

Research Article

A Random Classified-Storage Picking Path Model for V-Type Storage Layout

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Received 19 September 2019; Revised 29 November 2019; Accepted 27 December 2019; Published 10 February 2020

Guest Editor: Xuyun Zhang

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This paper studies a V-type layout design, establishes the area utilization model of a V-type layout based on big data technology, and verifies the validity of the area model. This paper studies the ABC classification and storage strategy of V-type layout and establishes a random model of return-shape picking paths for V-type layout. By calculating the sum of the expected picking distance in the main channel and the expected picking distance of the subchannel, a mathematical model for return-shape picking paths of the V-type layout is established. By using big data mining technology, this paper simulates a random picking path model and obtains simulated data for cases with multiple orders, providing a theoretical basis for research on random picking path models with a classified-storage strategy using an improved layout.

1. Introduction

Warehousing is a combination of logistics, information flow, and capital flow that acts as a transfer station connecting production, supply, and sales. In the complex logistics picking environment, the correlation between goods is obtained by edge calculation and objects in a warehouse are identified based on a neural network. The picking robot selects different intelligent grasping methods based on the different object categories to achieve improved storage picking intelligence and efficiency.

The warehouse layout is an important factor that determines the operational efficiency of the distribution centre, and it has an important influence on order picking and picking distance. In fact, warehouse layout design has an impact of over 60% on the total picking path distance. Thus, an efficient warehouse layout can greatly improve the throughput of the warehouse and the customer-demand response speed.

The research motivation of this paper is as follows: (i) Researchers have studied many optimization problems

under the traditional layouts but have proposed few new layout methods. (ii) The warehouse layout design has a high impact on order picking and the picking walking distance. By reducing the lengths of shelves and changing shelf placements, the V-type warehouse layout can offer more picking channels. (iii) A good storage strategy can reduce the moving distance between storage locations and make full use of the available storage space. Currently, classification storage strategies are the most widely used in practical production situations. Therefore, this paper establishes an area utilization model under an ABC classified-storage strategy with a V-type layout and establishes a return-shape picking path stochastic model for the V-type layout.

The primary contributions of this article are as follows: (i) summarize the existing literature on warehouse layouts and selection paths; (ii) establish an area utilization model for the V-type layout to verify the model validity; (iii) introduce linear cutting to conduct an ABC partition of the warehouse layout; (iv) establish the return-shape picking path model for the V-type layout; and (v) report the results of data simulations for multiple orders.

The remainder of this article is organized as follows: Section 2 introduces the previous literature on warehouse layouts and picking paths. Section 3 constructs the area utilization model for a V-type warehouse layout and verifies the model's validity. Section 4 divides the V-type layout into three ABC types and establishes a return-shape picking path stochastic model for the V-type layout. Section 5 simulates the V-type picking path model, compares it with the s-shape path, and provides an analysis. Section 6 summarizes the article and highlights its shortcomings.

2. Related Work

In the new e-commerce environment, in order to ensure the security of storage and the relevance of requirements, scholars have explored the protection of data privacy [1–5], and the storage of cargo space is no longer a traditional classification standard. Through edge calculation, Internet of things and other technologies to explore the high correlation between different goods, re-clustering goods based on a certain degree of association rules, so as to form a network of data between goods [6–8].

In terms of warehouse systems and classification of cargo space storage, Azadeh et al. and Bahrami et al. [9, 10] summarized the automatic robot processing system, discussed the storage strategy, and allocated cargo storage location. Ramanathan et al. and Rezaei and Dowlatshahi [11, 12] considered multiple criteria for inventory classification and proposed a simple classification scheme based on weighted linear optimization. Manzini et al. [13] introduced a multiparameter dynamic model for rapidly estimating the moving distance within the pick cycle. Lin et al. [14, 15] proposed an integrated random forest algorithm, which extended the multiresource scheduling and power consumption model of CloudSim. Wang et al. [16, 17] decomposed the multiobjective scheduling problem into a certain number of scalar quantum problems, dynamically matched supply and demand resources while considering the matching cost, and solved all subproblems in a single operation. Jiang et al. [18] developed a crowd perception incentive model based on the voting mechanism, enabling each participant to perform multiple tasks, which greatly improved the participants' execution ability. Scholars used class-based storage strategy, gray clustering, fuzzy c-means clustering, and other methods to classify the types of goods in orders [19–22]. On this basis, this paper replans the ABC classification of goods.

In recent years, experts and scholars worldwide have also conducted considerable research work to investigate new warehouse layouts.

In 2012, Cardona et al. [23] studied the fishbone warehouse layout and obtained the oblique channel with the optimal angle of the fishbone warehouse layout; Öztürkoğlu et al. [24] found that a V-type warehouse layout achieved the same performance as the fishbone warehouse layout. In 2014, Çelk and Süral [25] found that the fewer the number of product categories ordered, the greater the difference in the average walking time between a traditional storage centre

and the fishbone storage centre. In 2015, Cardona et al. [26] proposed a third design method for a fishbone layout; this approach used a mathematical finite sequence to model the arrangement of openings and generated a detailed fishbone layout design based on the four main characteristic values of the fishbone layout. In 2017, Zhang et al. [27, 28] studied a real production and warehousing case, proposed a comprehensive strategy combining warehouse layout with the volume batch problem, and proposed a heuristic method along with a variation to accommodate a large instance with real data.

In 2018, Pferschy and Schauer [29] considered the order batch when retrieving goods from the warehouse and processing the order through a picking process and a path stage. The positions of goods were sorted based on the minimum length route, and a heuristic algorithm based on the general graph model was proposed; Weidinger [30] studied the picker path problem in a rectangular scattered warehouse and the influence of heterogeneity of different order line levels on the picker cycle length.

