aisle distance from the pickup location of an item T to the nearest item in B
$\text{AMAD}(R, B)$ the average mutual-nearest-aisle distance between R's items and B's items

- Smallest Weighted-Aisle-Index Difference (SWAID) rule
The SWAID rule is based on the weighted-aisle-index of an order. The detailed steps of this rule are as follows. First, calculate the weighted-aisle-index of the order batch B and the weighted-aisle-index of every order R in QS. Eqs. (17) and (18) show how this is done. Second, calculate the $\text{WAID}(R, B)$ (i.e. the weighted-aisle-index difference between B and an order R) for every order R in QS. Third, from QS, select the order R^* with the smallest $\text{WAID}(R^*, B)$ as the accompanying order.

$$\text{WAI}(R) = \frac{\sum\limits_{T\in \text{IS}(R)} \text{AI}(T)}{\text{NofItems}(R)} \tag{17}$$

$$\text{WAI}(B) = \frac{\sum\limits_{T\in \text{IS}(B)} \text{AI}(T)}{\text{NofItems}(B)} \tag{18}$$

$$\text{WAID}(R, B) = |\text{WAI}(R) - \text{WAI}(B)| \tag{19}$$

where,
AI(T) the aisle index of the aisle that an item T is in
WAI(R) the weighted aisle index of R
WAI(B) the weighted aisle index of B
WAID(R, B) the weighted-aisle-index difference between R and B

5. Route-planning methods

Ho and Tseng (2006) used two route-planning methods to test their rules. As explained earlier, some rules from Ho and Tseng (2006) are adopted in this study to serve as the performance benchmark for the rules newly proposed by us. Thus, in order to have a fair comparison with rules proposed by Ho and Tseng (2006), route-planning methods used by them are also adopted here. These two methods are the Largest Gap (LA) method and the Largest Gap+Simulated Annealing (LA+SA) method. They are briefly described as follows. For more details of these methods, please refer to Ho and Tseng (2006).

5.1. The LG method

Under the LG method, the picker enters an aisle as far as the largest gap within an aisle. A gap represents the separation between any two adjacent picks, between the first pick and the front aisle, or between the last pick and the back aisle. The largest gap is the partition of aisle that the picker does not traverse (Hall, 1993). Researchers (e.g., Petersen, 1997; Petersen & Schmenner, 1999) have shown that the LG method outperforms other route-planning methods, such as the Traversal Strategy, the Return Strategy, and the Midpoint Strategy.

5.2. The LG+SA method

The LG+SA method combines the LG method and Simulated Annealing (SA) – a heuristic optimization technique that allows non-improving moves in its search process. Under this method, the LG method is first used to find an initial order-picking route. This initial order-picking route is then improved by SA to obtain an improved order-picking route. As explained in Ho and Tseng (2006), the purpose of using the LG+SA method is not to obtain optimal routes, but to obtain alternative routes which allow one to see how well the proposed rules will perform under different routing methods.

6. Experiments

To understand the performance of the rules introduced above, experiments were conducted. The performance measure is the Total order-picking Travel Distance (TTD). The environment of the experiments is the warehouse shown in Fig. 1. As explained earlier, the warehouse has 12 picking aisles and each aisle has 32 picking locations. Since we are also interested in the effects that Aisle-Picking-Frequency Distribution (APFD) has on the proposed rules' performance, two sets of order pools (Set I and Set II) were generated for the experiments. Each set contains 25 randomly generated order pools. Each order pool has 250 orders. Order pools from different sets follow different aisle-picking-frequency distributions. Table 1 shows the aisle-picking-frequency distributions of Set I and Set II. These distributions are identical to the ones in Ho and Tseng (2006) since we want to have a fair comparison with the rules adopted from their study. As shown, order pools in Set I have more realistic settings, since they follow a distribution in which the closer an aisle is to the I/O station, the greater its picking frequency becomes. In other words, the closer an aisle is to the I/O station, the greater the demand of those items stored in the aisle. Order pools in Set II follow a different distribution in which all aisles have equal chances to be visited by pickers. Set II tries to mimic a situation in which storage locations are randomly assigned to items. The purpose of Set II is for the comparison purpose. Furthermore, with Set II we are able to understand each rule's performance when the storage-location assignment factor is not present (i.e. storage locations are randomly assigned to items). Table 2 summarizes the

Table 1
The aisle-picking-frequency (%) distributions of Set I and Set II

Order pool set	Aisle No.											
	1	2	3	4	5	6	7	8	9	10	11	12
Set I	20	17	14	11	9	8	6	5	4	3	2	1
Set II	$8\frac{1}{3}$	$8\frac{1}{3}$	$8\frac{1}{3}$	$8\frac{1}{3}$	$8\frac{1}{3}$	$8\frac{1}{3}$	$8\frac{1}{3}$	$8\frac{1}{3}$	$8\frac{1}{3}$	$8\frac{1}{3}$	$8\frac{1}{3}$	$8\frac{1}{3}$

