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Optimizing Storage and Picking Routes in Dual-Zone Warehouses Using Genetic Algorithms: A Case Study of YY Company

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Abstract
This research addresses the optimization of storage locations and picking routes in YY's dual-zone warehouse, with the goal of cutting warehousing costs and enhancing operational efficiency. As the economy shifts and industrial structures upgrade, the logistics industry's significance in the national economy grows increasingly evident. The Apriori algorithm discerns order item associations, informing the reorganization of storage allocations for optimized efficiency. On this basis, a target optimization model is constructed to further enhance the rationality of the storage layout. Regarding the optimization of picking paths, this paper presents a path optimization model tailored for multi-vehicle operations, based on the layout characteristics of YY's warehouse. This paper validates the improved genetic algorithm's effectiveness and practicality in optimizing double-zone warehouse storage and picking paths through Matlab simulations and comparisons with traditional methods.

Keywords: Apriori algorithm, Genetic algorithm, Picking path optimization, Storage location optimization, YY Company (YY's).
JEL Classification: *L9; M.M10; M19.*

1. Introduction

1.1. Background of this Study

As China's economy grows, the logistics industry, vital for development, faces rising demands for efficiency and service quality. The double-zone warehouse, a typical layout, is crucial for accommodating diverse goods and enhancing logistics efficiency. Confronted with the escalating market demand, the double-zone warehouse is encountering increasingly significant challenges in cargo space allocation and picking path planning, which exert a direct influence on warehousing costs and operational efficiency.

In China, rising social logistics costs are significantly driven by warehousing, particularly in double-zone warehouses where inefficient management exacerbates cost inefficiencies. The increasing proportion of warehousing costs in China's total social logistics expenses suggests potential for cost control optimization in double-zone warehouses. This research aims to tackle the challenges faced by double-zone warehouses and devise efficient optimization strategies.

1.2. Research Significance

The strategic value of storage optimization: This study aims to boost warehouse space efficiency and streamline item handling by optimizing storage locations in dual-zone warehouses. An optimized storage layout minimizes inefficient activities, boosts goods circulation, and consequently reduces warehousing expenses. In addition, scientific storage management helps to improve the accuracy of inventory management, bringing more standardized and efficient warehousing services to enterprises.

The value of picking path optimization: Optimization of the picking path is crucial for improving the operational efficiency of double-zone warehouses. Implementing genetic algorithms for picking path optimization significantly reduces picker walking distances and times, boosts picking efficiency, and ultimately enhances the overall warehouse operation efficiency. Moreover, optimizing picking paths contributes to lower labor and training costs, thereby enhancing a company's market competitiveness.

1.3. Current Research Status

Research in warehouse optimization commonly encompasses two essential components: storage location optimization and path optimization. Recent years have seen significant advancements in warehouse optimization by scholars worldwide:

Regarding storage location optimization, Bortolini., et al (2015) introduced a novel integer linear programming model tailored for earthquake-prone industrial zones. Chou., et al (2012) developed a storage location allocation strategy, grounded in recursive properties and significant proximity, specifically tailored for tiered warehouse architectures. Liu (2020) applied an enhanced Apriori algorithm coupled with an immune genetic algorithm to optimize and resolve issues within storage management. Zhang and Li (2022) introduced a hybrid approach leveraging deep learning and genetic algorithms to optimize storage locations in automated warehouses, thereby enhancing storage efficiency.

Regarding path optimization, Chen., et al (2013) developed a picking congestion path algorithm rooted in Ant Colony Optimization (ACO) and carried out an extensive simulation research. Xu and Ma (2021) developed a mixed integer programming model focused on minimizing costs, employing an enhanced simulated annealing algorithm to optimize shelf storage locations. Furthermore, Xu., et al (2021) developed a mathematical model for the vehicle routing problem involving splittable demands, employing heuristic algorithms to optimize the solution.

Wang and Xu (2023) leveraged the integration of machine learning techniques and optimization algorithms to concurrently optimize the configuration of goods and picking paths within warehouses, thereby reducing operational duration and augmenting precision. Li and Qin (2024) harnessed reinforcement learning to create a dynamic storage location optimization strategy capable of self-adjusting storage locations in response to real-time inventory fluctuations.

Overall, while prior research has advanced model construction and algorithm application, this paper integrates the Apriori association rule model from SPSS MODEL with an enhanced genetic algorithm to optimize warehouse storage locations, subsequently refining picking paths based on this foundation. Leveraging Matlab for computational analysis, this study aims to articulate a more efficient and pragmatic warehouse optimization strategy.

1.4. Methods

1.4.1. Field Research

Initially, this research implemented field research to gather operational data and pertinent information from YY's warehouse. Throughout the working period, the researcher engaged directly in the warehouse's daily operations, acquiring firsthand data. This data encompasses goods access frequency, warehouse layout, and picking task characteristics. Upon completion of the work, the gathered data was methodically arranged and analyzed, laying the groundwork for subsequent model development and algorithmic simulations.

1.4.2. Virtual Simulation Research

In order to validate and refine the proposed genetic algorithm, this research employed Matlab for data simulation purposes. By creating a simulated warehouse environment, this research replicated various storage location and picking path setups, utilizing genetic algorithms to identify the best or nearly optimal solutions. Virtual simulation permits not only the observation of the algorithm's dynamic progression but also facilitates the assessment of its performance and efficacy through comparison with real-world operational data. Additionally, this research substantiated the superiority of the enhanced genetic algorithm in addressing double-zone warehouse optimization issues via comparative analysis against other optimization techniques.

2. Related Theoretical Foundations

2.1. Basic Concepts

Regarding warehouse layouts, domestic enterprises typically employ single-zone, double-zone, and multi-zone configurations, with this paper concentrating specifically on the double-zone variant. Figure 1 illustrates the typical warehouse layouts:

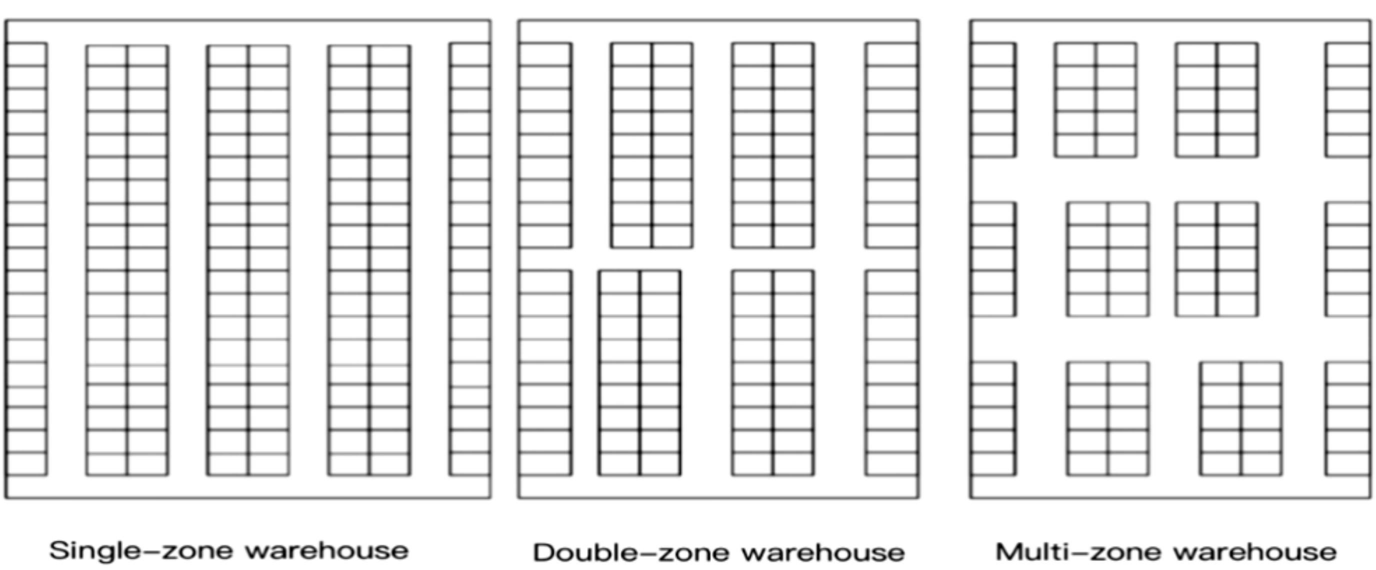

Figure 1. Common Warehouse Layouts.

2.1.1. Storage

Storage involves the process of enterprises retaining items in designated spaces to fulfill future requirements in production, sales, or logistics. This encompasses activities like the receipt and categorization of goods, while serving a crucial function within the supply chain for preservation, safeguarding, processing, and distribution

2.1.2. Storage Location

A storage location in a warehouse refers to a designated area with defined capacity and dimensions, designed for storing specific types, quantities, and sizes of goods. Storage locations are categorized into temporary and fixed types: temporary locations facilitate short-term storage and goods distribution, whereas fixed locations are optimized for long-term storage of homogenous goods. Efficient storage location management is essential for enhancing warehouse operational efficiency and minimizing inventory costs, serving as a pivotal element in the smooth functioning of the supply chain.

The commonly employed storage location management approaches and prevalent storage strategies are detailed in Table 1.