In 2019, Öztürkoğlu and Hosler [31] developed a new warehouse design called the “discrete cross aisle warehouse design.” Compared with the traditional two-group layout, the new design saves 7% of the order-picking trip and provides a method to reduce the transportation distance for the picking operation; Weidinger and others [32] found that for e-commerce retail retrieval of a set of chosen items, shelf access scheduling was an important optimization problem: they defined mixed warehouse shelves when choosing the resulting path problem—mixed shelf storage benchmarking with traditional storage strategy—which could adapt to the proportion of small and large orders under different scenarios. Zhou et al. [33] found that several densities and surfaces are more influential when blocking time than are picking speed and walking speed when items are picked individually. They constructed a discrete time Markov state transition probability matrix, studied the steady state of the matrix, and analysed the blocking time ratio under the chosen density. Then, the relationship between the number of surfaces, the blocking time, and the extreme value points are determined. Yener and Yazgan [34] studied warehouse designs, evaluated the effectiveness of various warehouse designs, and used an integer linear mathematical model to sort the paths for a large number of randomly selected picking requests. To reduce the picking distance, Zhou et al. [35] used the genetic algorithm, the ant colony algorithm, and the cuckoo algorithm to optimize the picking paths in warehouses with fishbone layouts and established an optimization model for selecting picking paths in warehouses with a fishbone layout.

Scholars have conducted many studies to optimize fishbone layouts; however, few studies exist regarding the utilization, storage, and picking path strategy for V-type layout areas. This article uses the V-type layout and storage policy classification to analyse the length of the return-shape picking path, for which a schematic diagram is shown in Figure 1. For a storage centre with a V-type layout, the random model of the return-shape and s-shape picking path is established, and the validity of the model is

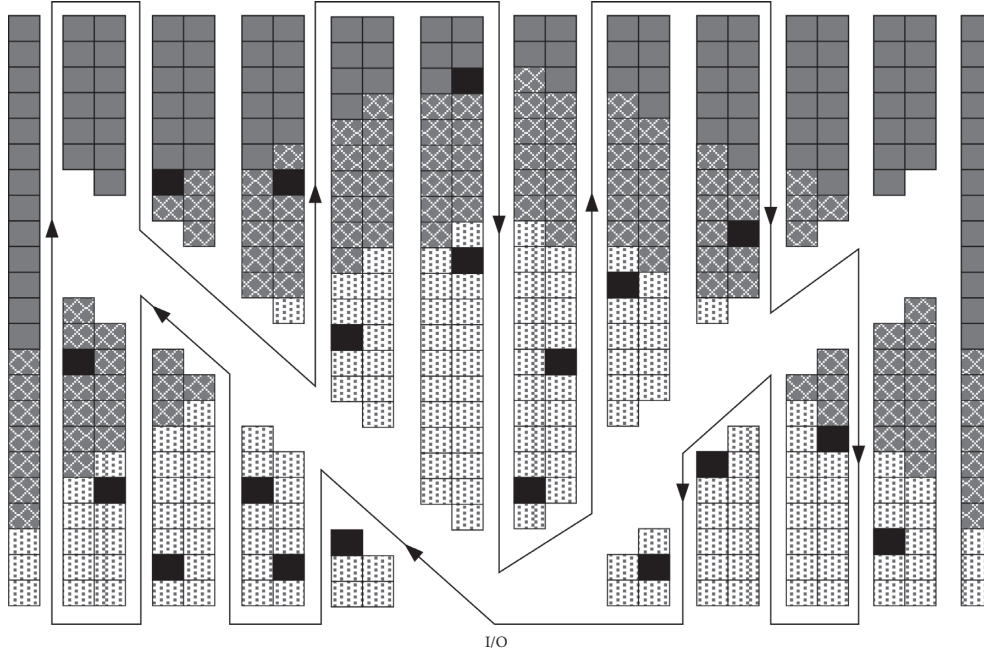


FIGURE 1: V-type layout return-shape picking path strategies for a given classification storage strategy.

verified by a simulation experiment. This paper also assesses whether the return-shape picking path strategy is better than the s-shape picking path strategy when the relevant parameters of the V-type layout and picking path are constant.

To improve the current rapid development of the logistics industry, this study will help improve the efficiency of storage centre selection, reduce the time cost, and improve the vitality of the logistics industry. For consumers, this type of improvement can reduce waiting times and improve service satisfaction. From a national economy viewpoint, the results of this study can help accelerate the efficiency of goods turnover and reduce warehousing occupancy rates, thus promoting economic development.

3. V-Type Warehouse Layout Area Utilization Model

3.1. V-Type Layout Area Utilization Model Construction. Figure 2 shows a schematic diagram of a V-type storage layout.

Assumptions. The warehouse has a rectangular shape. In this paper, we study only layouts on a plane and ignore the influence of height on warehouse layout. The warehouse has a single input/output (I/O) point located in the lower middle area of the warehouse. The aisles and passages have equal widths. Warehouse congestion is not considered. The

symbols used in the model are defined as follows: S_1 represents the storage area of the lower half; S_2 represents the storage area of the upper half; l_1 represents the aisle width; l_2 represents the shelf width; r represents the width of the warehouse; α represents the angle of the warehouse ramp; α_0 represents the right half of the diagonal angle of the warehouse; a represents half the length of the warehouse; and R represents the effective utilized area.

Due to the symmetry of the warehouse, only the right half of the warehouse is taken as an example. The oblique-angled aisles in the V-type layout mainly include two cases: (1) those greater than 0 degrees but less than the right-half diagonal angle and (2) those greater than the right-half diagonal angle but less than $\pi/2$. When the angles equal 0 or $\pi/2$, the V-type layout becomes a traditional warehouse layout, as shown in Figure 3.