Table 2
A summary of factors considered in the experiments and their levels

Level	Factor			
	Aisle-picking-frequency distribution (APFD)	Seed-order selection rule	Accompanying-order selection rule	Route-planning method
1	Set I	RDS	RDA	LG
2	Set II	SNPL	SNAPA	LG+SA
3		SNPA	GOA	
4		SAEWS	SOA	
5		SASWS	GOTR	
6		GASWS	SOTR	
7		SRCA	SACA	
8		GRCA	GACA	
9		SARD	GLAR	
10		SAED	SLAR	
11		SAAD	SAMRD	
12			SAMED	
13			SAMAD	
14			SWAID	

factors considered in the experiments and their levels. Full-factorial experiments were conducted. There are 616 ($2 \times 11 \times 14 \times 2$) combinations of factors. Since each combination was experimented 25 times (using 25 order pools), in all 15,400 experiments were conducted.

7. Experimental results

In this section, the TTD results of the experiments are analyzed and discussed. We conduct full factorial ANOVA on the TTD results and give the ANOVA result in Table 3. As shown in Table 3, the main effects of route-planning method and APFD are significant at an α of 0.05. Tables 4 and 5 summarize the TTD means, and the 95% confidence intervals of route-planning methods and APFDs, respectively. From Tables 4 and 5, one can conclude that the LG+SA method is significantly better (at an α of 0.05) than the LG method, suggesting SA can further reduce the travel distance of pickers. This conclusion agrees with the conclusion given by Ho and Tseng (2006). And, from Tables 3 and 5, one can also conclude that Set I is significantly better (at an α of 0.05) than Set II, indicating that placing high-demand items in aisles closer to the I/O point can result in better TTD performance. This conclusion agrees with the one in Ho and Tseng (2006).

The ANOVA in Table 3 shows the main effect of seed-order selection rule is significant at an α of 0.05. To understand the TTD performance of seed-order selection rules, we summarize the TTD means and the 95% confidence intervals of seed-order selection rules in Table 6 and their Duncan test result in Table 7. As shown, the SNPL rule has best performance, followed by the SRCA rule and the SNPA rule; however these three rules are not significantly different (at an α of 0.05) in their TTD performance since they are in the same subset. Two of these rules (i.e. the SNPL rule and the SNPA rule) are from Ho and Tseng (2006), and one (i.e. the SRCA rule) is newly proposed by us. As for the two aisle-weight-sum-based rules (i.e. the SAEWS and SASWS rules), one observes that the SASWS rule proposed by us is better than the SAEWS rule proposed by Ho and Tseng (2006). And, for the three distance-based rules (i.e. the SARD, SAED, and SAAD rules), one finds they are in the same subset, indicating they are not significantly different (at an α of 0.05) in the TTD performance, and

Table 3
Full factorial ANOVA on the TTD results

Source	Sum of squares	*df*	Mean square	*F*	*p*
Main effects					
APFD	9.94203 E+11	1	994,203,402,240	15,586.90332	.000**
Seed	27,377,976,320	10	2,737,797,632	42.92258835	.000**
Accompany	3.78268 E+12	13	290,975,121,408	4561.844238	.000**
Route	1,473,851,648	1	1,473,851,648	23.10672379	.000**
Two-way interactions					
APFD * seed	4,753,560,320	10	475,356,032	7.452527523	.000**
APFD * accompany	92,691,316,224	13	7,130,101,248	111.7841644	.000**
Seed * accompany	51,375,126,400	130	395,193,280	6.195753574	.000**
APFD * route	99,218,696	1	99,218,696	1.555528998	.212
Seed * route	63,461,985	10	6,346,199	0.099494308	1.000
Accompany * route	577,659,940	13	44,435,380	0.69664818	.769
Three-way interactions					
APFD * seed * accompany	22,407,775,520	130	172,367,504	2.702339888	.000**
APFD * seed * route	59,675,835	10	5,967,584	0.093558468	1.000
APFD * accompany * route	611,750,360	13	47,057,720	0.737760603	.727
Seed * accompany * route	683,781,735	130	5,259,860	0.082462929	1.000
Four-way interaction					
APFD * seed * accompany * route	695,665,360	130	5,351,272	0.083896071	1.000

Note: Two asterisks indicate significance at the 5 percent level or below.

Table 4
The TTD means and the 95% confidence intervals of the LG and LG+SA methods

Order-picking route-planning method	Mean	95% confidence interval	
		Lower bound	Upper bound
LG	99,424.49	99,349.45	99,499.53
LG+SA	98,975.99	98,900.95	99,051.03

Table 5
The TTD means and the 95% confidence intervals of Set I and Set II

Aisle-picking-frequency distribution	Mean	95% confidence interval	
		Lower bound	Upper bound
Set 1	92,042.05	91,967.01	92,117.09
Set 2	106,358.43	106,283.39	106,433.47

their performance is rather mediocre. Finally, from Tables 6 and 7, one can see the GASWS rule has the worst TTD performance, followed by the GRCA rule. Both rules perform worse than the RDS rule (a random rule), indicating they are not worth adopting.