Table 1. Storage Location Strategy.

Storage strategy	Definition		Peculiarity
Fixed Storage Location	Each type of goods has a fixed storage location, and the storage location remains consistent.	Pros	Convenient for picking; allows for adjustments to storage locations based on the characteristics of the goods, reducing mutual interference and shortening transportation distances.
		Cons	Low warehouse utilization rate; insufficient flexibility of storage locations.
Random Storage Location	The storage location assigned to goods can be randomly changed, and any storage location can store any type of goods.	Pros	Convenient for operation and storage; high storage efficiency; high warehouse utilization rate.
		Cons	Not convenient for outbound inventory checks; goods with high turnover may be stored in locations far from the In/Out gate.
Categorized Storage Location	Goods are stored in fixed locations based on certain characteristics.	Pros	Convenient for storage and retrieval; conducive to refined management.
		Cons	Convenient for storage and retrieval; conducive to refined management.
Categorized Random Storage Location	Each category of goods has a fixed storage location, but within each area, the assignment is random.	Pros	Each category of goods has a fixed storage location, but within each area, the assignment is random.
		Cons	Each category of goods has a fixed storage location, but within each area, the assignment is random.

2.1.3. Picking Path

Basic Definition: The picking path is the route taken by warehouse staff to fulfill order picking tasks within the facility, and enhancing warehouse picking efficiency and reducing picking costs can commence with the optimization of the picking path.

A well-structured picking path should encompass several key elements:

1).Shortest Path: The optimized path should be the shortest, reducing the total walking distance and picking time for the picker to minimize picking costs to the greatest extent.

2).Simplicity and Practicality: The picking path must be free of design flaws, such as culs-de-sac and crossroads, ensuring ease of operation for pickers equipped with picking devices to minimize the risk of errors.

Furthermore, operability and controllability must be considered, with the logistics system overseeing and managing the path. These aspects will not be extensively discussed in this paper. Designing a well-structured picking path can significantly enhance warehouse picking efficiency and reduce operational costs.

2.1.4. Picking Path

（1）Definition and Optimization Goals: The picking path is the route that warehouse personnel take to fulfill order picking tasks. The primary goal of optimizing this path is to enhance efficiency and reduce costs, focusing on:

1) Shortest Path: Minimize walking distance and time to reduce costs.

2) Practicality: Avoid dead ends and intersections to ensure smooth operations and minimize errors.

A well-designed picking path can substantially enhance warehouse operational efficiency.

（２）Types of Picking Paths:

1) Cross-type Path: The picker enters from one end of the aisle, selects items from both sides, and proceeds without returning, ideal for high-density picking. As illustrated in Figure 2:

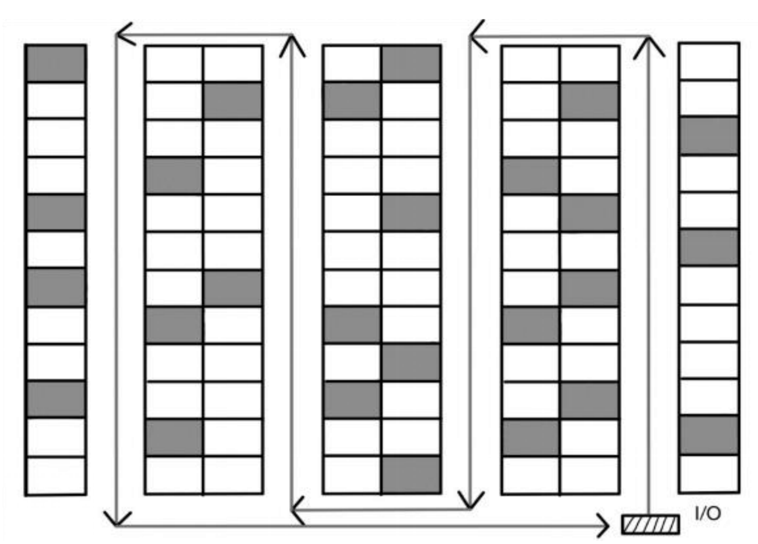

Figure 2. Cross-type Path.

2) Loop Path: In the loop path mode, the picker enters from one end of the aisle, selects items from one side, returns along the same path, and then picks items from the other side, eventually exiting from the same end. This method is ideal for situations where goods are concentrated at one end of the shelves, effectively reducing the total walking distance. As illustrated in Figure 3:

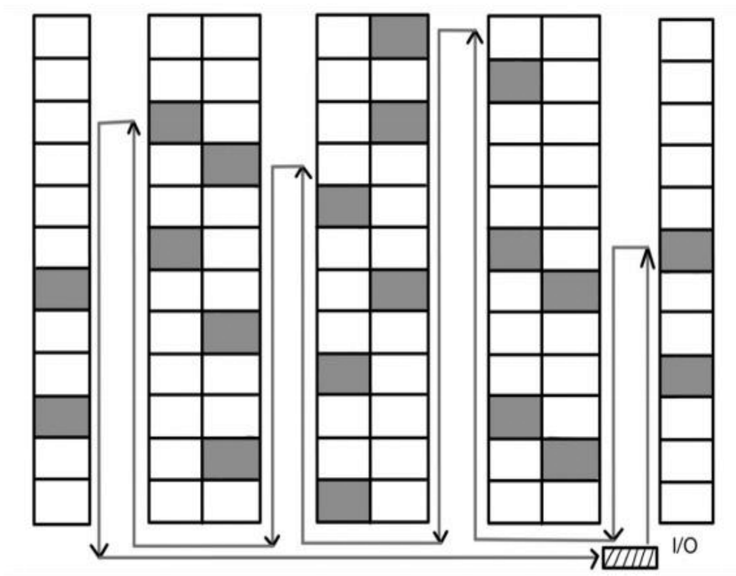

Figure 3. Loop path.

2.2. Related Algorithm Theories

2.2.1. Basic Principles of Genetic Algorithms

Concept: Genetic algorithms are adaptive optimization techniques extensively applied in search, optimization, and machine learning domains. Their strength lies in their capacity to adaptively seek the optimal solution, irrespective of the specific form of the problem. Algorithm Flow:

1) Population Initialization: The problem parameters are encoded, often in binary form, to facilitate computer processing.

2) Fitness Function: A measure used to assess the quality of chromosomes.

3) Selection Process: Chromosomes are chosen based on their fitness using techniques like roulette wheel selection.

4) Crossover and Mutation: Parent chromosomes are randomly selected for crossover (such as single-point crossover, with a crossover rate typically between 0.6 and 1) and mutation (with a mutation rate usually not exceeding 0.1) operations to produce offspring. As illustrated in Figure 4, the OX crossover method is frequently employed, yet there remains potential for enhancement.

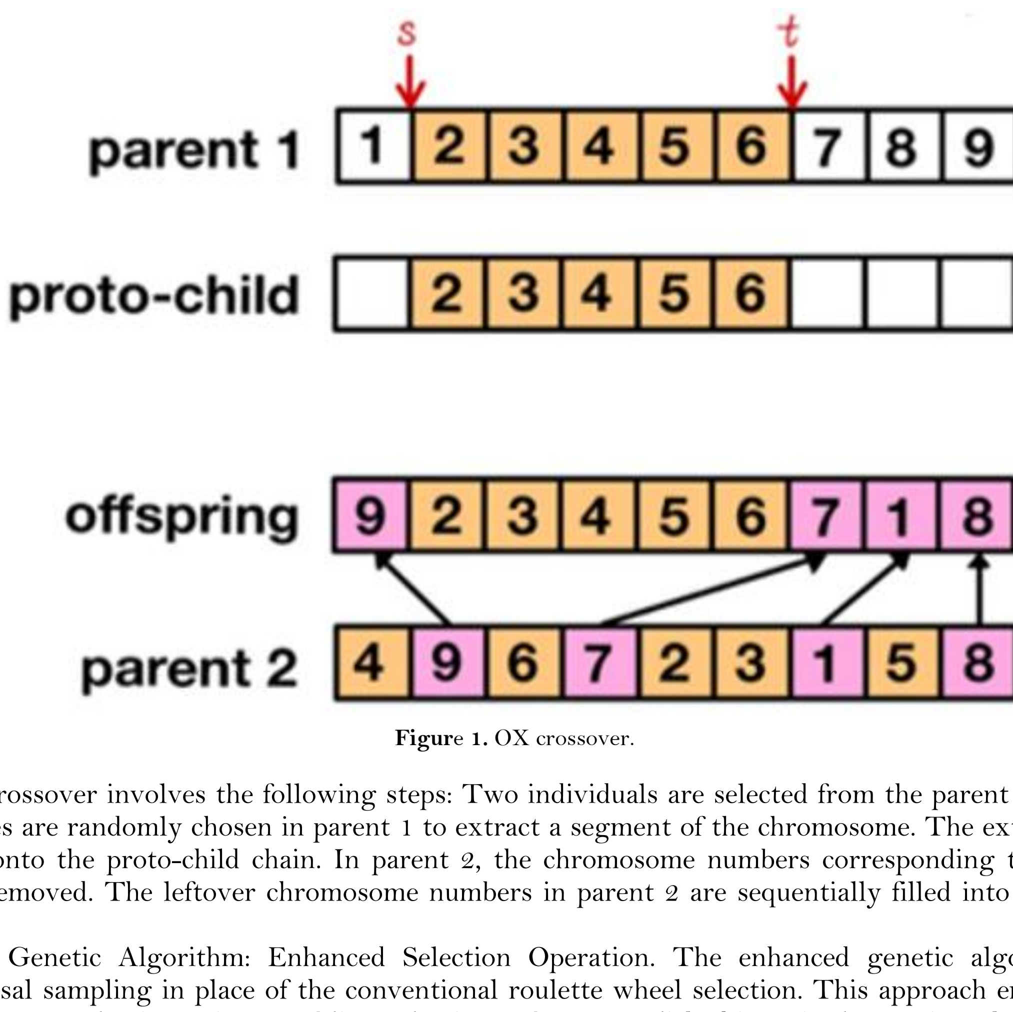

Figure 1. OX crossover.