When $0.01 \leq \alpha \leq \alpha_0$, the number of aisles in the right-half area is rounded down:

$$n = \left\lfloor \frac{a}{l_1 + l_2} \right\rfloor. \quad (1)$$

The bottom length of the first trapezoid is

$$r_0 = r - 2l_1 - l_1 = r - 3l_1. \quad (2)$$

And its bottom side is defined as

$$r_1 = r_0 - \frac{l_2}{2 \tan((\pi/2) - \alpha)}. \quad (3)$$

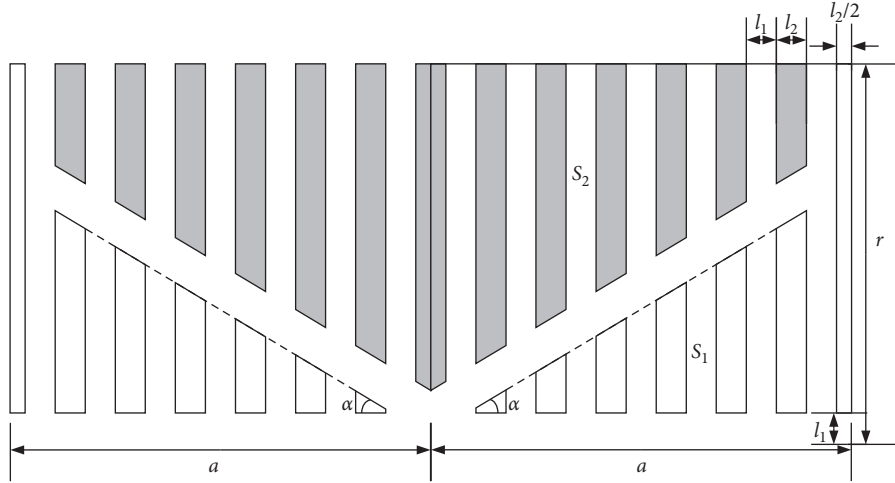


FIGURE 2: V-type storage layout diagram.

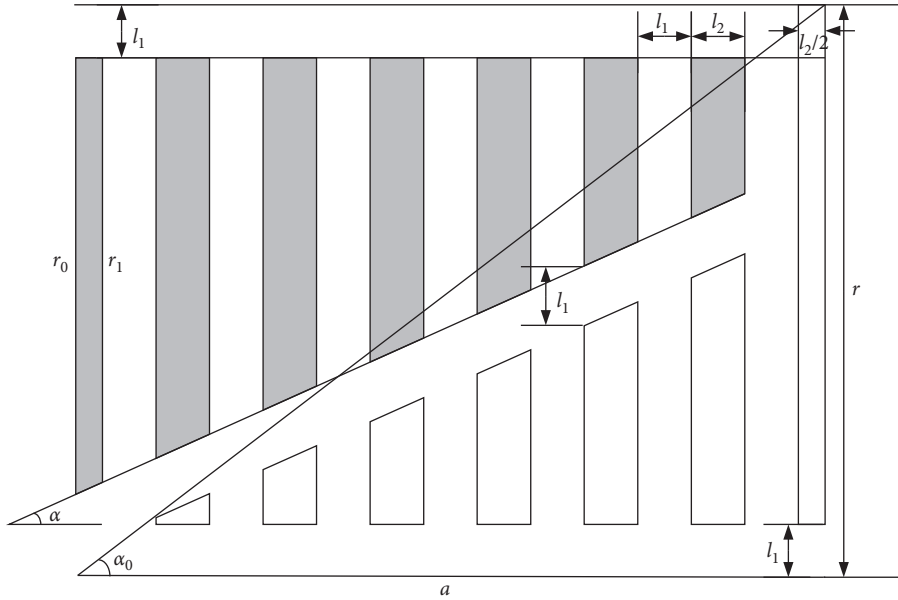


FIGURE 3: A diagram with a diagonal angle greater than 0 degrees and less than the right-half diagonal angle.

Therefore, the area of the first trapezoid is

$$S_f = \frac{1}{2} (r_0 + r_1) * \frac{l_2}{2} = \frac{1}{4} \left[r - 3l_1 + r_0 - \frac{l_2}{2 \tan((\pi/2) - \alpha)} \right] l_2. \quad (4)$$

The last shelf is a single row of shelves whose rectangular area is

$$S_b = \frac{1}{2} (r - 2l_1) * \frac{l_2}{2}. \quad (5)$$

The remaining shelf area is

$$S_r = (n - 1) * [(r - 2l_1) * l_2] - (n - 1) * \left(\frac{l_1}{\cos \alpha} * l_2 \right). \quad (6)$$

The area of all the shelves is as follows:

$$S = S_f + S_b + S_r = l_2 * \left[\frac{(8n - 2) * r + l_1 * (2 - 16n) - l_2 * (\cot \alpha)^{-1} + 2r_0}{8} - (n - 1) * \frac{l_1}{\cos \alpha} \right]. \quad (7)$$

Thus, the effective area utilization is

$$R = \frac{S}{S_l} = \frac{l_2 * \{(((8n - 2) * r + l_1 * (2 - 16n) - l_2 * (\cot \alpha)^{-1} + 2r_0)/8) - (n - 1) * (l_1 / \cos \alpha)\}}{a * r}. \quad (8)$$

When $\alpha_0 \leq \alpha \leq \pi/2$, as shown in Figure 4, the number of aisles in the right-half area is

$$n = \left\lfloor \frac{a}{l_1 + l_2} \right\rfloor. \quad (9)$$

We round down the number of aisles that exist over the length f_0 :

$$n' = \left\lfloor \frac{f_0 - (l_2/2)}{l_1 + l_2} \right\rfloor = \left\lfloor \frac{2f_0 - l_2}{2(l_1 + l_2)} \right\rfloor. \quad (10)$$

The bottom length of the first trapezoid is

$$r_0 = r - 2l_1 - l_1 = r - 3l_1. \quad (11)$$

And its upper edge is

$$r_1 = r_0 - \frac{l_2}{2 \tan((\pi/2) - \alpha)} = r_0 - \frac{l_2}{2 \cot \alpha} = r - 3l_1 - \frac{l_2}{2 \cot \alpha}. \quad (12)$$

