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An efficient correlation-based storage location assignment heuristic for multi-block multi-aisle warehouses

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ABSTRACT

The most labor-intensive and time-consuming part of warehouse operations is order picking. This paper proposes a correlation-based storage location assignment (CBSLA) approach to minimize the travel distance of the picker in a picker-to-parts warehouse. At first, the proposed CBSLA approach forms some groups of stock-keeping units (SKUs) for different warehouse aisles. Then these groups of SKUs are assigned to the storage locations considering both the correlations between SKUs in a group and the correlation between groups of SKUs for efficient order picking. The effectiveness of the proposed method is measured for various warehouse configurations using simulation and compared with other well-known storage allocation methods.

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1. Introduction

A warehouse is an essential part of the supply chain that stores and buffers products, materials, and other items [1]. It is an inevitable intermediary facility in most of the supply chains that connect upstream suppliers, distributors, and downstream customers [2]. It enables customers to receive combined deliveries of products consolidated from diverse suppliers in a timelier and more cost-effective manner. With the increase in the popularity of e-commerce, pressure is also rising on suppliers to deliver products timely [3]. The expenditure associated with the operations of warehousing is approximately 17% of the total supply chain management costs for a company [4]. Warehouse operations include receiving, put-away, storage, order-picking, sorting, packaging, and shipping [5]. Among all the warehousing operations, order-picking, the process of collecting the required items from a warehouse to fulfill customer orders, is

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considered to be the most labor-intensive and time-consuming operation. Order picking is responsible for around 55% of the total expense of warehouse operations [1]. The travel time is the most significant part of the order-picking operation, and it is accountable for roughly 50% of the overall order-picking operation time [6]. Therefore, the primary concern of the researchers is to develop models and solution methodologies to reduce travel time or distance. To shorten the travel time or distance for order-picking activities, Roodbergen and Koster [7] suggested four options, viz. (1) figuring out the most efficient order-picking route; (2) warehouse area division or zoning; (3) allocation of stock-keeping units (SKUs) to the appropriate storage locations; and (4) batching of orders. The third strategy is called storage assignment and has a more significant impact on order-picking efficiency. A well-designed storage assignment technique might substantially reduce the order-picking distance [8].

Generally, storage assignment is carried out according to some set of rules or strategies. The most popular strategies are random, dedicated, class-based, full turnover-based, cube-order-per-index (COI)-based, and correlated storage assignments. The random strategy assigns the incoming SKUs randomly to the available storage locations which result in poor order-picking efficiency but high space utilization [9]. In a dedicated storage policy, each incoming SKU is kept in a fixed location, which is always reserved even if the SKU gets out of stock [10]. It results in lower space utilization because of reserving spaces for the SKUs that are out-of-stock. The class-based strategy groups SKUs into a predefined number of classes and then allocates each class to a specific region of the warehouse [11]-[13]. In this method, the SKUs are arranged randomly within each class. As a result, order pickers may be required to visit several storage regions to fulfill a customer order that includes several SKUs from different classes. The COI-based method utilizes the ratio of the storage space requirement and order-picking frequency of an SKU. The SKU with the lowest ratio is kept closest to the input-output (I/O) point [14], [15]. Full turnover-based (FTB) storage is a type of dedicated storage where the SKUs with higher demand are kept close to the I/O point, and the SKUs with lower demand are kept far away from the I/O point [16], [17]. Both the COI-based and the full turnover-based methods fail to utilize the inherent characteristics of customer orders. Generally, an order consists of several SKUs, and some of the SKUs frequently appear together in different orders. These frequently appeared SKUs together are called correlated SKUs. Order-picking costs will increase when these SKUs with a strong correlation are stored far away from each other in the warehouse. To overcome this problem, the correlated storage allocation method, i.e., the relationship among SKUs is used to group similar or associated items so that they can be stored and retrieved together [3], [18]-[20].

Correlation-based storage assignment approach looks for correlations between SKUs in a warehouse based on their demand characteristics. It is expected that the order-picking distance will be reduced as more correlated SKUs are stored together. Customer orders are used to determine the correlation between SKUs. Several SKUs that are regularly purchased together have a strong correlation. Picking efficiency may be increased by recognizing these correlated SKUs and storing them near each other. Existing studies of correlated storage assignment typically assign SKUs based on the total or average picking frequency, which may lead to the separation of correlated SKUs across different groups due to capacity constraints. This can result in potential inter-correlation between groups and inefficient picking routes. However, no existing model simultaneously considers inter-group and intra-group correlations when allocating SKUs to the storage locations. The study introduces a novel approach to warehouse storage allocation that considers both inter-group and intra-group correlations among SKUs during assignment operations. By incorporating these correlations along with picking frequencies, the research aims to optimize storage allocation to narrow the distance between multiple correlated SKU groups, thereby reducing the total travel distance of order pickers. Moreover, the proposed approach is tested in a multi-block and multi-aisle warehouse to get more realistic results.

The remainder of the paper is structured as follows. Section 2 reviews the relevant research on correlated storage assignment strategy. Section 3 describes the problem environment, basic assumptions of storing and picking, and formulates the mathematical model to solve the correlated storage location assignment problems. Section 4 presents the heuristic method to solve the mathematical model. In section 5, a simulation model is developed to test the proposed heuristic. Section 6 reports the results of the simulation experiments. Finally, section 7 presents the conclusions and recommendations for future study.