The OX crossover involves the following steps: Two individuals are selected from the parent population, and two gene nodes are randomly chosen in parent 1 to extract a segment of the chromosome. The extracted segment is duplicated onto the proto-child chain. In parent 2, the chromosome numbers corresponding to the extracted segment are removed. The leftover chromosome numbers in parent 2 are sequentially filled into the gaps of the offspring.

Enhanced Genetic Algorithm: Enhanced Selection Operation. The enhanced genetic algorithm employs random traversal sampling in place of the conventional roulette wheel selection. This approach employs multiple equally spaced gene selection points, enabling selection to be accomplished in a single rotation, thereby enhancing efficiency and ensuring fairness in the selection process. Table 2 contrasts the differences between the traditional roulette wheel selection and random traversal sampling.

Table 1. Roulette Wheel vs. Random Traversal Sampling Method.

	Roulette Wheel	Random Traversal Sampling
Selection Times	Multiple Times	Once Time
Number of Selection Nodes	Single Gene Node	Multiple Gene Nodes, with Equal Distance Between Nodes
Selection Fairness	The probability of being selected is approximately equal to the order of fitness, with less randomness	Incorporating the selection of equidistant nodes into the indicator of fitness order introduces more randomness

In the random traversal sampling, individuals are selected via multiple nodes, with equal spacing between these nodes. The formula for equal distance is as depicted below:

$$Dis = F_t/N$$
$$r\epsilon[0,\frac{F_t}{N})$$

In this context, $\boldsymbol{Dis}$ represents the equal distance between nodes, $\boldsymbol{F_t}$ denotes the cumulative fitness of the individual, $\boldsymbol{Num}$ indicates the quantity of individuals to be chosen, $\boldsymbol{r}$ represents the position of the starting point in the node, That is, the starting point is randomly generated within the range$[\boldsymbol{0},\frac{\boldsymbol{F_t}}{\boldsymbol{N}})$. Figure 5 is an illustration of the random traversal sampling:

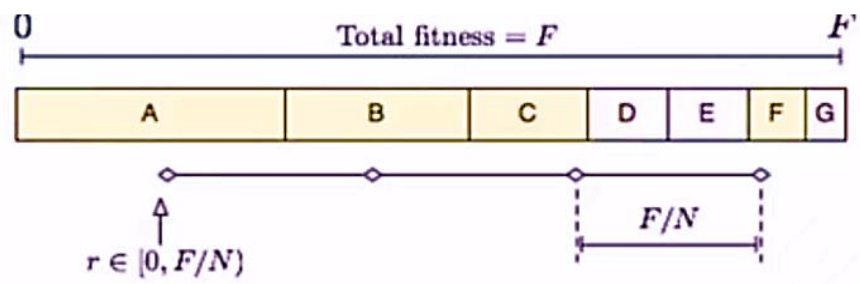

Figure 2. Random Traversal Sampling.

Enhancement in Crossover Operation: To overcome the limitation of the traditional OX crossover, which may not always produce new individuals, the improved approach involves randomly selecting two nodes at identical positions in two parent individuals and extracting the corresponding gene segments.

The extracted gene segments are positioned before and after the original parent individuals, respectively. Duplicate gene segments are eliminated, resulting in the formation of new individuals. This enhancement guarantees the generation of new child individuals even when the gene segments are identical, as illustrated in Figure 6.

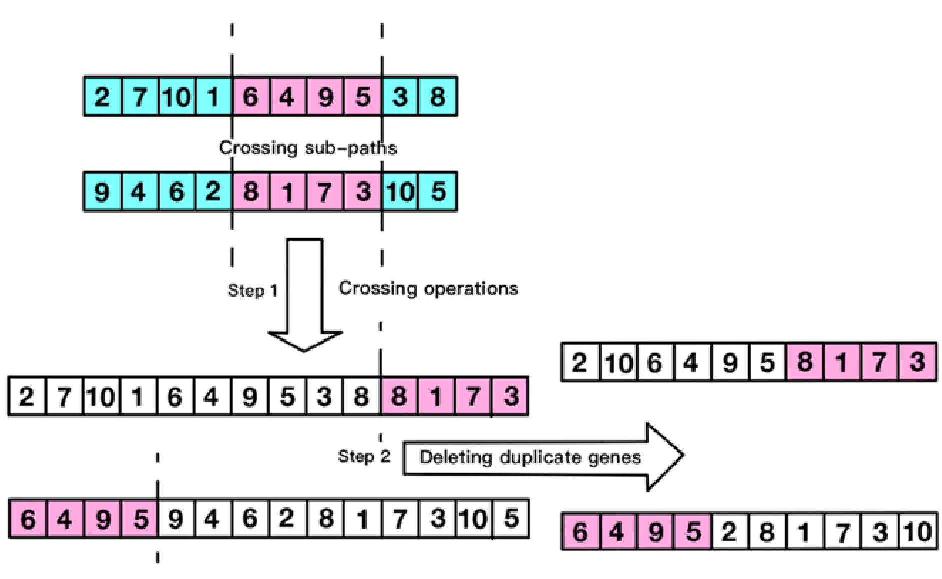

Figure 6. Crossover Process.

2.2.2. Basic Principles of Apriori Algorithm

Apriori Association Analysis is a technique employed to identify correlations between different data sets within extensive datasets. The pertinent indicators and their definitions are presented in Table 3:

Table 3. Related Indicators and Definitions.

Rule	Definition
Support	The frequency of the itemset appearing in transactions: the proportion of total purchases where products X and Y are purchased together
Confidence	Measures the reliability of the association rule: the proportion of purchases where product X is also purchased with product Y
Lift	Assesses the influence of the antecedent X on the occurrence of the consequent Y: Confidence / (Users purchasing Y / Total users)
Transaction	A commercial behavior, such as purchasing a product
Itemset	In the transaction table, the variable values and the specific items contained in the itemset

An association rule is typically structured as:

$$X \rightarrow Y,\quad X \cap Y = \emptyset$$

(1) For the rule X → Y, its rule ($Support$) is defined as:

$$S_{X\rightarrow Y} = \frac{N(X \cap Y)}{N}$$

Here, $N(X \cap Y)$ denotes the total count of transactions where both X and Y are present. $Support$, reflects the commonality of the association rules that are obtained.

(2) For the association rule X → Y, its rule ($Confidence$) is defined as:

$$C_{X\rightarrow Y} \frac{N(X \cap Y)}{N(X)} = \frac{S_{X\rightarrow Y}}{S_X}$$

Confidence is actually the probability of the latter occurring given that the former has occurred. In other words, the $Confidence$ of X → Y= $Support$ of {X, Y}/$Support$ of $\{X\}$。

2.2.3. Genetic Algorithm Combined with Apriori Algorithm

This study employs a hybrid approach of genetic algorithms and the Apriori algorithm for warehouse storage location optimization, following this process:

Genetic Algorithm Solves Optimization Model: 1) Input data, set parameters (e.g., population size, number of iterations).2) Initialize the population, assess individual fitness. 3) Conduct selection, crossover, and mutation operations. 4) Iterate calculations until the termination condition is met, then output the optimal solution.

Apriori Algorithm for Selecting Associated Product Combinations: 1) Import customer order data, conduct data preprocessing. Label data types, filter key values. 2) Utilize the Apriori algorithm for association rule analysis.

Adjust Storage Locations Based on Association Rules, Construct Optimization Model: 1) Utilize the results of the Apriori algorithm to place highly associated products in adjacent storage locations. 2) Construct a storage location optimization model with the goal of maximizing outbound rate and minimizing aisle distance.

3. Current Challenges in YY's Warehouse Management

3.1. YY's Overview

YY's is a chemical enterprise focused on adhesive production, situated in the High-tech Development Zone, boasting a production base of around 12,00 ㎡. The company represents internationally renowned brands and is among the leading domestic enterprises in the field of neoprene adhesives. Embracing the concept of technological innovation, YY's continually refines its product line through industry-academia-research collaboration, catering to industries like automotive, furniture, and decoration, and has developed new water-based adhesives, which have become a new growth area for the company.