Therefore, the area of the first trapezoid is

$$S_f = \frac{1}{2} (r_0 + r_1) * \frac{l_2}{2} = \frac{1}{4} \left(2r - 6l_1 - \frac{l_2}{2 \cot \alpha} \right) l_2. \quad (13)$$

The area being traversed is

$$S_f = n * l_2 \frac{l_1}{\cos \alpha}. \quad (14)$$

The area of the remaining trapezoidal part is

$$S_r = n * (r - 2l_1)l_2 - n * l_2 \frac{l_1}{\cos \alpha} = n'l_2 \left[r - l_1 \left(2 - \frac{1}{\cos \alpha} \right) \right]. \quad (15)$$

The area of the last rectangle is

$$S_b = \frac{(r - 2l_1)l_2}{2}. \quad (16)$$

The lower half area is

$$S = S_f + S_b + S_r = l_2 \left[r(1 + n') - \left(\frac{5}{2} + 2n' - \frac{1}{\cos \alpha} n' \right) l_1 - \frac{l_2}{8 \cot \alpha} \right]. \quad (17)$$

Therefore, the area utilization rate is

$$R = \frac{S}{S_l} = \frac{l_2 [r(1 + n') - ((5/2) + 2n' - (1/\cos \alpha)n')l_1 - (l_2/8 \cot \alpha)]}{ar}. \quad (18)$$

3.2. Area Model Validation. In this part, a simulation example is made for verifying the area utilization model. Therefore, some assumptions need to be made about the

parameters of the storage environment. The width of the warehouse is set to $r = 300$, and the half length of the warehouse is set to $a = 300$. The error between the model and the simulation is validated for aisle and shelf widths of $l_1 = l_2 = 1$, $l_1 = l_2 = 1.5$, and $l_1 = l_2 = 1.8$. The calculations indicated that the error margin was between plus or minus 1%, as shown in Figure 5.

When the angle of the main picking aisle is 0 or $\pi/2$, the V-type layout becomes a traditional storage layout and the area utilization rate reaches its highest level of approximately 0.485. When the angle of the main picking aisle is $\pi/4$, the effective area utilization rate of the V-type storage layout reaches its lowest level of 0.483. The difference between the highest and lowest utilization rates is approximately 0.002. Thus, when the V-type layout design, warehouse area utilization, and storage area layout utilization rate remain the same, the error margin is small. In this case, the warehouse layout can be ignored.

4. V-Type Layout Picking Path Random Model

4.1. ABC Classification of the V-Type Layout. The quantity and variety of goods in stock are large. Due to the limited resources in various aspects of the enterprise, ABC classification of the goods in stock can improve the selection efficiency according to the frequency of goods entering and leaving the warehouse.

Based on the design principle of setting the closest import and export for Class A articles, two straight lines are used to intercept the storage area of the Class A articles based on the V-type warehouse layout characteristics. It is important to confirm that the distances between the import and export from the furthest edge position of the Class A articles are equal (as in line segments $BC = BD + DE$ in Figure 6). When the positions are equal, the slope k_1 and the intercept c_1 of the first straight line can be determined as shown in the following example:

$$BF + FC = BD + DE,$$

$$BF + FC = BD + DH - EH,$$

$$BF = BD - EH,$$

$$EH = BD - BF,$$

$$\tan \beta = \frac{CH}{EH} = \frac{DF}{BD - BF} = \frac{l}{(l/\cos \alpha) - l * \tan \alpha}, \quad l = l_1 + l_2. \quad (19)$$

Using this formula, we can find the slope of the line, $k_1 = \tan[(\pi/2) + \arctan \beta]$, because the two segments are

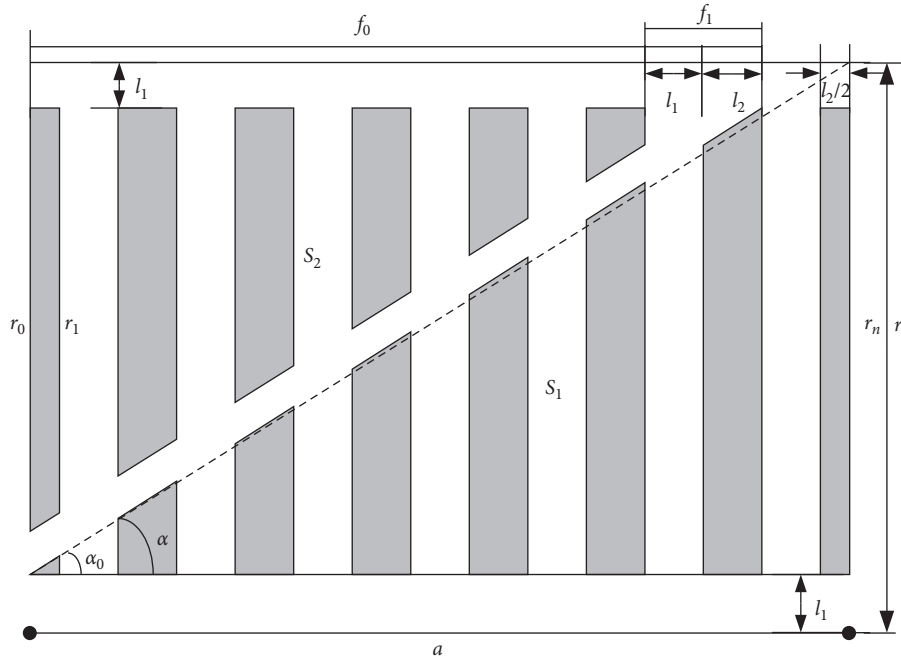


FIGURE 4: The diagonal angle is greater than the right-half diagonal angle and less than $\pi/2$ in the schematic.