2. Literature Review

Research on storage location assignment problem (SLAP) primarily focuses on optimizing the allocation of SKUs within a distribution center or warehouse, intending to maximizing space utilization and minimizing handling costs [21]. The SLAP is considered very complex due to the variation in volume, weight, or demand for SKUs [22]. In recent years, there has been a growing interest in the application of data analytics, machine learning, simulation and modeling techniques to optimize the SLAP by utilizing historical data, order patterns, and other relevant parameters. The purpose of this approach is to enhance decision-making processes and adapt to changes in demand patterns. The correlation-based storage assignment approach has been extensively explored during the last two decades. This assignment method performs better to minimize the travel distance compared to other storage allocation methods. The majority of the correlated assignment models are NP-hard problems [9], [23]-[25] and are solved by two-phase heuristic algorithms. In the first phase, the SKUs are grouped according to their correlation, and then these groups are assigned to storage locations in the second phase. Chuang et al. [26] presented a two-stage clustering assignment model based on the association between SKUs to solve the correlated storage assignment problems. However, the model is tested only for a single-aisle warehouse. Zhang [3] proposed two heuristic methods, viz. static seed and sum seed, to solve the correlated SLAP. The groups of SKUs are determined and sequenced with the help of these heuristics. These algorithms are very fast and perform reasonably well. However, in these algorithms, each SKU is considered sequentially assigned in a group. As a result, once an SKU has been assigned to a group, it is not possible to change the group to improve the solutions. Ansari and Smith [15] developed an algorithm for grouping the SKUs based on the principle of gravity. The algorithm is tested for the S-shaped routing method only. Jiang et al. [10] proposed a scattered storage strategy by assigning the same SKU to multiple locations. A zero-one integer programming model is formulated to minimize the sum of weighted distances between SKUs. To solve the model, two algorithms using the concept of genetic algorithm (GA) and particle swarm optimization (PSO) algorithm are developed. These algorithms can solve large-scale problems. However, this method may reduce storage space utilization by duplicating the same SKUs to different storage locations. Mirzaei et al. [9] proposed a mathematical model to group and assign SKUs to storage locations simultaneously. The objective is to minimize the travel time of order-picking operations. As a solution method, a greedy heuristic method is proposed to solve large-sized problems. The mathematical model may be solved using more efficient solution methods based on meta-heuristics to find better allocations of SKUs. Fontana and Nepomuceno [27] presented a multi-criteria decision approach for categorizing products and solving the SLAP in a multi-layer warehouse. Muppani and Adil [28] developed a branch and bound algorithm for solving a nonlinear integer programming model for the formation of storage classes, considering handling costs and storage space requirements. Muppani and Adil [29] developed a simulated annealing algorithm (SAA) to solve an integer programming model for group formation and storage assignment. The model takes into account all potential combinations of products, as well as the costs associated with storage space and order-picking.

Chiang et al. [30] introduced an association measuring technique called weighted support count (WSC). They proposed two heuristics based on the WSC. The first one is called the modified class-based heuristic, which modifies the characteristics of the traditional class-based approach. The second one is called the association seed-based heuristic, which maximizes the associations of SKUs within each aisle. Li et al. [23] proposed an integrated mechanism to solve dynamic SLAP. They introduced a product affinity-based algorithm to calculate the pairwise associations between SKUs. A greedy GA is developed to maximize the total associations between SKUs in each zone. Pang and Chan [5] proposed a data mining-based assignment algorithm to minimize the travel distance for order-picking as well as put-away operations in a randomized warehouse. Li et al. [31] proposed an association rule mining (ARM) based heuristic to create groups of SKUs. The method divides the SKUs into weight classes, i.e., heavy, medium, and light. These traditional data-mining methods require a large amount of computational time if the number of SKUs is large and avoid less frequently ordered SKUs from consideration. As a result, this approach requires the selection of a minimum support threshold value to consider SKUs or a set of SKUs. It is frequently challenging to find an appropriate threshold value because it largely depends on the dataset's nature. Sometimes, several SKUs are not grouped with the others due to the mining process.

In the existing studies, it is found that the SKU groups are assigned based on the total or average picking frequency of each group, and the SKUs within each group are also sorted according to the picking frequency. Due to the capacity constraint of the groups, there is a chance of splitting some correlated SKUs from a group and merging these SKUs into another group. As a result, an SKU of a group may have a strong correlation with some SKUs of other groups, i.e., there might be potential inter-correlation between these groups. On the other hand, some weakly correlated SKUs may be merged with a group to fill the group's capacity restriction. These merged SKUs may have a strong correlation with other groups. When these correlated groups are sequenced and assigned according to their picking frequency only, the distance among these inter-correlated groups may potentially be increased which results in greater travel distance of the order pickers. Moreover, SKUs within the same group that have a strong correlation are likely to be picked together. If these correlated SKUs are placed close to each other based on intra-group correlation, the travel distance for pickers can be minimized. This is because pickers do not have to travel long distances within a group to collect SKUs that are frequently ordered together.

It is evident from the literature that, no correlated storage assignment model considers the inter-group correlation as well as intra-group correlations among the SKUs during assignment operations. Existing solution methods may exhibit a preference for simplicity and do not incorporate the complexities of these correlations. So, there is a scope to consider these correlations along with the total picking frequency when assigning these groups to the storage areas. This approach may narrow down the distance between multiple correlated groups. Moreover, in the existing studies, it is found that most of the correlated assignment approaches were tested only in the single-block or single-aisle warehouse. To get more realistic results, it should be tested in a multi-block and multi-aisle warehouse. The setting of a multi-block warehouse layout is important and relevant because it provides practical benefits in terms of space utilization, order-picking efficiency, and congestion reduction. Furthermore, it provides an opportunity for academic exploration, research, and education in the fields of logistics, supply chain management, and optimization. Academic research may focus on how storage blocks are arranged and how these factors affect productivity, order-picking techniques, and inventory management. The overall research objective of the present study is to determine the storage locations of SKUs such that correlated SKUs are assigned close to each other to reduce the total travel distance of picking operations.

3. Mathematical Model

3.1 Problem Description

The system parameters, layout, and fundamental assumptions of the storage and picking systems in the warehouse are described in this sub-section. The travel distance for order-picking operation greatly depends on warehouse layout and operational parameters [32]. In this research, we considered a simplified multi-block with multi-aisles, single-level, and picker-to-parts warehouse for the experimental purpose. In a picker-to-parts warehouse, the workflow is organized around the movement of pickers, who travel along the storage aisles to retrieve items or SKUs from their designated storage locations [33], [34]. The layout of the multi-block warehouse is illustrated in Figure 1.