Table 3 shows the two-way interaction between the route-planning method and the seed-order selection rule is not significant at an α of 0.05. To understand their interaction, Table 8 summarizes the TTD means of the LG and LG+SA methods and the t-test result between them under every seed-order selection rule. As shown, the LG+SA method is significantly better than the LG method under every seed-order selection rule. Furthermore, to understand the effects of the LG and LG+SA methods on the TTD performance of seed-order selection rules, we conduct a Duncan test on them under the LG method and the LG+SA method. The result is shown in Table 9. From Table 9, it is observed that the routing planning methods do not affect the performance rankings of seed-order selection rules, as their rankings under the LG and LG+SA methods are identical. And, the subset groupings of seed-order selection rules are very similar between the LG and LG+SA methods. In addition, the SNPL, SRCA, and SNPA rules are ranked first, second and third, respectively,

Table 6
The TTD means and the 95% confidence intervals of seed-order selection rules

Seed-order selection rule	Mean	95% confidence interval	
		Lower bound	Upper bound
RDS	100,138.09	99,962.10	100,314.08
SNPL	98,162.85	97,986.86	98,338.84
SNPA	98,327.75	98,151.76	98,503.74
SAEWS	98,510.59	98,334.60	98,686.57
SASWS	98,481.92	98,305.93	98,657.90
GASWS	100,717.87	100,541.88	100,893.86
SRCA	98,226.16	98,050.18	98,402.15
GRCA	100,227.53	100,051.54	100,403.52
SARD	99,378.91	99,202.93	99,554.90
SAED	99,533.14	99,357.15	99,709.12
SAAD	99,497.82	993,21.83	99,673.81

Table 7
The Duncan test result on the TTD performance of seed-order selection rules

Main effect ($\alpha = 0.05$)	Subset					
	1	2	3	4	5	6
SNPL	98,162.85					
SRCA	98,226.16	98,226.16				
SNPA	98,327.75	98,327.75	98,327.75			
SASWS		98,481.92	98,481.92			
SAEWS			98,510.59			
SARD				99,378.91		
SAAD				99,497.82		
SAED				99,533.14		
RDS					100,138.09	
GRCA					100,227.53	
GASWS						100,717.87

Table 8
The TTD means of the LG and LG+SA methods and the *t*-test result between them under every seed-order selection rule

Seed-order selection rule	TTD mean		*t*-Test result	
	LG	LG+SA	*t* value	*p* value
RDS	100,366.64	99,909.54	16.126	.000**
SNPL	98,383.17	97,942.53	41.274	.000**
SNPA	98,547.31	98,108.19	28.925	.000**
SAEWS	98,740.23	98,280.94	21.186	.000**
SASWS	98,692.79	98,271.06	139.511	.000**
GASWS	100,944.16	100,491.59	123.946	.000**
SRCA	98,451.06	98,001.27	31.408	.000**
GRCA	100,450.94	100,004.11	45.228	.000**
SARD	99,605.33	99,152.50	150.75	.000**
SAED	99,762.20	99,304.07	152.073	.000**
SAAD	99,725.56	99,270.09	151.148	.000**

Note: Two asterisks indicate significance at the 5 percent level or below.

under the LG and LG+SA methods. And, the GASWS, GRCA, RDS rules are ranked last, second to last, third to last, respectively, under the LG and LG+SA methods. From the results of Tables 8 and 9 and the discussion above, one can understand why the two-way interaction between the route-planning method and the seed-order selection rule is not significant at an α of 0.05.

Table 9
The Duncan test result on the TTD performance of seed-order selection rules under the LG and LG+SA methods

LG	LG+SA
SNPL	**SNPL**
SRCA	**SRCA**
SNPA	**SNPA**
SASWS	**SASWS**
SAEWS	**SAEWS**
SARD	**SARD**
SAAD	**SAAD**
SAED	**SAED**
RDS	**RDS**
GRCA	**GRCA**
GASWS	**GASWS**

Note: Seed-order selection rules connected symbolically are not significantly different at an α of 0.05.

The ANOVA in Table 3 indicates that the two-way interaction between the APFD and the seed-order selection rule is significant at an α of 0.05. To further understand their interaction, Table 10 summarizes the TTD means of Set I and Set II and the *t*-test result between them under every seed-order selection rule. From Table 10, it is observed that Set I is significantly better (at an α of 0.05) than Set II under every seed-order selection rule. Additionally, to understand the APFD's effects on the TTD performance of seed-order selection rules, Duncan tests are conducted on seed-order selection rules' performance under Set I and Set II (see Table 11). As shown, the performance rankings of seed-order selection rules are different under Set I and Set II. For example, the SNPL rule is ranked first under Set I, but second under Set II. This result also explains why the two-way interaction between the APFD and the seed-order selection rule is significant at an α of 0.05.