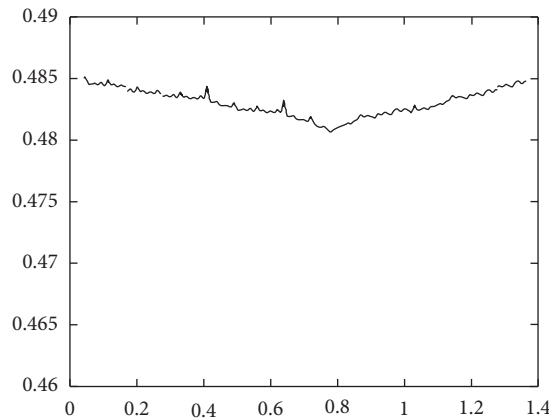


FIGURE 5: The V-type storage layout area utilization model changes based on the angle change in the utilization map.

symmetrical about the slanted channel. The second segment, k_2 , can be obtained from the angle of the slanted channel. For c_1 and c_2 , according to the area occupied by the category

of objects, one can find the intercept of the two straight lines c_1 and c_2 :

$$P_A = \frac{S_A}{S} = \frac{(1/2) * C * (C/k_1) - (1/2) * (C \tan \alpha / (\tan \alpha - k_1)) * ((-C/k_1) - (C/(k_1 - 2 \tan \alpha)))}{ab} \quad (20)$$

Using this formula, c_1 and c_2 can be determined.

The intercepts of the Class B and Class C articles can be determined similarly.

4.2. Picking Path Random Model Assumptions and Symbolic Description. Based on the cargo flow volume, the picked objects are classified into M categories based on the distances

from the warehouse entry point to the nearest object in descending order. The corresponding positions of the goods are obtained in sequence. Each type of cargo is randomly placed. Figure 7 shows the goods divided into conventional A, B, and C (fast, medium, and slow) classes.

The following assumptions are added to the previous conditions for the V-type layout: (1) the storage space is

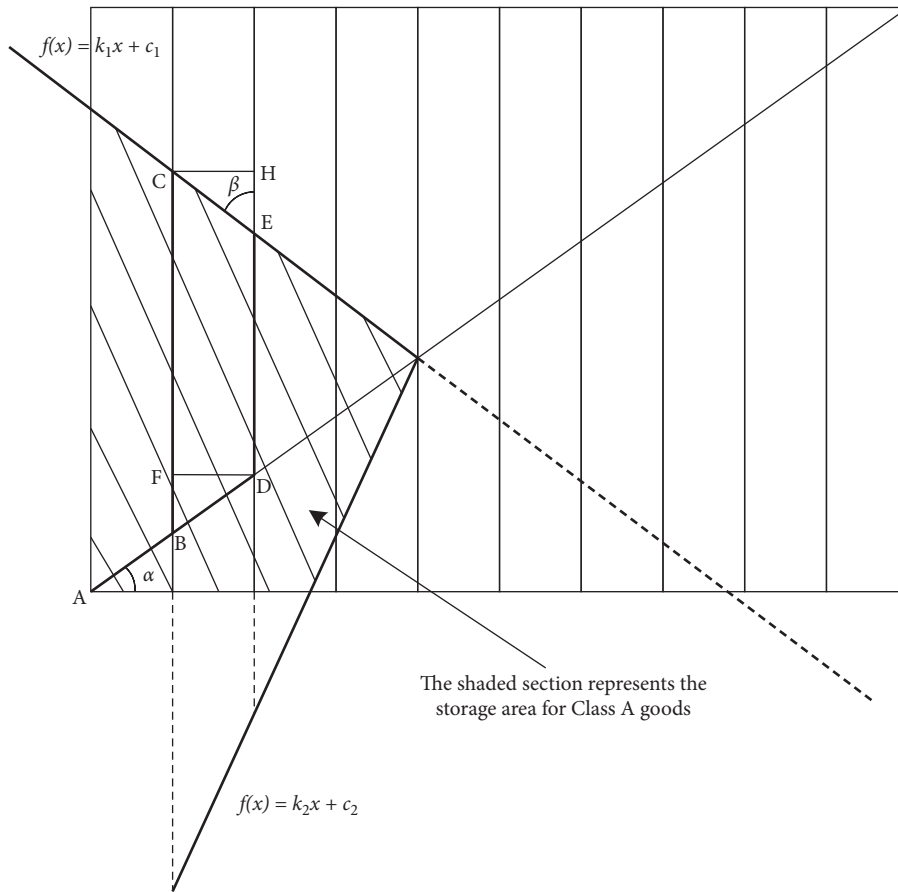


FIGURE 6: ABC classification diagram of V-type layout.

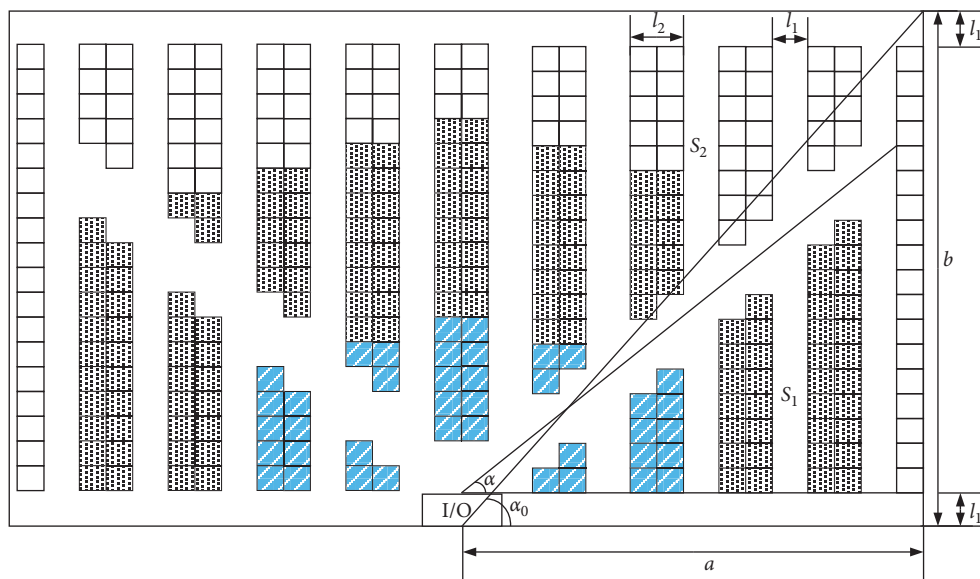


FIGURE 7: V-type layout diagram for a class-based storage strategy.