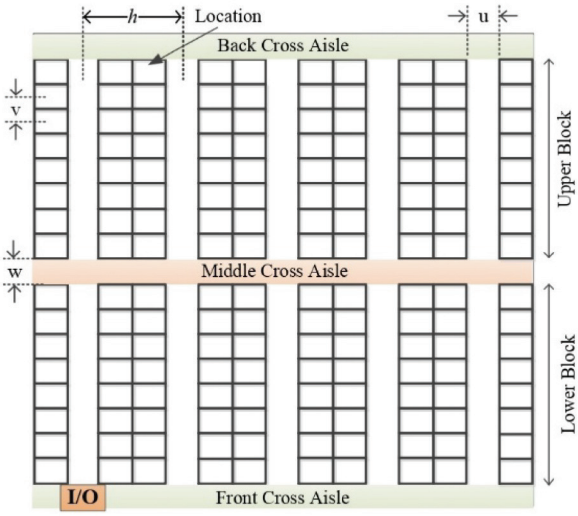

Figure 1. The layout of the multi-block warehouse

The storage space in the warehouse is set as a two-dimensional rectangular area with aisles that are often used in reality. There are multiple parallel picking aisles in each block. Furthermore, there are three cross aisles in the warehouse, viz. front cross-aisle, middle cross-aisle, and back cross-aisle. It is assumed that the middle cross aisle divides an aisle into the upper block aisle and lower block aisle. The storage spaces are placed on both sides of each picking aisle, allowing the storage and retrieval of SKUs on both sides of an aisle without a considerable change in positioning. The capacity of an aisle is measured by the available number of storage spaces. The storage capacity of all picking aisles is equal. The input-output (I/O) point of the warehouse is placed in the bottom left corner. The two-dimensional distance, i.e., along the cross aisles and the picking aisles, is considered to evaluate the performance. The distance between the

I/O point and the first storage location is defined as one unit, whereas *'v'* is the distance between two adjacent locations, and *'h'* is the distance between two adjacent aisles. The width of picking aisles is *'u'* and the width of the cross-aisle is *'w'*.

3.2 Model Assumptions

The following assumptions are considered for modeling purposes:

- Each type of SKU has a single storage location to avoid duplication in multiple locations.
- Each storage location has enough space to hold a sufficient number of SKUs of the same type in order to complete customer orders for a specific planning horizon.
- The size of each storage location is the same.
- Each aisle provides access to storage areas from both directions of an aisle, allowing a picker to enter and exit from both sides.
- The number of order pickers is one, thus, congestion is out of consideration.
- The picker is used to retrieve the requested SKUs only, which is called the single command cycle.
- The order picker picks a single order in a picking tour.
- The order picker has sufficient capacity to complete a customer order in a single trip.
- The quantity of each SKU in an order is not considered because the travel distance does not depend on how many units of each SKU are picked.

3.3 Parameter Setting

The definition of the variables and parameters used to develop the correlated storage assignment model is as follows:

Indices and sets

k, r Index of groups, $k, r = 1, 2, \ldots, K$
a, b Index of aisles, $a, b = 1, 2, \ldots, A$
i, j Index of SKUs, $i, j = 1, 2, \ldots, N$
l, q Index of storage locations, $l, q = 1, 2, \ldots, N$
p Index of orders, $p = 1, 2, \ldots, O$
S_k Set of SKUs in a group k
S_r Set of SKUs in a group r
L_a Set of locations in an aisle a

Parameters

O Total number of orders
N Total number of SKUs
K Total number of groups
A Total number of aisles
m Total number of locations in each aisle
C_{ij} Correlation between SKU i and SKU j and is equal to the number of orders containing both the SKUs
R_{kr} Total correlation between two groups k and r
T_k Total order frequency of group k
t_i Total order frequency of SKU i
D_{ab} Distance between the centers of aisle a and aisle b
D_a Distance from the I/O point to the center of aisle a
d_{lq} Distance between storage locations l and q in an aisle
d_l Distance from the I/O point to storage location l

Variables

f_{ip} Binary variable, if SKU i appears in order p, the value is 1; otherwise 0

$$x_{ik} = \begin{cases} 1 \text{ if SKU } i \text{ is assigned to group } k \\ 0 \ \text{ otherwise} \end{cases}$$

$$y_{ak} = \begin{cases} 1 \text{ if group } k \text{ is assigned to aisle } a \\ 0 \ \text{ otherwise} \end{cases}$$

$$z_{il} = \begin{cases} 1 \text{ if SKU } i \text{ is assigned to storage location } l \\ 0 \ \text{ otherwise} \end{cases}$$

3.4 Model Formulation

In this sub-section, zero-one QAP model is formulated to solve the correlated storage assignment problems. The objective of the model is to make sure that correlated SKUs are assigned in the adjacent locations to minimize the travel distance of the order-picking operations. The model consider the SKU demand and co-purchase patterns as well as the relative distances between storage locations. The problem is decomposed into the following three sequential stages:

Stage I: Grouping of correlated SKUs

In this stage, highly correlated SKUs are assigned into groups. The metric that is used to represent the correlation strength between SKU i and SKU j is C_{ij}, which is the co-appearance frequency of the SKUs (i and j) in customer orders. The number of SKUs in a group must be equal to the capacity of an aisle in the storage area. As the size of each aisle is the same, it is essential to uniformly group all the SKUs so that highly correlated SKUs can be located in the same aisle. Therefore, the objective of grouping the SKUs is to maximize the sum of correlation between

SKUs in the groups and is expressed with the following mathematical model.

$$Maximize \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{j=i+1}^{N} C_{ij}\, x_{ik}\, x_{jk} \tag{1}$$

Subject to:

$$\sum_{k=1}^{K} x_{ik} = 1 \qquad \forall i = 1,2,\dots,N \tag{2}$$

$$\sum_{i=1}^{N} x_{ik} = m \qquad \forall k = 1,2,\dots,K \tag{3}$$

$$C_{ij} = \sum_{p=1}^{O} f_{ip} f_{jp} \qquad \forall i,j = 1,2,\dots,N \tag{4}$$

$$x_{ik} \in \{0,1\}; \qquad \forall i = 1,2,\dots,N;\ \forall k = 1,2,\dots,K \tag{5}$$

The objective function (1) maximizes the total correlation where the pair-wise selection of the $x_{ik}\, x_{jk}$ term ensures that the correlation accumulates only when SKU i and SKU j are in the same group. Constraints (2) guarantee that each SKU is assigned to one group only. Constraints (3) make sure that each group has exactly m number of SKUs. Equation (4) is the calculation of the correlation value between SKU i and SKU j. Finally, conditions (5) define the type and range of the decision variable, x_{ik}.