The ANOVA in Table 3 also indicates that the main effect of accompanying order is significant at an α of 0.05. To further understand the TTD performance of accompanying-order selection rules, we summarize the TTD means and their 95% confidence intervals of accompanying-order selection rules in Table 12. We also conduct a Duncan test on their TTD performance and summarize the test result in Table 13. As shown, the top four rules are the SAMAD, SNAPA, SAMRD, and SAMED rules. These top four rules are significantly better (at an α of 0.05) than the other 10 accompanying-order selection rules. Among these top four rules, the second-ranked rule, i.e. the SNAPA rule, was proposed by Ho and Tseng (2006), and the rest of

Table 10
The TTD means of Set I and Set II and the *t*-test result between them under every seed-order selection rule

Seed-order selection rule	TTD mean		*t*-Test result	
	Set I	Set II	*t* value	*p* value
RDS	93,018.33	107,257.86	−82.606	.000**
SNPL	90,960.54	105,365.16	−89.946	.000**
SNPA	91,156.49	105,499.01	−88.602	.000**
SAEWS	91,278.14	105,743.03	−94.168	.000**
SASWS	91,278.24	105,685.60	−91.611	.000**
GASWS	93,735.09	107,700.66	−84.089	.000**
SRCA	91,105.19	105,347.14	−87.651	.000**
GRCA	93,271.06	107,184.00	−83.961	.000**
SARD	92,198.16	106,559.67	−94.923	.000**
SAED	92,153.79	106,912.49	−94.013	.000**
SAAD	92,307.53	106,688.11	−88.022	.000**

Note: Two asterisks indicate significance at the 5 percent level or below.

Table 11
The Duncan test result on the TTD performance of seed-order selection rules under Set I and Set II

Set I	Set II
SNPL	**SRCA**
SRCA	**SNPL**
SNPA	**SNPA**
SAEWS	**SASWS**
SASWS	**SAEWS**
SAED	**SARD**
SARD	**SAAD**
SAAD	**SAED**
RDS	**GRCA**
GRCA	**RDS**
GASWS	**GASWS**

Note: Seed-order selection rules connected symbolically are not significantly different at an α of 0.05.

Table 12
The TTD means and the 95% confidence intervals of accompanying-order selection rules

Accompanying-order selection rule	Mean	95% confidence interval	
		Lower bound	Upper bound
RDA	113,516.03	113,317.49	113,714.570
SNAPA	77,687.98	77,489.44	77,886.52
GOA	100,733.39	100,534.85	100,931.93
SOA	110,515.52	110,316.98	110,714.06
GOTR	111,841.21	111,642.67	112,039.75
SOTR	112,176.56	111,978.02	112,375.11
SACA	100,739.74	100,541.20	100,938.28
GACA	110,465.63	110,267.09	110,664.17
GLAR	93,142.26	92,943.72	93,340.81
SLAR	115,562.29	115,363.75	115,760.83
SAMRD	80,394.74	80,196.20	80,593.28
SAMED	82,339.66	82,141.12	82,538.21
SAMAD	74,931.97	74,733.43	75,130.51
SWAID	104,756.37	104,557.83	104,954.91

them are proposed by us. Furthermore, three of the top four rules (i.e. the SAMAD, SAMRD, and SAMED rules) are distance-based rules and one (i.e. the SNAPA rule) is aisle-based rule. The GLAR, GOA, SACA, and SWAID rules are ranked fifth, sixth, seventh, and eighth, respectively. Their performance is rather mediocre. And, the performance of the two covering-area to total-covering-area ratio rules (i.e. the GOTR and SOTR rules) is rather disappointing. From Tables 12 and 13, one also sees that the SLAR rule is ranked last. Its performance is significantly worse than the other accompanying-order selection rules. The SLAR rule is also the only accompanying-order selection rule that performs worse than the RDA rule (a random rule), indicating it is not worth adotping.

Table 3 shows that the two-way interaction between the route-planning method and the accompanying-order selection rule is not significant at an α of 0.05. To further understand their interaction, we conduct t-test on the performance of the LG and LG+SA methods under every accompanying-order selection rule. The result is shown in Table 14. As shown, the LG+SA method is significantly better than the LG method under every accompanying-order selection rule. We also conduct a Duncan test on the performance of accompanying-order selection rules under the LG and LG+SA methods. The result is shown in Table 15. As shown, the performance rankings of accompanying-order selection rules are identical under the LG and LG+SA methods. The subset groupings of accompanying-order selection rules are also

Table 13
The Duncan test result on the TTD performance of accompanying-order selection rules