calculated based on shelf length; shelf height is not considered; (2) when picking in an aisle, goods can be picked from both sides of the aisle and the distance between the two sides is ignored when picking the goods; (3) the selected

items are random and independent of each other; (4) in the given order, the probability of picking each item for each type of goods is the same; (5) the same items are randomly assigned to a space, and each item is stored in only one space;

(6) within a channel, the lengths of the shelves holding each item for a specific category of articles is evenly distributed; and (7) the oblique and normal aisles have equal widths. The symbols used in the model are defined as follows: l_1 indicates the aisle width; l_2 represents the width of a shelf; b indicates the width of the warehouse; α indicates the angle of the warehouse ramp; α_0 represents the right half of the warehouse diagonal angle; and a represents half the length of the warehouse.

4.3. Return-Shape Picking Path Model Construction. When $0.01 \leq \alpha \leq \alpha_0$, the oblique aisle runs through all the picking aisles in the right half of the area; thus, the number of picking aisles in Areas 1 and 2 is the same, that is, $n = n_1 = n_2$. The number of channels in the right half is then rounded down as follows:

$$n = \left\lfloor \frac{a - 0.5(l_1 + l_2)}{l_1 + l_2} \right\rfloor. \quad (21)$$

When $\alpha_0 \leq \alpha \leq (\pi/2)$,

$$n_1 = \left\lfloor \frac{f_0 - (l_2/2)}{l_1 + l_2} \right\rfloor = \left\lfloor \frac{2f_0 - l_2}{2(l_1 + l_2)} \right\rfloor, \quad (22)$$

$$n_2 = \left\lfloor \frac{a - 0.5(l_1 + l_2)}{l_1 + l_2} \right\rfloor.$$

Category A items in zones 1 and 2 account for an aisle length of j :

$$\begin{aligned} m_{1aj} &= \max(0, \min(a, c_1b + (l_1 + l_2) * (j - 0.5) \\ &\quad * \tan\left(\frac{\pi}{2} + \arctan \cos(\alpha)\right) - (l_1 + l_2) \\ &\quad * (j - 0.5) * \tan(\alpha))) , \quad j = 1, 2, \dots, n_1, \\ m_{2aj} &= \max\left(0, \min\left((l_1 + l_2) * (j - 0.5) * \tan(\alpha), (l_1 + l_2) \right. \right. \\ &\quad * (j - 0.5) * \tan(\alpha) - (2 \tan(\alpha) * (l_1 + l_2) * (j - 0.5) \\ &\quad - \left. \left. \left(\tan\left(\frac{\pi}{2} + \arctan(\cos(\alpha))\right) * (l_1 + l_2) \right. \right. \right. \\ &\quad \left. \left. \left. * (j - 0.5) + c_2b\right)\right)\right), \quad j = 1, \dots, n_2. \end{aligned} \quad (23)$$

Category C items in zones 1 and 2 account for an aisle length of j :

$$\begin{aligned} m_{1cj} &= a - m_{1bj} - m_{1aj} - (l_1 + l_2) * (j - 0.5) * \tan(\alpha), \\ m_{2cj} &= a - m_{2bj} - m_{2aj} - (l_1 + l_2) * (j - 0.5) * \tan(\alpha), \\ m_{aj} &= m_{1aj} + m_{2aj}, \\ m_{bj} &= m_{1bj} + m_{2bj}, \\ m_{cj} &= m_{1cj} + m_{2cj}. \end{aligned} \quad (24)$$

The probability of picking items of type A/B/C within aisle j is as follows:

$$\begin{aligned} p_{aj} &= p_a \frac{m_{aj}}{\sum_{j=1}^{n_1+n_2} m_{aj}}, \\ p_{bj} &= p_b \frac{m_{bj}}{\sum_{j=1}^{n_1+n_2} m_{bj}}, \\ p_{cj} &= p_c \frac{m_{cj}}{\sum_{j=1}^{n_1+n_2} m_{cj}}. \end{aligned} \quad (25)$$

For any aisle j in the right half of the area, the categories of the items to be selected on the shelves for categories A, B, and C obey a binomial distribution $b(K; T)$, assuming that the type of item to be sorted in aisle j is T_j . The probability $p_{aj}^{(K)}$ that there are K types of goods in the T_j types of goods in the A/B/C type storage area of aisle j is as follows:

$$\begin{aligned} p_{aj}^{(K)} &= C_T^K (1 - p_{aj})^{T-K} (p_{aj})^K, \quad K = 0, 1, \dots, T; 1 \leq j \leq n_1 + n_2, \\ p_{bj}^{(K)} &= C_T^K (1 - p_{bj})^{T-K} (p_{bj})^K, \quad K = 0, 1, \dots, T; 1 \leq j \leq n_1 + n_2, \\ p_{cj}^{(K)} &= C_T^K (1 - p_{cj})^{T-K} (p_{cj})^K, \quad K = 0, 1, \dots, T; 1 \leq j \leq n_1 + n_2. \end{aligned} \quad (26)$$

Assume that there are K types of orders in aisle j that need to select Class A items and that the items in the Type A item storage region in aisle j are evenly distributed. The maximum distance that needs to be walked in the aisle to pick a Type A item is expected to be $d_{aj}^{(K)}$; thus,

$$d_{aj}^{(K)} = E(\max(\xi_{a1}, \xi_{a2}, \dots, \xi_{aK})). \quad (27)$$

The distribution function of $\max(\xi_{a1}, \xi_{a2}, \dots, \xi_{aK})$ is

$$F(x) = p\{\max(\xi_{a1}, \xi_{a2}, \dots, \xi_{aK}) < x\} = \frac{x^K}{m_{aj}^K} (0 \leq x \leq m_{aj}). \quad (28)$$