Stage II: Assigning the groups to the storage aisles

In this stage, the groups are assigned to storage aisles. Due to the size constraint of the groups, some correlated SKUs may appear in different groups. So, there might be some potential correlations between groups. These correlated groups should be assigned near each other to minimize the travel distance incurred during order-picking. The following mathematical model is formulated to decide which group is assigned to which aisle.

$$Minimize \sum_{k=1}^{K}\sum_{a=1}^{A}\sum_{r=k+1}^{K}\sum_{\substack{b=1\\ a\neq b}}^{A} R_{kr} D_{ab}\, y_{ak}\, y_{br} + \sum_{k=1}^{K}\sum_{a=1}^{A} T_k D_a y_{ak} \tag{6}$$

Subject to:

$$\sum_{a=1}^{A} y_{ak} = 1 \qquad \forall k = 1,2,\dots,K \tag{7}$$

$$\sum_{k=1}^{K} y_{ak} = 1 \qquad \forall a = 1,2,\dots,A \tag{8}$$

$$T_k = \sum_{\substack{i=1\\ i\in S_k}}^{m}\sum_{p=1}^{O} f_{ip} \qquad \forall k = 1,2,\dots,K \tag{9}$$

$$R_{kr} = \sum_{\substack{i=1\\ i\in S_k}}^{m}\sum_{\substack{j=1\\ j\in S_r}}^{m} C_{ij} \qquad \forall k,r = 1,2,\dots,K;\ k\neq r \tag{10}$$

$$y_{ak} \in \{0,1\}; \qquad \forall k = 1,2,\dots,K;\ \forall a = 1,2,\dots,A \tag{11}$$

The first term in the objective function (6) minimizes the total travel distance among all groups, i.e., total inter-group distance. The second term of the objective function (6) minimizes the total distance of the groups from the I/O point. Constraints (7) guarantee that each group of SKUs is assigned to one storage aisle only. Constraints (8) represent that each aisle must contain exactly one group. Equation (9) is the calculation of the total order frequency of group k. Equation (10) is the calculation of the total correlation between two groups, k and r. Conditions (11) define the type and range of the decision variable, y_{ak}.

Stage III: Determining the storage locations for SKUs in each aisle

The SKUs of a group should be assigned in the designated aisle in such a way that highly correlated SKUs are stored in adjacent locations. As a result, the total intra-group travel distance of the picker will be minimal. The mathematical model for this purpose is expressed as follows.

$$Minimize \sum_{\substack{i=1\\ i\in S_k}}^{m}\sum_{\substack{l=1\\ l\in L_a}}^{m}\sum_{\substack{j=i+1\\ j\in S_k}}^{m}\sum_{\substack{q=1\\ q\in L_a, l\neq q}}^{m} C_{ij} d_{lq} z_{il} z_{jq} + \sum_{i=1}^{m}\sum_{l=1}^{m} t_i d_l z_{il} \tag{12}$$

Subject to:

$$\sum_{l=1}^{m} z_{il} = 1 \qquad \forall i = 1,2,\dots,m \tag{13}$$

$$\sum_{i=1}^{m} z_{il} = 1 \qquad \forall l = 1,2,\dots,m \tag{14}$$

$$t_i = \sum_{p=1}^{O} f_{ip} \qquad \forall i = 1,2,\dots,m \tag{15}$$

$$z_{il} \in \{0,1\}; \qquad \forall i = 1,2,\dots,m;\ \forall l = 1,2,\dots,m \tag{16}$$

The objective function in equation (12) is to minimize the sum of total intra-group travel distance when group k is assigned to aisle a. Constraints (13) guarantee that each SKU is located in one storage location. Constraints (14) make sure that each storage location contains an SKU only. Equation (15) is the calculation of the total order frequency of SKU i. Finally, Conditions (16) define the type and range of the decision variable, z_{il}.

4. Solution Method

The QAP model formulated in section 3 are regarded as NP-hard problems. It takes a considerable amount of computational time to solve the problem, even with a small number of SKUs and as the number of SKUs increases, the computational time grows exponentially. The problem becomes computationally expensive for large-scale warehouses with thousands of SKUs and storage locations. In this section, an effective correlation-based storage location assignment (CBSLA) heuristic method is developed to find good solutions for large-scale problems within a reasonable time limit. The flowchart of the heuristic approach is depicted in Figure 2.

4.1 Measuring the Correlation between SKUs

The historical customer order data is used to calculate the correlation between SKUs. The correlation between SKU i and SKU j (C_{ij}) denotes how many times they appear together in the customer orders. The steps for generating the correlation matrix are described below:

1. Select an order from the customer order list.
2. For every pair of SKUs (SKU i and SKU j) in the order, increase the values of C_{ij} by 1, where $i > j$. If j is greater than i, then swap the SKUs in the pair.
3. Select the next order from the order list and return to step 2 until all the orders are considered.