Main effect ($\alpha = 0.05$)	Subset											
	1	2	3	4	5	6	7	8	9	10	11	12
SAMAD	74,931.97											
SNAPA		77,687.98										
SAMRD			80,394.74									
SAMED				82,339.66								
GLAR					93,142.26							
GOA						100,733.39						
SACA						100,739.74						
SWAID							104,756.37					
GACA								110,465.63				
SOA								110,515.52				
GOTR									111,841.21			
SOTR										112,176.56		
RDA											113,516.03	
SLAR												115,562.29

Table 14
The TTD means of LG and LG+SA and the *t*-test result between them under every accompanying-order selection rule

Accompanying-order selection rule	TTD mean		*t*-Test result	
	LG	LG+SA	*t* value	*p* value
RDA	113,743.55	113,288.51	25.542	.000**
SNAPA	77,897.31	77,478.66	16.577	.000**
GOA	100,938.44	100,528.35	28.120	.000**
SOA	110,748.42	110,282.62	133.489	.000**
GOTR	112,060.55	111,621.87	28.442	.000**
SOTR	112,402.49	111,950.64	19.857	.000**
SACA	100,945.27	100,534.20	30.994	.000**
GACA	110,701.46	110,229.80	20.592	.000**
GLAR	93,365.29	92,919.24	39.107	.000**
SLAR	115,786.04	115,338.55	28.243	.000**
SAMRD	80,635.07	80,154.40	79.591	.000**
SAMED	82,583.80	82,095.53	48.156	.000**
SAMAD	75,145.66	74,718.29	127.491	.000**
SWAID	104,989.53	10,4523.22	129.950	.000**

Note: Two asterisks indicate significance at the 5 percent level or below.

Table 15
The Duncan test result on the TTD performance of accompanying-order selection rules under the LG and LG+SA methods

LG	**LG+SA**
SAMAD	**SAMAD**
SNAPA	**SNAPA**
SAMRD	**SAMRD**
SAMED	**SAMED**
GLAR	**GLAR**
GOA	**GOA**
SACA	**SACA**
SWAID	**SWAID**
GACA	**GACA**
SOA	**SOA**
GOTR	**GOTR**
SOTR	**SOTR**
RDA	**RDA**
SLAR	**SLAR**

Note: Accompanying-order selection rules connected symbolically are not significantly different at an α of 0.05.

identical under the LG and LG+SA methods. These results indicate that the LG and LG+SA methods do not affect the performance of the accompanying-order selection rules. These results can also explain why the two-way interaction between the route-planning method and the accompanying-order selection rule is not significant at an α of 0.05.

Table 3 also shows the two-way interaction between the APFD and the accompanying-order selection rule is significant at an α of 0.05. We conduct *t*-tests on the TTD performance of Set I and Set II under every accompanying-order selection rule. Table 16 summarizes the result. As shown, the TTD performance of Set I is significantly better (at an α of 0.05) than that of Set II under every accompanying-order selection rule. We also conduct a Duncan test on the TTD performance of accompanying-order selection rules under Set I and Set II. The result is shown in Table 17. The result shows the performance rankings of accompanying-order selection rules are not identical under Set I and Set II. For example, the GOA rule is ranked sixth under Set I,

Table 16
The TTD means of Set I and Set II and the *t*-test result between them under every accompanying-order selection rule

Accompanying-order selection rule	TTD mean		*t*-Test result	
	Set I	Set II	*t* value	*p* value
RDA	105,190.82	121,841.24	−108.859	.000**
SNAPA	70,449.53	84,926.44	−99.210	.000**
GOA	95,826.86	105,639.93	−65.846	.000**
SOA	102,825.31	118,205.73	−100.438	.000**
GOTR	103,842.18	119,840.24	−110.651	.000**
SOTR	104,437.16	119,915.96	−110.586	.000**
SACA	96,001.89	105,477.58	−59.940	.000**
GACA	102,857.82	118,073.44	−98.403	.000**
GLAR	88,013.40	98,271.13	−69.611	.000**
SLAR	107,325.35	123,799.24	−107.105	.000**
SAMRD	73,322.42	87,467.06	−95.990	.000**
SAMED	74,602.89	90,076.44	−106.441	.000**
SAMAD	67,565.11	82,298.84	−110.379	.000**
SWAID	96,327.96	113,184.78	−107.862	.000**

Note: Two asterisks indicate significance at the 5 percent level or below.

Table 17
The Duncan test result on the TTD performance of accompanying-order selection rules under Set I and Set II

Set I	**Set II**
SAMAD	**SAMAD**
SNAPA	**SNAPA**
SAMRD	**SAMRD**
SAMED	**SAMED**
GLAR	**GLAR**
GOA	**SACA**
SACA	**GOA**
SWAID	**SWAID**
SOA	**GACA**
GACA	**SOA**
GOTR	**GOTR**
SOTR	**SOTR**
RDA	**RDA**
SLAR	**SLAR**

Note: Accompanying-order selection rules connected symbolically are not significantly different at an α of 0.05.

but seventh under Set II. And, the SOA rule is ranked ninth under Set I, but tenth under Set II. From the result, one can understand why the two-way interaction between the APFD and the accompanying-order selection rule is significant at an α of 0.05.