3.2. Analysis of YY's Warehouse Operation Status

3.2.1. Overview of YY's Warehouse

YY's warehouse, operational since 2001, spans 4,600 ㎡ and is equipped with comprehensive facilities. The warehouse features a double-zone structure, consisting of north and south zones, and is equipped with 16 rows and 32 columns of shelves. Each column of shelves contains 20 storage compartments, each measuring 2.4m x 1m. The warehouse is equipped with 8 aisles, with entrances and exits situated on the right side of the main aisle, close to the sorting area. Figure 7 presents the warehouse layout.

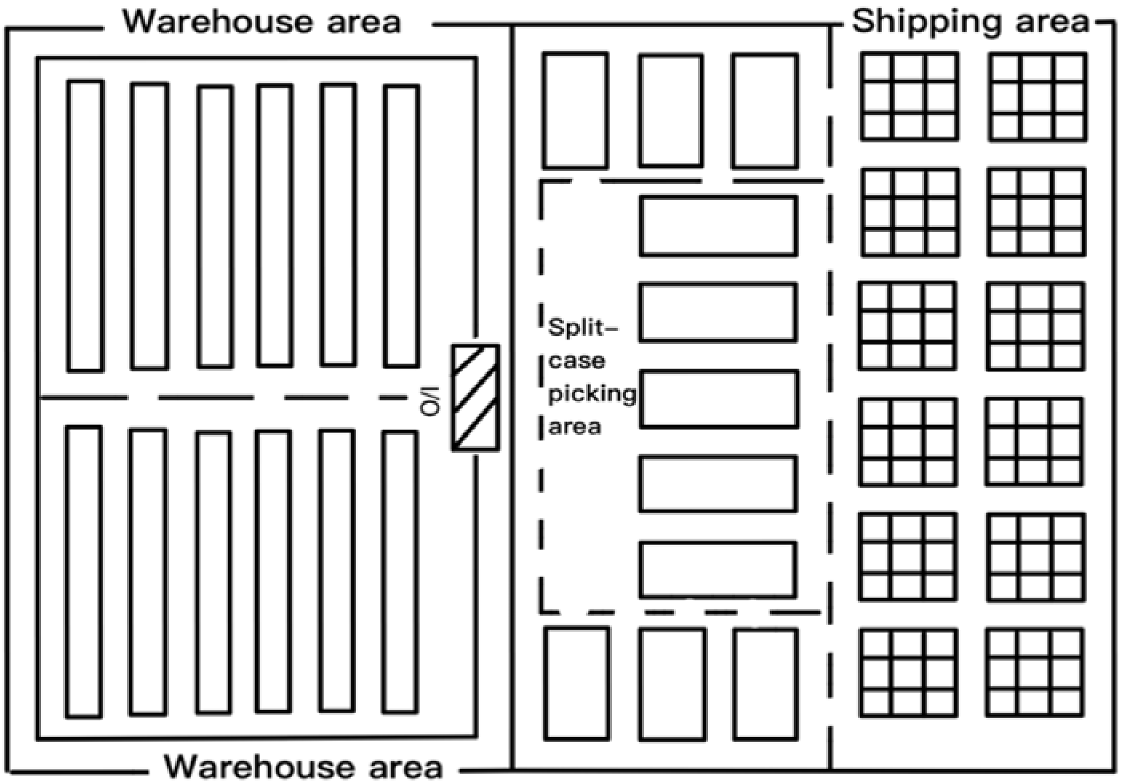

Figure 7. Warehouse Layout Plan.

3.2.2. Analysis of Warehouse Inventory Product Characteristics

YY's manufactures four main series of adhesive products, which include: 1) Porsche Series: including transparent nails, electronic white glue, etc. 2) Industrial Adhesives: such as grafting spray glue, SBS spray glue, etc. 3) Adhesives for decoration and renovation: including Porsche adhesive, Baodeli 208, etc. 4)Water-based adhesives (environmental series): such as Porsche water-based spray glue, etc.

The product features encompass a wide variety of types and substantial quantities of goods for storage and retrieval. The four major categories are further divided into over 60 subcategories, with some products classified under multiple categories. The detailed product classification is presented in Table 4.

Table 4. Partial Product Subcategory.

Product Category	Product Name
Porsche Series Products	Edge Sealing Glue Electronic White Glue Nail-Free Glue
Industrial Adhesives	PP/PE Glue Spray Glue Series Yellow Glue Series
Decorative and Renovation Specific Adhesives	Baodeli 208 Porsche Adhesive Gaoerte
Water-based Adhesives	Porsche 550 PVC Carpet Glue Porsche 800 Anti-Static Glue Porsche Water-based Spray Glue

High Volume of Product Inbound and Outbound: YY's finished product warehouse handled an average monthly inbound volume of 80,000 units and an outbound volume of 25,000 units in December 2022, with a daily outbound weight of 9 tons and a monthly outbound weight of 270,000 tons. The data indicates that the company has a significant number of outbound shipments and the goods are heavy, but the turnover rate of the goods is relatively low.

3.2.3. Analysis of the Current Status of YY's Warehouse Management

Storage Location Strategy: YY's employs a random storage location system, where warehouse personnel place goods based on their entry and exit sequence, and the storage locations for the same type of goods are not fixed. The details of the storage location arrangement are depicted in Figure 8.

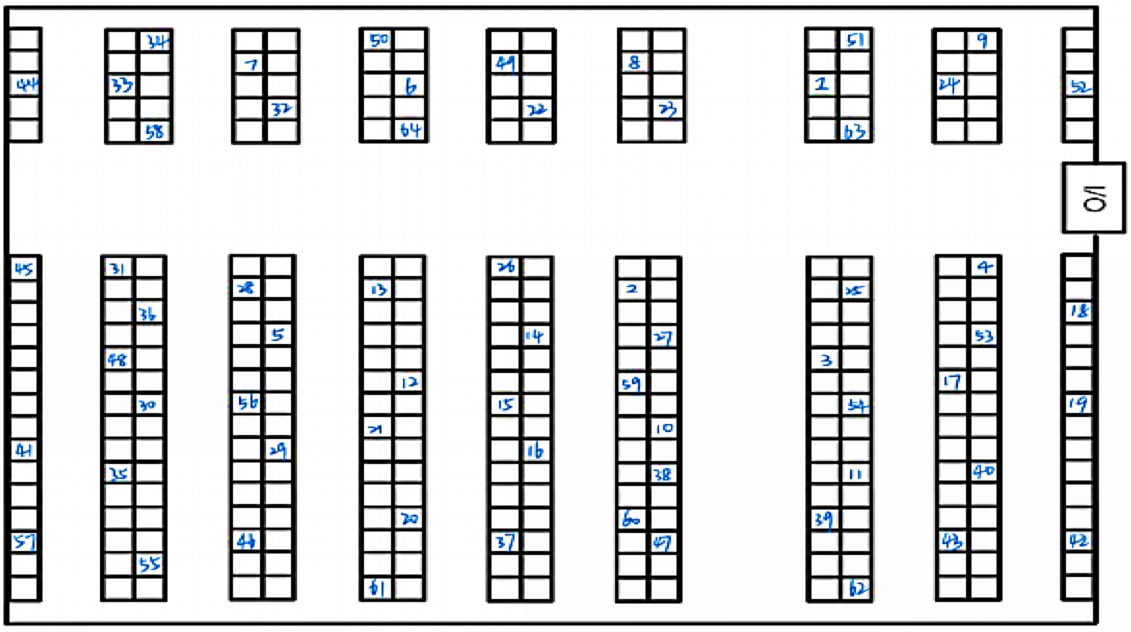

Figure 8. Storage Location Map of Goods.

Picking Method: The company uses a manual picking method, where employees pick goods from the shelves according to the orders and then perform centralized sorting.

Picking Path: In YY's double-zone warehouse, the main aisle is 6 meters wide, and the aisles are 4 meters wide. The picking path combines cross-type and return-type paths, and during peak hours, the picking behavior is relatively disorganized.

3.3. Problems in the Management of YY's Finished Product Warehouse

Improper Storage Location Management: The disorganized stacking of goods makes it difficult to locate them; the lack of skills among warehouse personnel leads to longer picking paths due to experiential picking, which reduces efficiency; unclear management systems lack standardized operations.

3.3.1. Low Picking Efficiency

Picking Efficiency (E) is determined by the quantity of goods picked and the time taken to pick them. The specific measurement standard is the ratio of the number of goods picked (N) to the time taken (T). The longer the time taken to pick the goods, the lower the efficiency. By analyzing the process of picking operations, a formula for calculating the time consumed can be derived:

$$T_t = \frac{L_w}{S} + T_a \times N + T_w$$

Where T_t denotes the total time spent on picking, L_w denotes the path length, Sdenotes the walking speed, T_a denotes the average time spent on picking a single item, N denotes the number of items picked, T_w denotes the time window caused by external constraints. The above formula indicates that the picking efficiency of YY is affected by several factors:

Inappropriate Storage Strategy Selection: The random storage strategy employed by YY is not conducive to outbound inventory checks. Goods with high turnover may be stored in locations far from the In/Out gates, leading to the same type of goods not being stored in the same area. Therefore, the random storage method can lead to an increase in the average time spent on picking a single item（T_a）, When there is a large volume of goods in and out of storage, the lack of equipment can cause sequential waiting at each stage, increasing the time cost（T_w）.