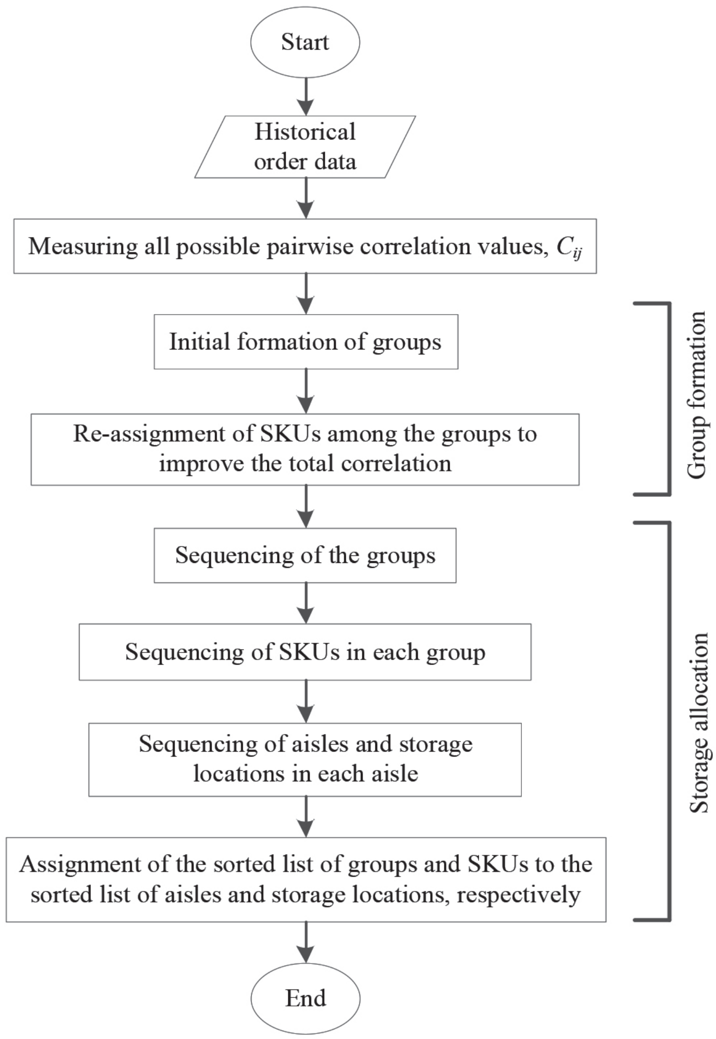

Figure 2. The flowchart of the proposed heuristic algorithm

4.2 Grouping of Correlated SKUs

There are two main phases for grouping the correlated SKUs. In the first phase, an initial feasible solution of K groups is formed. The step-by-step procedure of this phase is described as follows:

Phase I: Initial formation of groups

1. Set k=1.
2. Select the SKU with the highest order frequency from the SKU list I and insert it into the group k.
3. Find an SKU that has the highest total correlation with the selected SKUs of the group k.
4. Repeat step 3 until the total number of SKUs in the group k is equal to size m.
5. Remove all the SKUs inserted into the group k from the SKU list I.
6. Set k=k+1, and return to step 2 until the SKU list I is empty.

In this phase, each SKU is considered sequentially. Once an SKU is assigned to a group, there is no longer a chance to change its group. So, there is a scope to improve the cumulative correlation by interchanging the SKUs among the groups in a systematic way. Phase II is an iterative procedure that begins with the initial solution of K groups formed in phase I. The philosophy is to exchange SKUs between groups if possible so that the total correlation is increased as much as possible. The more the cumulative correlation is improved, the more the possibility that total travel distance will be reduced during the order-picking operations. The step-by-step procedure of phase II is described as follows:

Phase II: Re-assignment of SKUs among the groups to improve the total correlation

1. Set k=1.
2. Select an SKU i from the current group k.
3. Consider each SKU j one by one from the remaining groups and calculate the possible improvement of total correlation if SKU i and SKU j exchange their groups.
4. Find an SKU j from another group for which the improvement is maximum, and if it improves the current total correlation, then exchange SKU i and SKU j between their current groups.
5. Select another SKU, i=i+1, and go to step 3 until all the SKUs are selected from the current group k.
6. Select the next group, k=k+1, and return to step 2 until all the groups are selected.

4.3 Allocation of SKUs to the Storage Locations

Once the SKU groups are formed, the groups as well as the SKUs in the group are allocated to the storage area. There are three phases of the storage allocation process described below:

Phase I: Sequencing of the groups

In the first phase, a score or fitness value is calculated for each group considering both the correlation strength and the popularity of the group. Here, the popularity of a group is the total order frequency of all the SKUs in the group. A group with a higher fitness value is allocated to a closer aisle of the I/O point. The process of sequencing the groups is as follows:

1. Calculate the total order frequency of each group k from the group set G.

$$T(k) = \sum_{\substack{i=1 \\ i \in S_k}}^{m} \sum_{p=1}^{O} f_{ip} \qquad \forall k = 1,2, \ldots .. K \tag{17}$$

2. Select the group k which has the highest total order frequency i.e., $\max\{T(k)\}$.
3. Set r=1.
4. Exchange the position of group k and group r in the group set G.
5. Calculate the fitness value of each of the remaining groups with group r according to the following equation.

$$F(k) = \alpha \sum_{\substack{i=1 \\ i \in S_k}}^{m} \sum_{\substack{j=1 \\ j \in S_r}}^{m} C_{ij} + (1-\alpha) \sum_{\substack{i=1 \\ i \in S_k}}^{m} \sum_{p=1}^{O} f_{ip}$$

$$\forall k = (r+1), \ldots K \tag{18}$$

The first term of equation (18) is the weighted correlation of group k with other group r, and the second term indicates the weighted total frequency of the group. Here, the factor α is a quantitative value between 0 and 1 that indicates the weight of the correlation strength.

6. Select the group k that has the maximum fitness value, i.e., $\max\{F(k)\}$.
7. Set r=r+1.

8. Exchange the position of group k and group r in the group set G.
9. Repeat steps 5 to 8 until all the groups are sequenced.

Phase II: Sequencing of the SKUs in each group

In this phase, the SKUs within each group are sequenced based on their order frequency and correlation. The process of sequencing the SKUs in a group is as follows:

1. Select the SKU i, which has the highest order frequency in group k.
2. Set j=1.
3. Exchange the position of SKU i and SKU j in the group k.
4. Calculate the fitness value of each of the remaining SKU i with the SKU j according to the following equations.

$$F(i) = \alpha C_{ij} + (1-\alpha)\sum_{p=1}^{O} f_{ip}$$
$$\forall i = (j+1), \ldots m \tag{19}$$

5. Select the SKU i that has the maximum fitness value, i.e., max$\{F(i)\}$.
6. Set j=j+1.
7. Exchange the position of SKU i and SKU j in the group k.
8. Repeat steps 4 to 7 until all the SKUs are sequenced.

Phase III: Sequencing of the aisles and storage locations in each aisle

In this phase, the warehouse aisles are sequenced based on the zig-zag positioning rule [32] as shown in Figure 3. The zig-zag positioning rule, also known as the "serpentine" pattern, is a strategy used in warehouse storage to optimize space utilization, enhance organization, and support overall operational effectiveness. The zig-zag pattern allows for efficient use of space by minimizing gaps between correlated groups as well as SKUs. Moreover, a zig-zag design creates an organized visual layout, making it easier for warehouse personnel to locate and identify SKUs quickly. After positioning the aisles, the storage locations in each aisle are arranged in ascending order of distance from the I/O point. Finally, the sorted list of SKUs in a group is assigned to the sorted list of storage locations in an aisle.