Table 18 gives the TTD mean of every combination of seed-order selection rule and accompanying-order selection rule. As shown, one can see the combination of SNPA and SAMAD has the best TTD performance, followed by the combination of SRCA and SAMAD, and the combination of SAEWS and SAMAD. The combination of RDS and SLAR has the worst performance, followed by the combination of GASWS and SLAR, and the combination of GRCA and SLAR.

The ANOVA in Table 3 indicates that the two-way interaction between the seed-order selection rule and the accompanying-order selection rule is significant at an α of 0.05. To further understand the interaction between them, a Duncan test is conducted on the performance of seed-order selection rules under every

Table 18
The TTD mean of every combination of seed-order selection rule and accompanying-order selection rule

Accompanying-order selection rule	Seed-order selection rule										
	RDS	SNPL	SNPA	SAEWS	SASWS	GASWS	SRCA	GRCA	SARD	SAED	SAAD
RDA	114,651	112,975.9	112,202.3	112,846.1	112,078.5	114,763.4	112,578.5	114,835.5	113,947.3	114,130	113,667.8
SNAPA	80,668.2	74,997.7	74,525	74,409.7	74,522.5	86,005.1	76,347.5	83,844.3	76,272.2	76,396.2	76,579.4
GOA	101,271.3	99,893.3	99,904.3	100,224.4	100,197.9	101,010.8	100,371.1	100,695.5	101,328.3	101,401.1	101,769.3
SOA	110,539.5	109,732.3	110,557.5	110,851.5	110,381.3	110,645.2	109,252.9	110,273.5	111,064.2	111,460.4	110,912.4
GOTR	112,761.9	110,758.3	110,844.1	110,698.3	111,294.5	113,076.9	110,618.5	113,276.2	112,069	112,466.2	112,389.4
SOTR	113,267.9	111,516.3	112,064.7	111,947.4	112,001.7	114,064.9	110,759.8	113,860.5	111,197.2	111,499.4	111,762.4
SACA	101,074.7	99,969.3	100,195.3	100,150.3	100,257.3	100,522.4	100,406.7	100,364.9	101,363.4	101,510.5	102,322.3
GACA	111,330.7	109,609.1	110,637.7	110,284.5	110,393.3	110,077.9	108,788.1	110,204.6	111,656	111,287.6	110,852.4
GLAR	93,444.9	92,062.5	92,633.3	92,846.9	92,435.9	93,313.2	92,496.7	93,091.9	94,159.5	94,180.3	93,899.8
SLAR	116,713.5	114,474.5	114,549.7	114,871.7	115,119.9	116,628.5	114,551.7	116,440.5	115,838.2	115,734.8	116,262.2
SAMRD	81,041	79,079.9	79,338.5	79,984.1	79,730.4	82,611.7	79,207.0	81,964.4	80,350.4	80,638.8	80,395.9
SAMED	82,996.7	80,944	81,319.3	81,585.9	81,809.5	84,629.2	81,527.5	83,328.1	82,378.1	82,402.8	82,815.2
SAMAD	76,319.5	74,494.7	73,582.1	74,045.7	74,236.1	76,781.9	73,994.6	75,359.8	75,168.2	75,506.8	74,762.3
SWAID	105,852.5	103,772.1	104,234.7	104,401.7	104,288.1	105,919.1	104,265.7	105,645.7	104,512.8	104,849	104,578.7

accompanying-order selection rule. The results are shown in Table 19. As shown, the rankings of seed-order selection rules are not identical under different accompanying-order selection rules. One also observes that no seed-order selection rule is ranked first under all accompanying-order selection rules. The best two seed-order selection rules are the SRCA and SNPL rules, as they are ranked first under four and seven accompanying-order selection rules, respectively. They are also the only two rules appearing in the first subset grouping under every accompanying-order selection rule. This result can explain why the SRCA and SNPL rules are the top two seed-order selection rules in the overall TTD performance. On the other hand, the GASWS rule has the worst performance as it appears in the last subset grouping under every accompanying-order selection rule. It is also ranked last under six accompanying-order selection rules. This result agrees with the result in Table 7, which shows the GASWS rule has the worst overall TTD performance.

We also conducted a Duncan test on the performance of accompanying-order selection rules under every seed-order selection rule. Table 20 gives the results. As one can see, the rankings of accompanying-order selection rules are not identical under different seed-order selection rules. The SAMAD rule is ranked first under all seed-order selection rules. It is also the only rule that is in the first subset grouping under all seed-order selection rules. The SNAPA rule is second under eight out of 10 seed-order selection rules. This result agrees with the result in Table 13, which shows the SAMAD and SNAPA rules are the best and second best accompanying-order selection rules, respectively, in the overall TTD performance. On the other hand, the SLAR and RDA rules are the worst and second worst accompanying-order selection rules, respectively, under all seed-order selection rules. The SOTR rule is in the third place from last under seven seed-order selection rules.