Therefore,

$$\begin{aligned} E(\max(\xi_{a1}, \xi_{a2}, \dots, \xi_{aK})) &= \int_0^{m_{aj}} x d\left(\frac{x^K}{m_{aj}^K}\right) = \frac{K}{K+1} m_{aj}, \\ d_{aj}^{(K)} &= \frac{K}{K+1} m_{aj}. \end{aligned} \quad (29)$$

Based on formula (27), formulas (28) and (29) show that when sorting T types of goods at a time, the aisle j picking walking distance is

$$d_{aj}(T) = E(d_{aj}^{(K)}) = \sum_{K=0}^T p_{aj}^{(K)} d_{aj}^{(K)}, \quad j = 1, 2, \dots, n. \quad (30)$$

The probability of stocking in aisle j is

$$p_j = \frac{p_{aj} + p_{bj} + p_{cj}}{p_a + p_b + p_c}. \quad (31)$$

Because the number of aisles in the areas above and below the slant aisle differs and the storage area in the right half is divided into two picking areas, region 1 and region 2, the desired picking distances for main aisle 1 and aisle 2

must be determined separately. From the above relation, we know that R_{far} must be obtained, and the probability of using the farthest access aisle $j_{1\text{far}}$ in region 1 when picking T kinds of articles is denoted as $p_{1j_{1\text{far}}/T}$, which yields

$$\begin{cases} p_{1j_{1\text{far}}} = (p_{1j_{1\text{far}}})^T, \\ p_{1j_{1\text{far}}} = \left(\sum_{j_1=1}^{j_{1\text{far}}} p_{1j_1} \right)^{T-1} * (p_{1j_{1\text{far}}}), \end{cases} \quad (32)$$

$$j_{1\text{far}} = 1, 2 \leq j_{1\text{far}} \leq n_1.$$

The farthest expected passage for picking goods is

$$\bar{j}_{1\text{far}} = E(j_{1\text{far}}) = \sum_{j_{1\text{far}}=1}^{n_1} j_{1\text{far}} \frac{p_{1j_{1\text{far}}}}{\sum_{j=1}^{n_1} p_{1j}}. \quad (33)$$

In summary, the farthest path from which goods can be picked up is

$$R_{1\text{far}} = (\bar{j}_{1\text{far}} - 0.5) \frac{(l_1 + l_2)}{\cos(\alpha)}. \quad (34)$$

In this case, R_{far} is required, and the probability of picking T items from the farthest access aisle $j_{2\text{far}}$ in area 2 is $p_{2j_{2\text{far}}/T}$, which gives

$$\begin{cases} p_{2j_{2\text{far}}} = (p_{2j_{2\text{far}}})^T, & j_{2\text{far}} = 1, \\ p_{2j_{2\text{far}}} = \left(\sum_{j_2=1}^{j_{2\text{far}}} p_{2j_2} \right)^{T-1} * (p_{2j_{2\text{far}}}), & 2 \leq j_{2\text{far}} \leq n_1. \end{cases} \quad (35)$$

Therefore, the farthest expected passage for picking goods is

$$\bar{j}_{2\text{far}} = E(j_{2\text{far}}) = \sum_{j_{2\text{far}}=1}^{n_2} j_{2\text{far}} * \frac{p_{2j_{2\text{far}}}}{\sum_{j=1}^{n_2} p_{2j}}. \quad (36)$$

In summary, the farthest path from which goods can be picked up is

$$R_{2\text{far}} = (\bar{j}_{2\text{far}} - 0.5) \frac{(l_1 + l_2)}{\cos(\alpha)}. \quad (37)$$

From type 1, type 5, type 9, and type 12, we can obtain the return path strategy of the selected walking distance as follows:

$$\begin{aligned} D_{\text{return}}(T) &= (2 * \max(R_{1\text{far}}, R_{2\text{far}})) \\ &+ \sum_{j=1}^n d_{aj}(T) + \sum_{j=1}^n d_{bj}(T) + \sum_{j=1}^n d_{cj}(T). \end{aligned} \quad (38)$$

5. Simulation Verification

To verify the effect of picking a random model of V-type warehouse layout in obtaining an optimal classification storage strategy, the model simulation results must be compared with those of the return-shape picking path model. According to different goods-ordering

frequencies and storage space allocations, we construct five cases; the specific data are shown in Table 1. With reference to the actual data for a distribution centre, it is assumed that $a = 300$, $b = 300$, and $\alpha = \pi/4$ for the warehouse and that the width of the picking passageways and shelves is 2. In this case, there is one order with 8 order items to be picked. The differences between the return-shape picking path model, and the simulation results are shown separately.

5.1. Simulation Validation of the Return-Shape Picking Path Random Model. According to the known conditions, the results of the random model and the simulation results of the return-shape path picking model under the above five cases are obtained as shown in Table 2 and Figure 8.

The abscissa in Figure 8 shows the five classification cases, and the ordinate shows the picking path length. The comparison leads to the following conclusions: the model and simulation results are generally consistent, and the maximum error is approximately 7%. The model accords with the simulation results, and the model is effective. Additionally, the V-type distribution centre return-shape picking walking distances for the types A, B, and C storage areas varied among the different areas. The area proportion of the type A storage area was smallest, that of type B was second smallest, and the proportion of the type C storage area was the largest. The shorter the picking distance is, the higher the operational efficiency of the storage centre is.

5.2. Comparison of Two Picking Strategies. The warehousing centre adopts two different picking strategies, return-shape picking and S-shape picking, and obtains the random model and simulation results for these two strategies under the same conditions and constraints to perform comparative analysis. The results are shown in Table 3 and Figure 9 (the authors obtained the data for the S-shape picking route based on the same method. Only the results are used in this article; no specific descriptions are given).