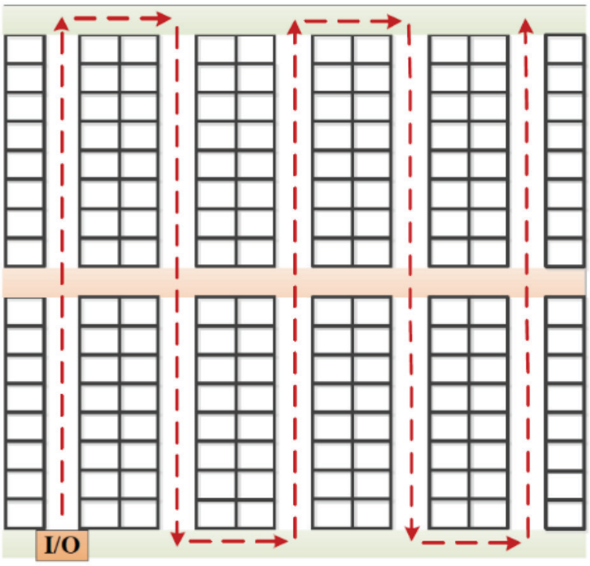

Figure 3. Sequencing of aisles based on the zig-zag positioning rule [32]

5. Simulation Model

In this section, a computer simulation program is run several times to demonstrate the working of the proposed CBSLA approach for the order-picking operations and evaluate the results for various scenarios. Due to the difficulty of obtaining real-life data for a warehouse, a random order generation scheme is used in the simulation model. The performance of the suggested approach is compared with various storage assignment strategies such as full-turnover-based (FTB) [17], ABC class-based [23], and the correlated storage assignment strategy (CSAS) proposed by Zhang [3]. All these storage assignment policies are coded in the simulation model using C++ language. The simulation of order-picking operations is conducted with different warehouse sizes and configurations to calculate the total travel distance for various storage allocation methods. The flowchart of the simulation model is shown in Figure 4.

5.1 Random Order Generation

Obtaining real-world data from warehouses is challenging due to privacy concerns and internal policies restricting data sharing. As a result, we have generated the probability for each SKU set and the probabilistic relationships among SKUs within each set to create random order datasets for the simulation model. The random order generation procedure is done in three consecutive steps. In the first step, some SKU sets are generated with random sizes between a minimum and a maximum value. In the second step, a random probability distribution is gen-

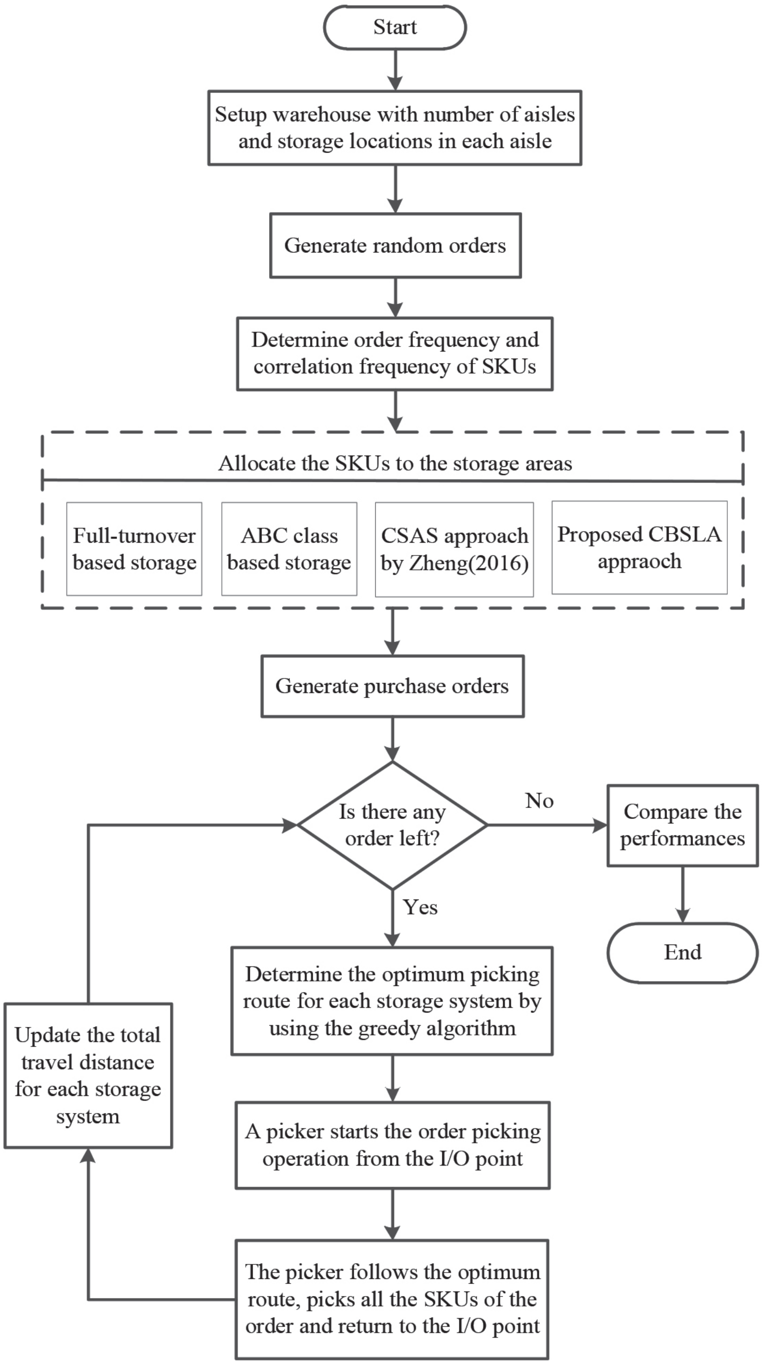

Figure 4. The flowchart of the simulation model

erated for selecting an SKU set as well as selecting SKUs from the set. Finally, the random orders are generated in the third step. The procedure begins with generating an order size between predefined ranges. To fill up the order, an SKU set is selected randomly, and some SKUs of the order are selected from the SKU set based on their picking probabilities and correlation strengths. Similarly, another SKU set is selected randomly, and pick some SKUs of the order from this SKU set. This procedure repeats until all the SKUs of the order have been selected. In this way, a required number of orders are generated.