8. Summary and conclusions

In this paper, we continue the study of Ho and Tseng (2006) by developing more order-batching methods. Each of these methods is made up of one seed-order selection rule and one accompanying-order selection rule. In all, 11 seed-order selection rules and 14 accompanying-order selection rules are investigated in this paper. Among these rules, three seed-order selection rules and four accompanying-order selection rules are from Ho and Tseng (2006). These rules have been shown by them to perform well in minimizing the travel distance of pickers. They are included in this study to serve as the benchmark for the rules newly developed for this study. Experiments were conducted to test performance of the rules studied here. In addition, two different route-planning methods and two different aisle-picking-frequency distributions are considered in the experiments. The performance measure is the Total Travel Distance (TTD) of pickers. By analyzing the experimental results, many findings were obtained. Some important ones are summarized as follows. It is hoped that the knowledge learned from this study can benefit practitioners in distribution centers with order-batching operations.

- The SNPL, SRCA, and SNPA are the top three seed-order selection rules. The Duncan test result shows that they are in the first subset, meaning they are not significantly different in their TTD performance. Among these three rules, the SRCA rule is proposed by us. The other two are from Ho and Tseng (2006).
- The performance of the three distance-based seed-order selection rules (i.e. the SARD, SAAD, and SAED rules) is rather mediocre. They are not significantly different (at an α of 0.05) among themselves in their TTD performance, but are all significantly worse than the SNPL, SRCA, SNPA, SASWS, and SAEWS rules.
- The two aisle-weight-sum-based rules (i.e. the SASWS and the SAEWS rules) perform well in minimizing the TTD of pickers. Both of them and the SNPA rule are in the subset of the Duncan test result (see Table 7), indicating they are not significantly different (at an α of 0.05) in their TTD performance.
- The GRCA and GASWS rules are the only two seed-order selection rules that perform worse than the RDS rule (which is a random rule), indicating they are not worth adopting.
- The SAMAD, SNAPA, SAMRD, and SAMED rules are the top four accompanying-order selection rules. Among them, three of them are proposed by us. The SNAPA rule is from Ho and Tseng (2006). The SAMAD, SAMRD, and SAMED rules are all distance-based rules.
- The SAMAD rule has the best TTD performance and it is significantly better (at an α of 0.05) than the rest of accompanying-order selection rules.

Table 19
The Duncan test result on the TTD performance of seed-order selection rules under different accompanying-order selection rules

	Accompanying-Order Selection Rule				
	RDA	SNAPA	GOA	SOA	GOTR
Seed-Order Selection Rule	SASWS	SAEWS	SNPL	SRCA	SRCA
	SNPA	SASWS	SNPA	SNPL	SAEWS
	SRCA	SNPA	SASWS	GRCA	SNPL
	SAEWS	SNPL	SAEWS	SASWS	SNPA
	SNPL	SARD	SRCA	RDS	SASWS
	SAAD	SRCA	GRCA	SNPA	SARD
	SARD	SAED	GASWS	GASWS	SAAD
	SAED	SAAD	RDS	SAEWS	SAED
	RDS	GRCA	SARD	SAAD	RDS
	GASWS	RDS	SAED	SARD	GASWS
	GRCA	GASWS	SAAD	SAED	GRCA

	Accompanying-Order Selection Rule				
	SOTR	SACA	GACA	GLAR	SLAR
Seed-Order Selection Rule	SRCA	SNPL	SRCA	SNPL	SNPL
	SARD	SAEWS	SNPL	SASWS	SNPA
	SAED	SNPA	GASWS	SRCA	SRCA
	SNPL	SASWS	GRCA	SNPA	SAEWS
	SAAD	GRCA	SAEWS	SAEWS	SASWS
	SAEWS	SRCA	SASWS	GRCA	SAED
	SASWS	GASWS	SNPA	GASWS	SARD
	SNPA	RDS	SAAD	RDS	SAAD
	RDS	SARD	SAED	SAAD	GRCA
	GRCA	SAED	RDS	SARD	GASWS
	GASWS	SAAD	SARD	SAED	RDS

	Accompanying-Order Selection Rule			
	SAMRD	SAMED	SAMAD	SWAID
Seed-Order Selection Rule	SNPL	SNPL	SNPA	SNPL
	SRCA	SNPA	SRCA	SNPA
	SNPA	SRCA	SAEWS	SRCA
	SASWS	SAEWS	SASWS	SASWS
	SAEWS	SASWS	SNPL	SAEWS
	SARD	SARD	SAAD	SARD
	SAAD	SAED	SARD	SAAD
	SAED	SAAD	GRCA	SAED
	RDS	RDS	SAED	GRCA
	GRCA	GRCA	RDS	RDS
	GASWS	GASWS	GASWS	GASWS

Note: Seed-order selection rules connected symbolically are not significantly different at an α of 0.05.