Through the model and the comparative simulation result analysis in the centre of the V-type storage layout of warehouse, the ABC classification, storage strategy, and return-shape and S-shape picking route stochastic models, the largest order-picking walking distance is approximately 15%, while the smallest is approximately 3%. In the simulation results of the two types of picking routes, the largest picking walking distance was 26% and the smallest was approximately 2%. Through comparative analysis, we found that both the model results and simulation results clearly show that the walking distance of the return-shape picking strategy is shorter. It can be concluded that compared with the S-shape picking strategy, the return-shape picking strategy has better applicability in V-type storage centres with an ABC classified-storage strategy. This strategy can improve the operational efficiency of the storage centre to some extent.

TABLE 1: Various types of goods-ordering frequencies and storage area ratios.

Order frequency/space allocation	Class A	Class B	Class C
Situation 1	33.33/33.33	33.33/33.33	33.33/33.33
Situation 2	45/30	30/30	25/40
Situation 3	60/25	25/30	15/45
Situation 4	75/20	20/30	5/50
Situation 5	85/15	10/30	5/55

TABLE 2: Comparison of the random model and simulation results for return-shape picking paths.

Walking distance	Situation 1	Situation 2	Situation 3	Situation 4	Situation 5
Model	1817.4	1590.7	1268.8	799.6122	608.5995
Simulation	1799.3	1682.2	1198.346	765.364	653.324
Absolute error	18.1	-91.5	70.454	34.2482	-44.7245
Relative error	0.009959	-0.05752	0.055528	0.042831	-0.07349

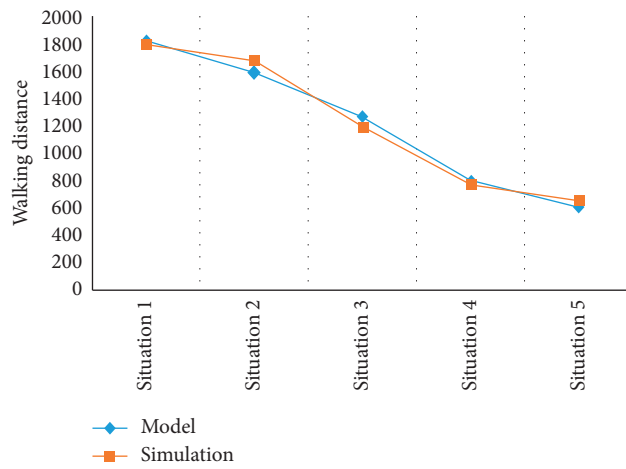


FIGURE 8: Comparison of the return-shape picking random model results and the simulation results.

TABLE 3: Comparison of the random model results for two picking paths.

Walking distance	Situation 1	Situation 2	Situation 3	Situation 4	Situation 5
Return-shape picking model	1817.4	1590.7	1268.8	799.6122	608.5995
S-shape picking model	1951.7	1731.8	1402.5	925.0627	805.178
Absolute error	-134.3	-141.1	-133.7	-125.451	-196.579
Relative error	-0.0739	-0.0887	-0.10538	-0.15689	-0.323

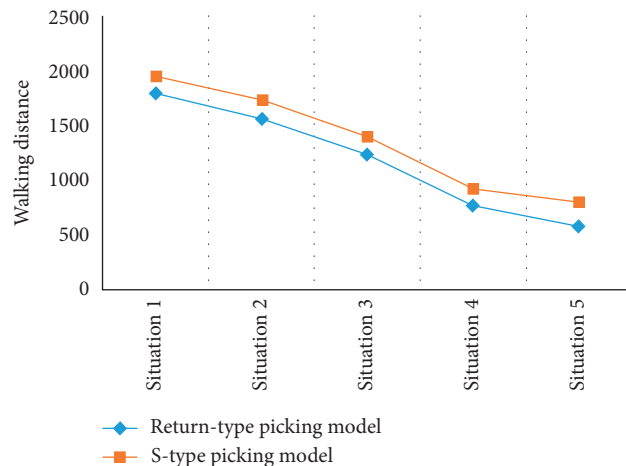


FIGURE 9: Comparison of the random model results of two types of pickup paths.

6. Conclusion

Based on the storage area ratio and the picking probability for goods classified as A, B, and C, this paper divided a storage centre using a V-type layout into three types of storage areas. By segmenting the storage areas of both layouts along a straight line, the layouts were divided into sets of areas sized proportionally to meet the requirements for ABC classification. By equalizing the boundary picking paths in the region, the slope and intercept of the cross section are obtained. These results provide a foundation for future model construction and research. For storage centres with V-type layouts, a random model of return-shape and S-shape picking paths is established, and the validity of the model is verified through simulations. When determining the relevant parameters of the V-type layout and picking orders, we found that the return-shape picking path strategy is superior to the S-shape picking path strategy.

This paper uses the theory and mathematical model of storage picking to study the V-type storage layout, but the paper still has some deficiencies. First, other new storage layouts (such as leaf and chevron layouts) are not considered in this paper. Second, this paper finds that for a V-type layout, the return pattern picking path strategy is superior to the s-shaped picking path; however, other path strategies (such as the ergodic picking path strategy, midpoint return picking path strategy, optimal route-picking strategy, etc.) were not studied and verified in this paper. These remain to be investigated in future studies.

Data Availability

To facilitate follow-up research, the simulation data in this paper were all self-created based on actual data of a distribution centre, the ordering frequencies of different types of goods, and the storage space distribution.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This study was supported by the National Nature Science Foundation of China “Research on warehouse picking system blocking influence factors and combined control strategy” (no. 71501015), the Beijing Great Wall Scholars Programme (no. CIT & TCD20170317), the Beijing Tongzhou Canal “Leading Talent Plan,” and the Beijing Collaborative Innovation Centre.

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