5.2 Routing Method

Routing is an important part of the picking operation. The travel distance depends upon the route followed by the picker. Determining the optimal path for a single order is a specific instance of the Traveling Salesman Problem (TSP). Generally, trying to identify the optimal paths to these problems is time-consuming. To find an appropriate path, there are many simple and effective heuristics available [35]. A greedy routing approach, as shown in Figure 5, is adopted in this research to calculate the total travel distance. The greedy approach is used as a tool to facilitate the evaluation and comparison of the proposed storage assignment approach with different well-known storage assignment policies. This method is integrated into the simulation model to quickly approximate the travel distance of the picker. The decision to employ the greedy approach is inspired by the study of Kim et al. [24], where they also utilized this approach in a similar context. The rationale behind adopting the greedy approach is to simplify the calculation of picker travel distance within the simulation model and avoid unwanted complexity. The primary principle of the policy is that an order picker picks an SKU closest to the present location and travels there through the shortest possible path. Assuming a picker begins to pick from the I/O point, it will move to the closest location among the picking points. The picker will then proceed to the next closest location from the present location. The process is repeated until all the SKUs of an order are collected. After collecting all the SKUs, the order picker returns to the I/O point through the shortest path.

5.3 Simulation Parameters

The specifications of the warehouse configuration as presented in section 3, are used for the simulation experiment. Initially, 100,000 random orders are generated as order history to allocate the SKUs to the storage areas. Besides, another 100,000 random orders are generated as purchase orders to simulate the order-picking operations for each of the storage systems to compare the results. The proposed method is tested in six warehouse configurations with an increasing number of available storage locations to compare the total travel distance. The number of storage locations ranges from 400 to 3000, and the number of aisles varies between 10 and 30 as shown in Table 1. The purpose of the large-scale test is to illustrate how efficiently the proposed method can solve large-size problems. For each configuration, it is assumed that the distance from the I/O point to the first storage location is 1 meter, and the distance between two adjacent locations is also 1 meter. The distance between two adjacent aisles is 3 meters.

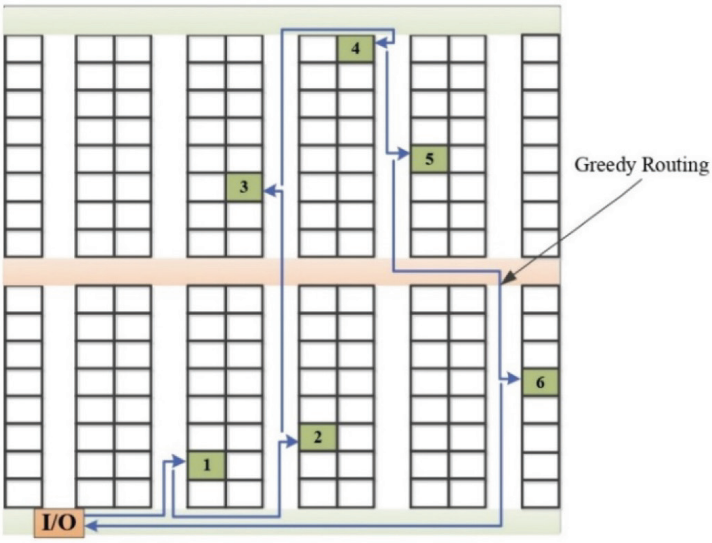

Figure 5. Greedy routing policy [24]

Table 1. Experimental design setup

	No. of storage locations	No. of aisles	No. of orders	Maximum order size	Distance between two adjacent locations, v (m)	Distance between two adjacent aisles, h (m)	Picking aisle width, u (m)	Cross aisle width, w (m)
Configuration -1	400	10	100000	10	1	3	1	1
Configuration -2	600	15	100000	10	1	3	1	1
Configuration -3	900	15	100000	15	1	3	1	1
Configuration -4	1200	20	100000	15	1	3	1	1
Configuration -5	2000	25	100000	20	1	3	1	1
Configuration -6	3000	30	100000	30	1	3	1	1

Moreover, the width of both the picking aisle and cross-aisle is 1 meter. For each warehouse configuration, the simulation is run five times to ensure that the randomness does not affect the optimization results. The experiments were conducted on a Windows 10 (64-bit) platform with Intel Core i7-10700 CPU at a clock speed of 2.90 GHz and 8GB of RAM.

6. Results and Discussion

To demonstrate the effectiveness of the suggested method a set of experiments are conducted based on the experimental setup described in section 5. The experimental results of each storage allocation method for the warehouse according to configuration 1 are presented in Table 2 for five trials with the data sets of different purchase orders. As mentioned earlier, the criterion for comparison is the total travel distance to pick up all the SKUs of orders from the warehouse. The total travel distance is calculated for each storage allocation method for the same set of data. The results indicate that the total travel distances are consistent for a particular method for different trials.

Table 3 shows the overall performance of each storage allocation method. The results for each configuration refer to the average over the 5 replications. The full turnover-based storage method is used as the benchmark for comparison purposes as this policy is indeed one of the most commonly implemented strategies in warehouse management due to its simplicity and effectiveness in optimizing SKUs placement based on their turnover rates. The ABC class-based method performs worse than the full turnover-based method. The travel distance increases from 7.21% to 9.80% because the SKUs are stored randomly in each class of the ABC class-based policy. Compared to the full-turnover storage policy, the CSAS approach proposed by Zhang [3] can reduce the travel distance ranging from 14.56% to 34.13%. The results also demonstrate that the proposed CBSLA method considerably improves the order-picking efficiency. It can reduce the travel distance of the picker ranging from 22.55% to 39.67%. Moreover, for all configurations, the results can be obtained within a reasonable amount of CPU time. It appears that CUP time increases with problem size since large numbers of customer orders require a significant amount of computing effort to calculate. The authors believe that the utilization of a higher-performance computer system has the potential to reduce CPU time.