- The TTD performance of all area-based accompanying-order selection rules (i.e. the GLAR, GOA, SACA, GACA, SOA, GOTR, and SOTR rules) is rather mediocre.
- The SLAR rule is the only accompanying-order selection rule that performs worse than the RDA rule (which is a random rule), indicating it is not worth adopting.
- The seed-order selection rules and the accompanying-order selection rules affect each other's TTD performance.

Table 20
The Duncan test result on the TTD performance of accompanying-order selection rules under different seed-order selection rules

Accompanying-Order Selection Rule	Seed-Order Selection Rule: RD	SASWS	GASWS
	SAMAD	SAMAD	SAMAD
	SNAPA	SNAPA	SAMRD
	SAMRD	SAMRD	SAMED
	SAMED	SAMED	SNAPA
	GLAR	GLAR	GLAR
	SACA	GOA	SACA
	GOA	SACA	GOA
	SWAID	SWAID	SWAID
	SOA	SOA	GACA
	GACA	GACA	SOA
	GOTR	GOTR	GOTR
	SOTR	SOTR	SOTR
	RD	RD	RD
	SLAR	SLAR	SLAR

Accompanying-Order Selection Rule	Seed-Order Selection Rule: SRCA	GRCA	SARD
	SAMAD	SAMAD	SAMAD
	SNAPA	SAMRD	SNAPA
	SAMRD	SAMED	SAMRD
	SAMED	SNAPA	SAMED
	GLAR	GLAR	GLAR
	GOA	SACA	GOA
	SACA	GOA	SACA
	SWAID	SWAID	SWAID
	GACA	GACA	SOA
	SOA	SOA	SOTR
	GOTR	GOTR	GACA
	SOTR	SOTR	GOTR
	RD	RD	RD
	SLAR	SLAR	SLAR

Accompanying-Order Selection Rule	Seed-Order Selection Rule: SAED	SAAD	SNPA
	SAMAD	SAMAD	SAMAD
	SNAPA	SNAPA	SNAPA
	SAMRD	SAMRD	SAMRD
	SAMED	SAMED	SAMED
	GLAR	GLAR	GLAR
	GOA	GOA	GOA
	SACA	SACA	SACA
	SWAID	SWAID	SWAID
	GACA	GACA	SOA
	SOA	SOA	GACA
	SOTR	SOTR	SOTR
	GOTR	GOTR	GOTR
	RD	RD	RD
	SLAR	SLAR	SLAR

Accompanying-Order Selection Rule	Seed-Order Selection Rule: SNPL	SAEWS
	SAMAD	SAMAD
	SNAPA	SNAPA
	SAMRD	SAMRD
	SAMED	SAMED
	GLAR	GLAR
	GOA	SACA
	SACA	GOA
	SWAID	SWAID
	GACA	GACA
	SOA	GOTR
	GOTR	SOA
	SOTR	SOTR
	RD	RD
	SLAR	SLAR

Note: Accompanying-order selection rules connected symbolically are not significantly different at an α of 0.05.

- The performance rankings of the seed-order selection rules and the accompanying-order selection rules are not affected by route-planning methods, but are affected by aisle-picking frequency distributions.
- The combination of the SNPA and SAMAD rules has the best TTD performance, while the combination of the RDS and SLAR rules the worst TTD performance.

Finally, we conclude this paper by presenting two problems that need further investigation in the future research. First, in this paper, the order batches were formed one at a time through the application of a seed-order selection rule and an accompanying-order selection rule. Although this approach has the benefit of finding order batches effectively and efficiently, the overall optimality of order batches cannot be guaranteed. This is because these order batches were found one at a time, not simultaneously. In order words, our order-batching approach adopts a divide-and-conquer strategy, which divides the order-batching problem into many small problems and in each problem only one order batch is found. It is thus suggested that in the future research one should explore approaches that can solve the order-batching problem as a single problem, so that the order batches can be found simultaneously and the overall optimality of these order batches can be obtained. Second, in this paper it is assumed if an order's cart-capacity demand is greater that the picking cart's capacity, it will be split into two or more smaller orders, whose cart-capacity demands do not exceed the picking cart's capacity. In this paper, we did not propose any order-splitting methods orders. Orders in this study are randomly split. Since how orders are split can affect the content of an order pool, which subsequently affects the order-batching result, it is thus suggested the problem of splitting orders for better order batching be investigated in the future. The significance of this problem will increase with the percentage of orders (in the order pool) that require splitting operations. We believe the knowledge learned from the investigation of these two problems can further benefit managers of distribution centers/warehouses in optimizing their order-picking operations.

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