Inappropriate Picking Method Selection: The manual picking method employed by YY's warehouse pickers, when completing goods order picking, can lead to unnecessary repeated picking paths（L_w）due to the diverse quantity of goods, resulting in low picking efficiency.

Random Picking Path: YY's warehouse employs a picking path method that integrates both cross-type and return-type paths. In situations where order demands are large and diverse, the random combination of picking paths and non-standardized operations by pickers can lead to relatively unnecessary increases in the picking path（L_w）, resulting in reduced picking efficiency.

4. Construction and Solution of YY's Storage Location Optimization Model

This study aims to optimize storage locations in two stages: initially, conduct goods association analysis based on order data to guide storage location allocation; subsequently, optimize the allocated storage locations through modeling.

4.1 Goods Association Application

4.1.1. Goods Association Analysis

This study aims to uncover customer purchasing behavior and identify combinations of goods purchased simultaneously. Using the Apriori algorithm in SPSS Modeler to analyze customer order data, Table 5 presents some customer order records within a week.

Table 5. Customer Weekly Order Data.

Product Customer	28	11	32	4	5	18	27	48	9	57	44	12	63	14
A	4	1	1	2	1	1	3	3	1	1	1	0	0	0
B	3	0	0	2	0	0	0	1	1	2	0	1	1	1
C	0	0	0	2	0	0	0	0	1	0	0	0	0	0
D	6	0	2	5	1	0	4	4	0	2	2	1	1	3
E	2	0	1	0	1	0	1	0	2	4	2	4	2	0
F	1	0	0	1	0	0	3	0	3	0	2	1	0	0
G	2	0	1	4	0	3	5	1	2	2	1	1	0	0
H	2	0	0	1	0	0	0	0	1	2	0	2	2	0
I	3	0	0	0	2	0	0	0	0	1	0	0	0	0
J	1	0	0	1	0	1	2	1	1	5	1	1	1	2
K	1	1	1	1	6	0	5	2	2	2	0	0	3	0
L	0	1	0	3	2	0	0	1	3	1	1	2	3	0
M	0	0	0	0	0	0	0	0	0	2	4	2	2	0
N	0	0	0	0	0	0	4	3	2	0	1	0	0	0
O	3	0	0	3	0	0	0	1	0	1	1	1	1	0
P	3	1	1	5	0	0	0	2	2	1	1	0	0	1
Q	1	0	0	3	0	1	0	0	0	2	0	0	0	0
R	5	1	1	3	0	0	3	2	2	0	0	2	1	2
S	0	0	0	2	0	0	8	1	2	3	0	0	1	0
T	0	0	0	5	0	0	1	0	3	0	0	0	0	0

The Apriori association rule model actually uses data information from 113 customers and 64 types of ordered products. However, Table 5 only presents partial information on the order quantities of 20 customers and 14 product categories. Based on customer order data, the Apriori model is used to solve and analyze the association rules of outbound product categories. In this study, the relevant rules are set as shown in Table 6:

Table 6. Association Rule Parameter Setting.

Rule	Interval
Support	0.7,1
Confidence	0.9,1

4.1.2. Analysis of Association Degree Results

Due to space constraints, a selection of association rules is presented in Table 7.

Table 7. Association Rule.

Rule(Support, Confidence)		
1→12 (71.43%,97.56%)	1→14 , 7 (71.43%,96.23%)	16→13 , 1 , 7 (75%,90.48%)
15→14 , 1 (71.43%,90.3%)	16→14 , 1 , 7(71.43%,90%)	16→15 , 1 , 7 (75%,90.88%)
16→12 , 1 (71.43%,91.2%)	1→15 , 7 (75%,93.67%)	1→7 (92.86%,92.78%)
7→14 (71.43%,92.6%)	7→16 , 1 (85.71%,90.23%)	15→14 (71.43%,90%)
16→1 (92.86%,92.31%)	1→16 , 7 (85.71%,91.74%)	16→14 (71.43%,90.47%)
7→15 (75%,90.44%)	16→13 , 7 (75%,90.48%)	1→14 (71.43%,94.71%)
1→16 (85.71%,90.12%)	7→13 (78.57%,95.45%)	16→12, 7 (71.43%,90.69%)
16→7 (92.86%,92.31%)	1→15 (75%,96.23%)	7→12 (71.43%,90.74%)
7→1 (92.86%,90.85%)	7→16 (85.71%,91.44%)	15→14 , 7 (71.43%,90%)
16→12 (71.43%,90%)	16→1 , 7 (92.86%,92.31%)	7→13 , 1 (75%,90.47%)
16→14 , 1 (71.43%,90%)	7→12 , 1 (71.43%,90.64%)	16→14, 7 (71.43%,90.96%)
1→13 , 7 (75%,91.42%)	16→13 , 1 (75%,90.48%)	16→12 , 1 , 7 (71.43%,90%)
16→15 (75%,90.48%)	1→13 (78.57%,95.45%)	15→14 , 1 , 7 (71.43%,90%)
1→12 , 7 (71.43%,92.61%)	16→15 , 1 (75%,90.48%)	7→15 , 1 (75%,91.47%)
7→14 , 1 (71.43%,90.49%)	16→15 , 7 (75%,90.48%)	16→13 , 1 , 7 (75%,90.48%)

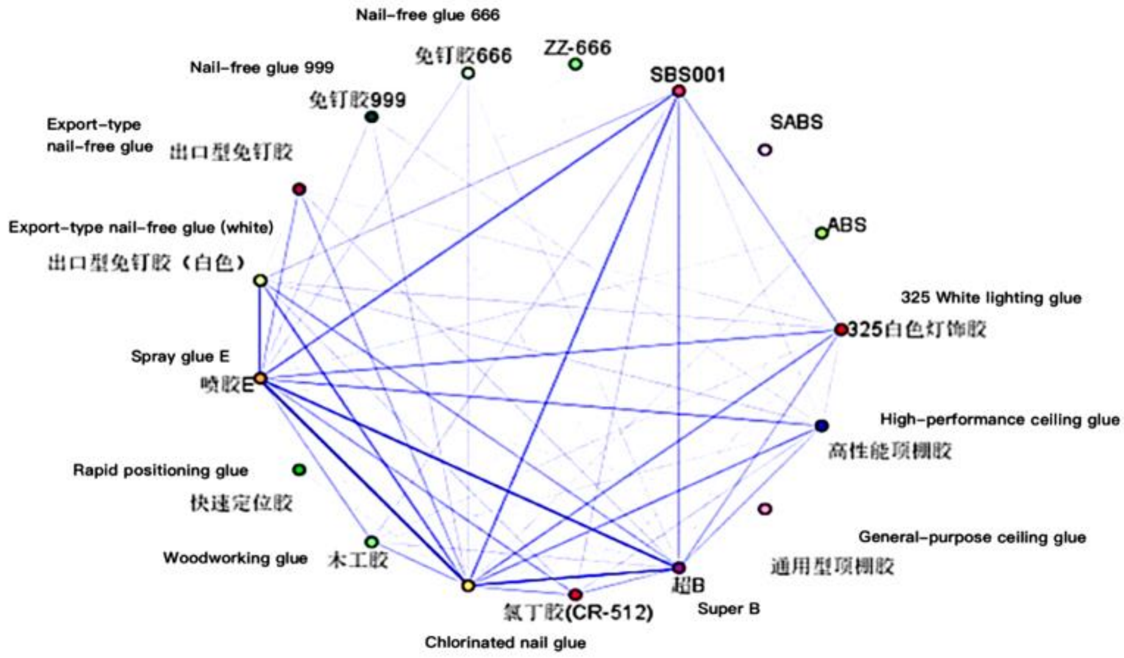

Figure 9. Association Network Diagram.

Based on the above table, the derived goods association rules are as follows: when purchasing goods 1, goods 12 will also be purchased; when customers purchase goods 15, they will also purchase goods 14 and 1; and so on for the rest. The network diagram illustrating the specific association rules is presented in Figure 9:

Based on the above association analysis, the following suggestions can be made: sort and combine the items based on the level of association, and adjust the original storage locations to place items with high association in adjacent areas, so that high-association items can be picked together, thereby improving picking efficiency. The storage locations optimized based on the association rules are as depicted below:

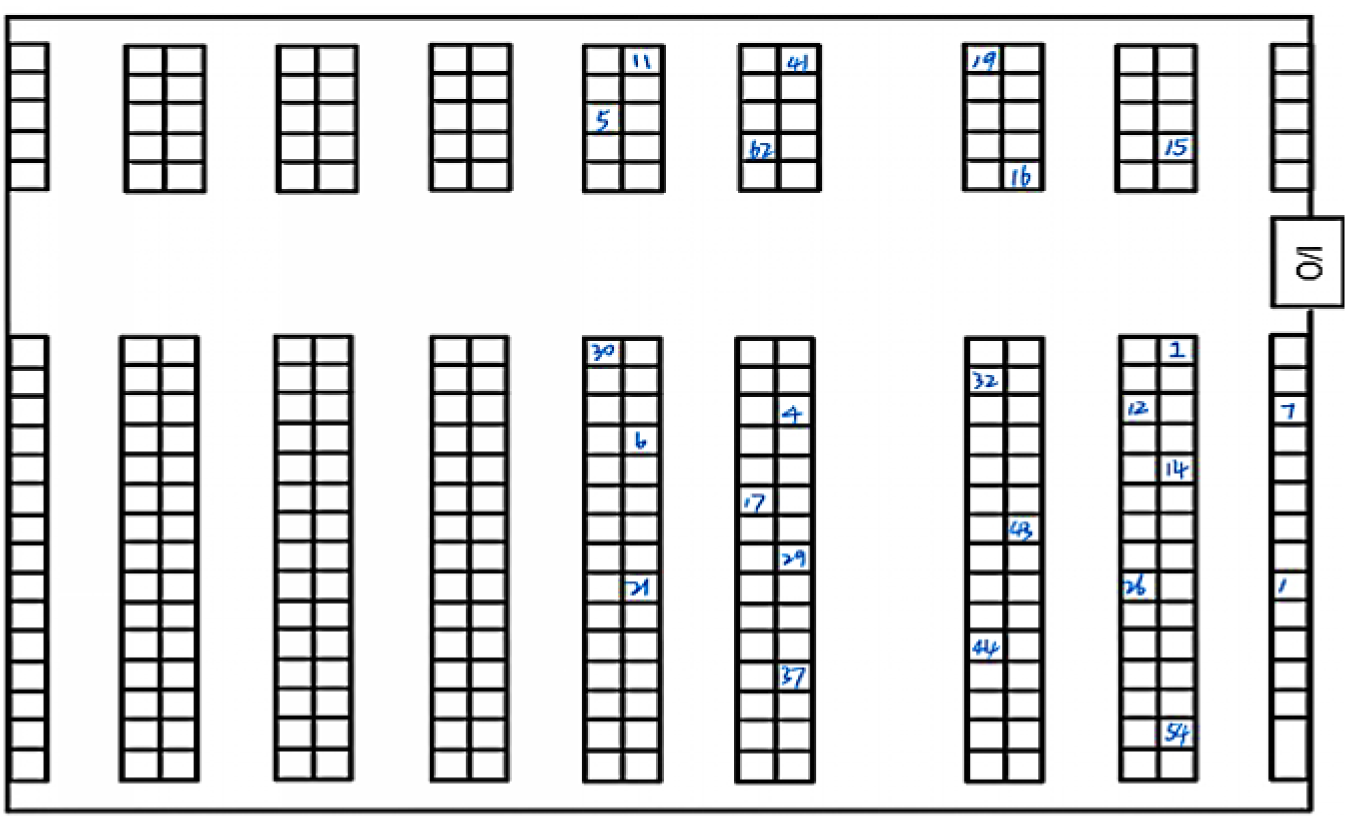

Figure 10. Partial Goods Storage Location Optimization Diagram.

4.2. Constructing the Storage Location Optimization Model

4.2.1. Problem Description

In a warehouse with 64 types of goods, 32 shelves, and 8 aisles, it is necessary to optimize storage location allocation based on the average outbound rate of goods and the distance from the aisles to the entrance/exit to minimize the picking distance.

4.2.2. Conditions for Applying Genetic Algorithm

The frequent itemsets identified by the Apriori algorithm serve as the genes for the genetic algorithm, providing key information for establishing the initial population and genetic operations to achieve optimization objectives.

The Apriori algorithm reduces non-frequent itemsets through pruning, enhancing the search efficiency of the genetic algorithm, which aids in rapidly identifying the optimal solution.

Therefore, the data processed by Apriori is suitable for the genetic algorithm, with the expectation of achieving good optimization results.

4.2.3. Construction and Solution of the Mathematical Model

Model Assumptions: Based on the goods association analysis in 4.1, goods are combined, and on this basis, the objective function is established with the outbound rate and aisle distance as the criteria. Adjusting Goods Storage Locations: The higher the frequency of goods being taken out, the closer the adjusted storage location is to the warehouse entrance and exit. Based on the layout of YY's warehouse, the following model assumptions are made:

(1) Each order is picked by a single picker, and the number of vehicles and weight are known；

(2) The same SKU is stored in only one storage location, with the same quantity stored, and the weight is known；

Symbols and Variables Description: To establish a mathematical model for warehouse storage location allocation, the following variables are defined:

1）Index

n：The product category number, n=1, …, N；

t：The aisle number, t=1, …, T；

2）Symbol

N：The total number of product categories;

R：The outbound rate of goods, R_n: The outbound rate of the n^{th} category of goods;

d_{t0}：The distance from the tth aisle to the warehouse In/Out gate;

$Sign_{n(t0)}$：The association degree value between product n and aisle t, with a value range of 0-1.

Model Construction: Based on theoretical assumptions and storage location optimization objectives, a model is established to determine the optimal allocation of goods that allows pickers to achieve the shortest distance:

$$minF = \sum_{n=1}^{N}\sum_{t=1}^{T} R_n\, d_{t0} Sign_{n(t0)} \quad (1)$$

$$s.t: Sign_{n(t0)} = \begin{cases} 0, \text{The } nth \text{ type of goods is not allocated to aisle } t\text{；} \\ 1, \text{The } nth \text{ type of goods is allocated to aisle } t. \end{cases} \quad 2)$$

$$\sum_{n=1}^{N} Sign_{n(t0)} \geq 1, t = 1,2,3 \ldots, T \quad (3)$$

$$\sum_{t=1}^{T} Sign_{n(t0)} \geq 1, n = 1,2,3 \ldots, N \quad (4)$$

Equation（1）is the model's objective function, which represents the shortest distance for all combinations of goods to the In/Out area; Equation（2）is the decision variable in the model, indicating whether the n^{th} type of goods has been allocated in aisle t; Equation (3) indicates that a single aisle can store one or multiple categories of goods; Equation (4) indicates that the same type of goods must be stored in the same aisle.

Solving the Storage Location Optimization Model Using the Enhanced Genetic Algorithm:

1）Algorithm Design: Based on the objective model listed above, and considering the overall layout and goods situation of YY's warehouse, the software is used to optimize and solve the problem. Some parameters in the algorithm are shown in Table 8.

Table 8. Algorithm Parameter.

Parameter	Definition	Value
NIND	Population Size	100
MAXGEN	Maximum Iteration Number	200
P_c	Crossover Probability	0.9
P_m	Mutation Probability	0.05
GGAP	Selection Probability (Generation Gap)	0.9
d_{t1}	The distance from aisle 1 to the In/Out gate	2
d_{t2}	The distance from aisle 2 to the In/Out gate	8
d_{t3}	The distance from aisle 3 to the In/Out gate	14.8
d_{t4}	The distance from aisle 4 to the In/Out gate	21.6
d_{t5}	The distance from aisle 5 to the In/Out gate	27.6
d_{t6}	The distance from aisle 6 to the In/Out gate	33.6
d_{t7}	The distance from aisle 7 to the In/Out gate	39.6
d_{t8}	The distance from aisle 8 to the In/Out gate	45.6

2) Optimization Effect Analysis: Based on the parameter settings mentioned above, input the specific information data of warehouse goods, and the output results are shown in Table 9. Due to space constraints, only a portion of the data is displayed. This table represents the storage location allocation derived from the optimization mathematical model.

Table 9. Output Results.

Variable	Value	Reduced Cost
C(1, 8)	1.000000	5.016000
C(2, 6)	1.000000	5.376000
C(3, 7)	1.000000	4.752000
C(4, 4)	1.000000	6.480000
C(5, 7)	1.000000	4.752000
C(6, 6)	1.000000	6.384000
C(7, 1)	1.000000	1.100000
C(8, 6)	1.000000	5.040000
C(9, 6)	1.000000	4.704000
C(10, 5)	1.000000	6.348000
C(11, 5)	1.000000	5.796000
C(12, 7)	1.000000	5.148000
C(13, 1)	1.000000	1.220000
C(14, 6)	1.000000	5.712000
C(15, 2)	1.000000	2.960000
C(16, 2)	1.000000	3.440000
C(17, 1)	1.000000	1.060000
C(18, 2)	1.000000	3.280000

The figure indicates that goods 1 should be placed in aisle 8, goods 2 in aisle 6, goods 3 in aisle 7, and so on, with only a portion of the data displayed due to space limitations.

To demonstrate the effectiveness of the improved genetic algorithm in solving the storage location optimization problem, a specific dataset is formed by randomly selecting customer orders, and the path distances before and after storage location optimization are compared. The random customer orders are shown in Table 10, and the specific comparison results of the picking paths are shown in Table 11:

Table 10. Random Order Partial Data.

Product Category	Original Aisle Number	Current Aisle Number
1	3	8
3	3	7
4	1	4
7	7	1
8	4	6
11	2	5
14	4	6
17	2	1
18	1	2

Table 11. Algorithm Effect Comparison Diagram.