Table 2. Simulation results for warehouse configuration 1

	Total travel distance (m)			
	Full turnover-based policy	ABC class-based policy	CSAS approach	Proposed CBSA approach
Trial 1	6,965,742	7,583,010	5,721,488	5,290,414
Trial 2	6,963,090	7,573,028	5,682,944	5,312,390
Trial 3	6,853,094	7,591,868	5,675,922	5,243,216
Trial 4	7,033,662	7,661,900	5,649,144	5,338,894
Trial 5	6,883,480	7,689,294	5,679,638	5,351,292

Table 3. Comparison of results for different storage assignment policies

	Full turnover-based (FTB) policy	**ABC class-based policy**		**CSAS approach**		**Proposed CBSLA approach**		**Average CPU time (sec)**			
	Avg. total travel distance (m) **(Benchmark)**	Avg. total travel distance (m)	Improv. (%)	Avg. total travel distance (m)	Improv. (%)	Avg. total travel distance (m)	Improv. (%)	FTB	ABC	CSAS	CBSLA
Config-1	6,939,814	7,619,820	-9.80	5,681,827	18.13	5,307,241	23.52	< 1	< 1	< 1	6
Config-2	8,806,596	9,612,592	-9.15	7,524,713	14.56	6,820,562	22.55	< 1	< 1	< 1	8
Config-3	11,977,640	12,878,278	-7.52	9,068,610	24.29	8,514,403	28.91	< 1	< 1	2	15
Config-4	14,652,384	16,004,577	-9.23	11,163,972	23.81	10,361,317	29.28	< 1	< 1	4	22
Config-5	20,009,983	21,634,507	-8.12	14,461,112	27.73	13,250,521	33.78	< 1	< 1	10	71
Config-6	28,272,334	30,311,537	-7.21	18,622,117	34.13	17,055,084	39.67	< 1	< 1	23	227

Figure 6 provides a graphic representation of the total travel distance mentioned in Table 3 for the four storage allocation methods. It indicates that total travel distance increases as the configuration size increases. Obviously, in this case, the picker has to travel more distance to pick SKUs from the large-sized warehouses.

7. Conclusions and future research scopes

Order-picking is the most important function of a warehouse. The travel distance of the picker largely depends upon how SKUs are organized and assigned in the storage areas. From the historical customer orders, it is seen that certain SKUs are usually ordered together, called correlated SKUs. The travel distance will be reduced if these correlated SKUs are stored together. The correlation strength between SKUs is determined by how frequently these SKUs are ordered together in a given period. This study proposes a CBSLA method that organizes the SKUs into groups and assigns these groups to the storage aisles in such a way that the distance between correlated groups, as well as the distance between correlated SKUs in each group, is minimized. The proposed method is effective in retrieving customer orders by traveling through a few aisles in the warehouse. A simulation experiment is conducted to demonstrate that the proposed heuristic method is effective in reducing the total travel distance when compared with other storage allocation methods. Therefore, the suggested CBSLA approach can assist warehouse managers in creating an effective storage assignment strategy, enabling them to reduce travel distances and operate more quickly. The method is easy to apply in a multi-block warehouse and performs much better in large-scale problems.

However, this study only considers single order-picking operation with a single order picker. So, the research can be extended where multiple order pickers, as well as the batching of customer orders, will be considered. The research can also be extended for scattered storage systems, where each SKU type can occupy multiple storage locations. In addition, future research should incorporate an effective order data updating method to capture the changes in demand patterns.

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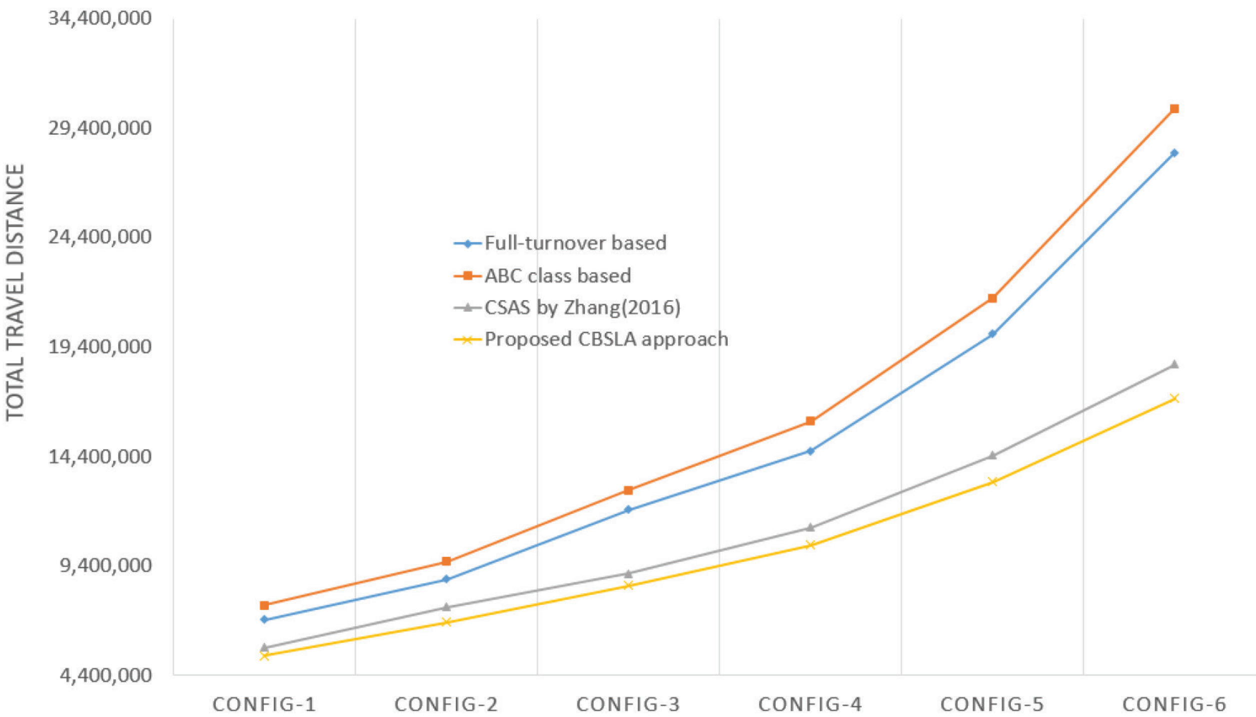

Figure 6. Total travel distance of different policies under various configurations

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