Order	S-shaped Path (m)	Optimized Path (m)	Difference value(m)	Path Distance Savings %
1	603.2	478.2	125.2	20.7%
15	637.8	518.6	119.2	18.7%
26	644	496.4	147.6	22.9%

In summary, the optimized storage location allocation is shown in Figure 11:

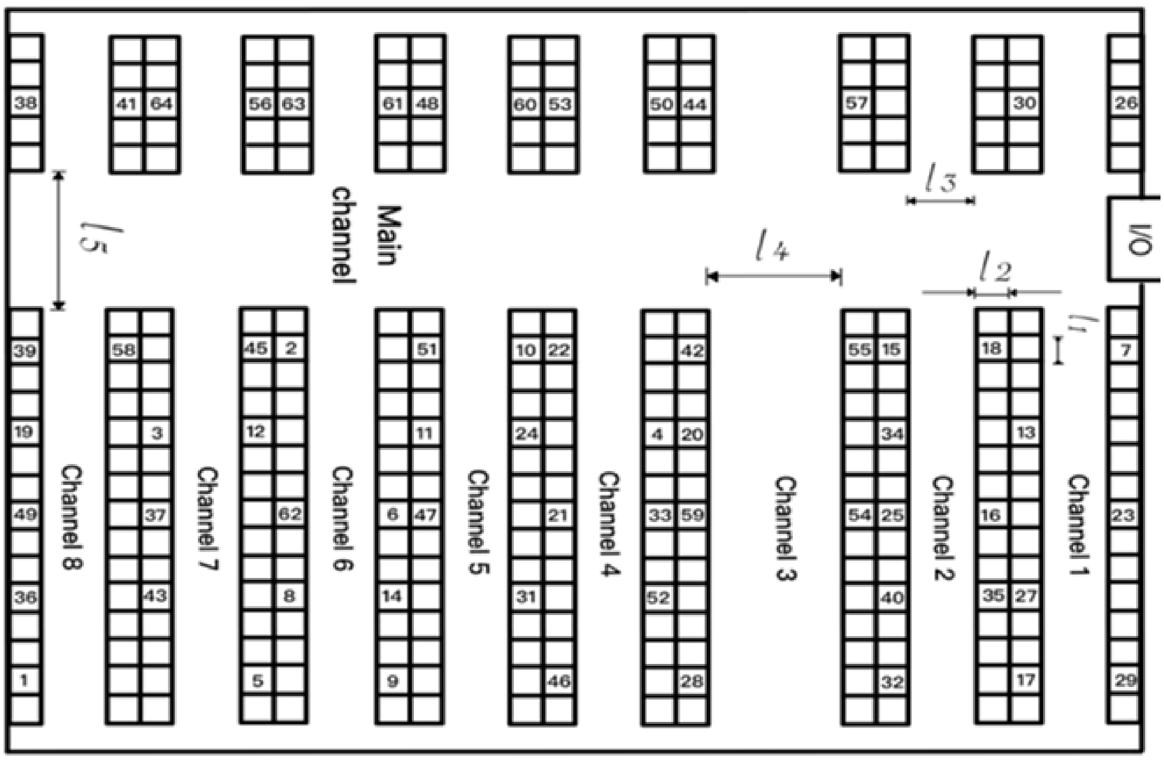

Figure 11. Storage Location Optimization Allocation.

5. Construction and Solution of the Picking Path Optimization Model

Building on the storage location optimization, this study further refines the picking strategy and sequence for YY's warehouse to minimize the picking path.

5.1. Path Calculation

During the picking process, the quantity of goods and storage location information need to be collected. After entering the system, computer-aided management of picking operations is implemented. Pickers proceed from the In/Out gate to the storage location according to the list until the vehicle is fully loaded or the order is completed. The following briefly describes the shortest path calculation method, considering the characteristics of YY's warehouse.

5.1.1. Symbols and Variables Description

Considering the zone-type characteristics of YY's warehouse, achieving the shortest path requires classifying and discussing the situation. The warehouse is divided into two zones, upper (north) and lower (south), with a total of 16 rows of shelves from left to right, numbered 1-16. Each column in the two zones has 20 storage locations from bottom to top, numbered 1-15, 16-20. The specific layout is shown in Figure 12, and the specific symbols and variables are described as follows:

(1) a_i : The upper (north) and lower (south) 2 zones of the warehouse,

$$a_i = \begin{cases} 1, north \\ 0, south \end{cases};$$

(2) $i\,, j$: Storage location. $i\,, j = 1, ,2,3, \dots, Z$;

(3) X : Goods. A good in a specific aisle is represented as X_t, with the storage location being X_i and X_j;

(4) Any storage location in the warehouse to be picked is represented as $P_i(T_i\,, a_i, c_i)\,, i = 1,2,3, \dots, Z$; Where T_i represents the aisle number, $T_i \epsilon \{1,2,3 \dots, a\}$; c_i represents the storage compartment number, $c_i \epsilon \{1,2,3 \dots, m\}$, The maximum storage compartment number is m, $1 \rightarrow m \times \frac{15}{20}$ represents the southern half of the warehouse, $m \times \frac{15}{20} + 1 \rightarrow m$ represents the northern half of the warehouse;

(5) Z: The total number of storage compartments in the warehouse, in this paper Z=320;

(6) l_1 is the length of the storage compartment, l_2 is the length of the storage compartment, l_3 is the width of the aisle, l_4 is the width of the middle passage, l_5 is the width of the main passage. In this paper, l_1=2.4m, l_2=1m , l_3=4m, l_4=5.6m, l_5=6m ;

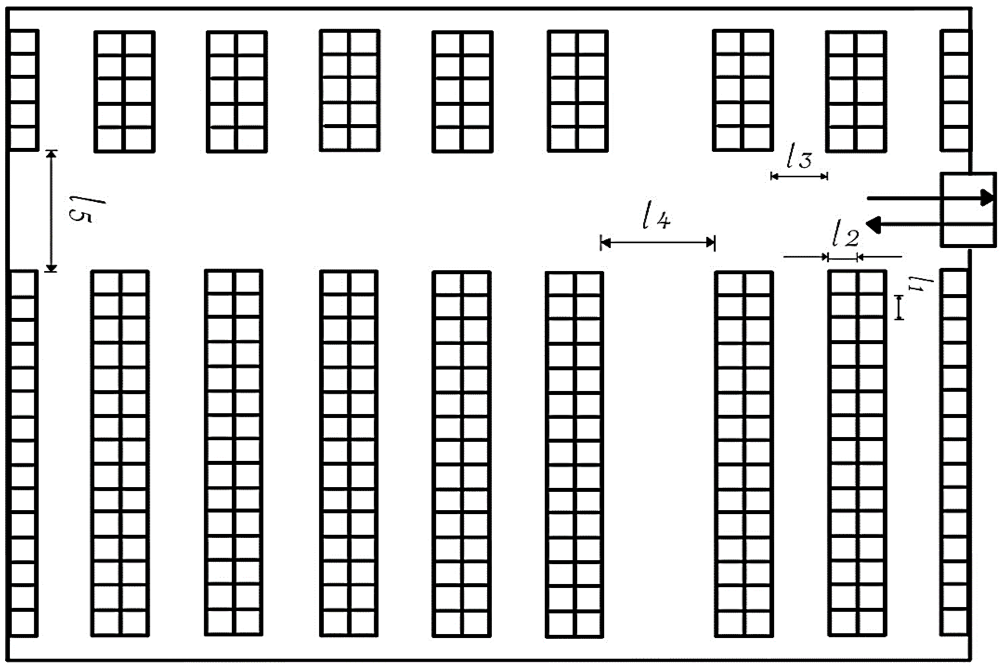

Figure 12. Warehouse Layout Diagram.

5.1.2. Analysis of Picking Path Scenarios

For the picking of goods in the warehouse, the scenarios can be roughly categorized into the following types:

(1) When goods A and B are distributed in the same aisle, there are two situations: the first is that the goods are in the same area (either both in the upper zone or both in the lower zone), $a_A, a_B = 1\ or\ a_A, a_B = 0$; The second is that the goods are distributed in different areas, $a_A = 1, a_B = 0\ or\ a_A = 0, a_B = 1$.

(2) When two goods to be picked are in the same area but different aisles, there are three major situations: the first is when the goods are in the same area, $a_A = a_B = 0$; The second is when the goods are in the same area, $a_A = a_B = 1$; The third is when two goods to be picked are in different areas, $a_A \neq a_B$。

(3) Additionally, when goods A,B are in the same area, there are two walking paths, as shown in the specific process diagram in Figure13. In the path calculation, these two walking paths each have a 50% probability, as reflected in the specific case analysis in 5.1.3.

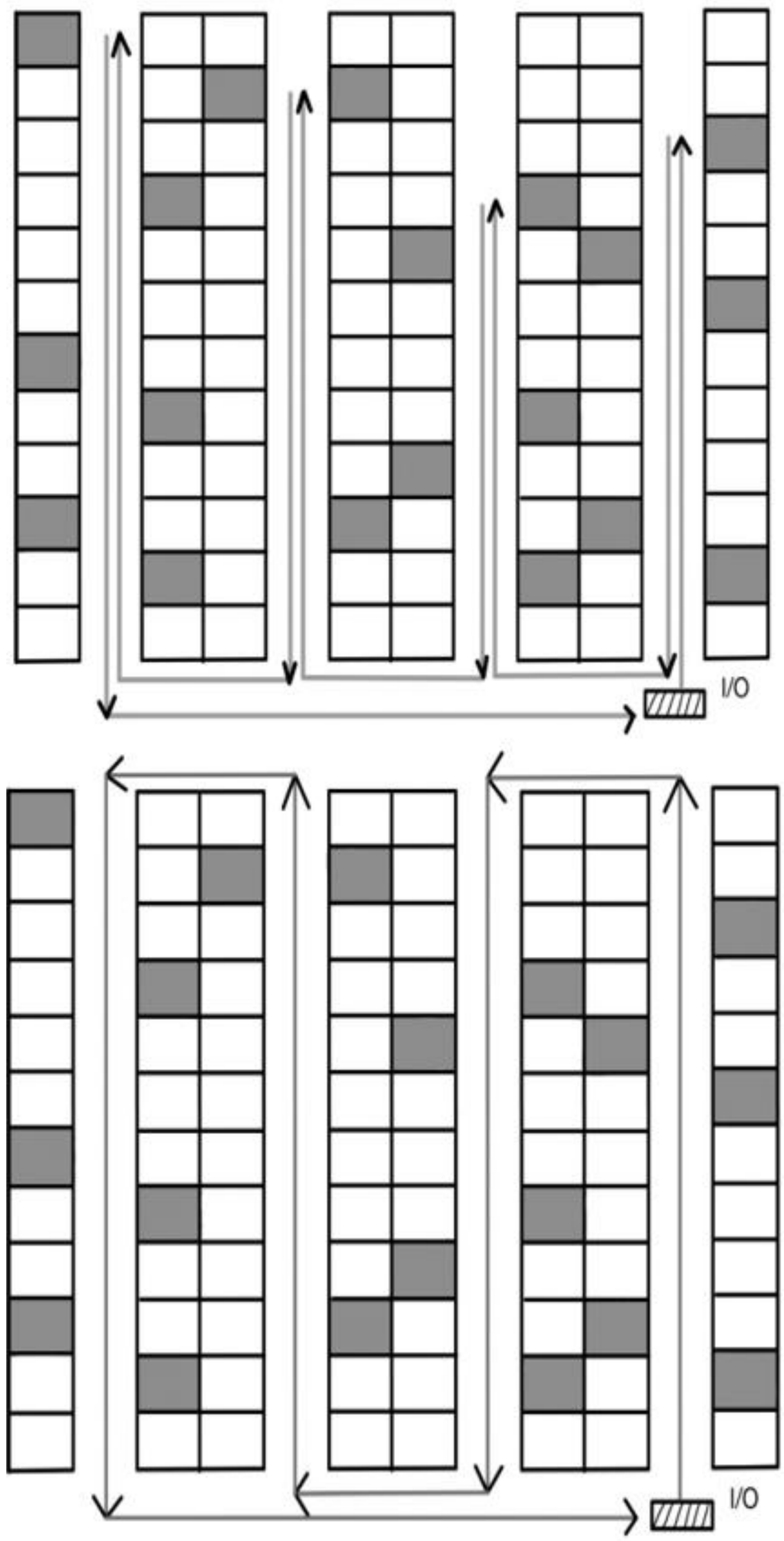

Figure 13. Walking Path Schematic Diagram.

5.1.3. Specific Case Analysis

(1) When any two goods X_i and X_j in the picking area are distributed in the same aisle, $X_{Ti} = X_{Tj}$ $(i \neq j)$, there are several situations:

1). When the goods are in the same area $(a_i = a_j)$, $1 \leq c_i, c_j \leq 15m/20$ or $15m/20 + 1 \leq c_i, c_j \leq m$,

d_{ij}=$|c_i - c_j| \times l_1$

2). When the goods are in different areas $(a_i \neq a_j)$,

$1 \leq c_i \leq 15m/20, 15m/20 + 1 \leq c_j \leq m \quad or \quad 15m/20 + 1 \leq c_i \leq m, 1 \leq c_j \leq 15m/20$

d_{ij}=$|c_i - c_j| \times l_1 + l_5$

(2) When two goods to be picked are in the same area but different aisles, $X_{Ti} \neq X_{Tj}$, there are several situations:

1).When the goods are in the same area, $a_i = a_j = 0$, the distance between goods in the southern area is:

①$1 \leq c_i \leq 15m/40$ and $1 \leq c_j \leq 15m/40$

$$d_{ij} = \begin{cases} (c_i + c_j) \times l_1 + |T_i - T_j| \times (l_3 + 2l_2), & X_i, X_j \text{ doesn't pass through aisle 3 or } X_i \text{is in aisle 3} \\ (c_i + c_j) \times l_1 + |T_i - T_j| \times 2l_2 + (|T_i - T_j| - 1) \times l_3 + l_4, & X_i, X_j \text{ pass through aisle 3 or } X_j \text{is in aisle 3} \end{cases}$$

② $15m/40+1 \le c_i \le m$ and $15m/40+1 \le c_j \le m$ (50%)

$$d_{ij}=\begin{cases}[(10-c_i)+(10-c_j)]\times l_1+|T_i-T_j|\times(l_3+2l_2), & X_i,X_j \text{ doesn't pass through aisle 3 or } X_i \text{ is in aisle 3}\\ [(10-c_i)+(10-c_j)]\times l_1+|T_i-T_j|\times 2l_2+(|T_i-T_j|-1)\times l_3+l_4, & X_i,X_j \text{ pass through aisle 3 or } X_j \text{ is in aisle 3}\end{cases}$$

③ $1 \le c_i \le 15m/40,\ 15m/40+1 \le c_j \le 15m/20$ or $1 \le c_j \le 15m/40,\ 15m/40+1 \le c_i \le 15m/20$

$$d_{ij}=\begin{cases}[min(c_i+c_j),(20-c_i-c_j)]\times l_1+|T_i-T_j|\times(d_3+2d_2), & X_i,X_j \text{ doesn't pass through aisle 3 or } X_i \text{ is in aisle 3}\\ [min(c_i+c_j),(20-c_i-c_j)]\times l_1+|T_i-T_j|\times 2l_2+(|T_i-T_j|-1)\times l_3+l_4, & X_i,X_j \text{ pass through aisle 3or } X_i \text{ is in aisle3}\end{cases}$$

2).When the goods are in the same area, $a_i=a_j=1$, the distance between goods in the northern area is:

① $15m/40+1 \le c_i \le 35m/40$ and $35m/40+1 \le c_j \le 35m/40$:

$$d_{ij}=\begin{cases}[(c_i-10)+(c_j-10)]\times l_1+|T_i-T_j|\times(l_3+2l_2), & X_i,X_j \text{ doesn't pass through aisle 3 or } X_i \text{ is in aisle 3}\\ [(c_i-10)+(c_j-10)]\times l_1+|T_i-T_j|\times 2l_2+(|T_i-T_j|-1)\times l_3+l_4, & X_i,X_j \text{ pass through aisle 3 or } X_j \text{ is in aisle 3}\end{cases}$$

② $\frac{35m}{40}+1 \le c_i \le m$ and $35m/40+1 \le c_j \le m$:

$$d_{ij}=\begin{cases}[(20-c_i)+(20-c_j)]\times l_1+|T_i-T_j|\times(l_3+2l_2), & X_i,X_j \text{ doesn't pass through aisle 3 or } X_i \text{ is in aisle 3}\\ [(20-c_i)+(20-c_j)]\times l_1+|T_i-T_j|\times 2l_2+(|T_i-T_j|-1)\times l_3+l_4,, & X_i,X_j \text{ pass through aisle3 or } X_j \text{ is in aisle 3}\end{cases}$$

③ $15m/20+1 \le c_i \le 35m/40, 35m/40+1 \le c_j \le m$ or $35m/40+1 \le c_i \le m, 15m/20+1 \le c_j \le 35m/40$:

$$d_{ij}=\begin{cases}[min(c_i+c_j-20),(40-c_i-c_j)]\times l_1+|T_i-T_j|\times(l_3+2l_2), & X_i,X_j \text{ doesn't pass through aisle 3 or } X_i \text{ is in aisle 3}\\ [min(c_i+c_j-20),(40-c_i-c_j)]\times l_1+|T_i-T_j|\times 2l_2+(|T_i-T_j|-1)\times l_3+l_4, & X_i,X_j \text{ through aisle 3 or } X_j \text{ is in aisle 3}\end{cases}$$

(3) When two goods to be picked are in different areas, $a_i \ne a_j$, the distance between goods across the half areas is:

$$d_{ij}=\begin{cases}|c_i+c_j|\times l_1+|T_i-T_j|\times(l_3+2l_2)+l_5, & X_i,X_j \text{ doesn't pass through aisle 3 or } X_i \text{ is in aisle 3}\\ |c_i+c_j|\times l_1+|T_i-T_j|\times 2l_2+(|T_i-T_j|-1)\times l_3+l_4+l_5, & X_i,X_j \text{ is distributed in aisles } 1-8\end{cases}$$

(4) The distance from a storage location in the warehouse to the In/Out gate:

1). $1 \le c_i \le 15m/20$:

$$d_{ij}=\begin{cases}\left(\frac{10m}{20}-c_i\right)\times l_1+\frac{l_5}{2}+(T_i-1)\times(2l_2+l_3)+l_2, & X_i \text{ is located in aisles 1 to 3;}\\ \left(\frac{10m}{20}-c_i\right)\times l_1+\frac{l_5}{2}+(T_i-2)\times l_3+(T_i-1)\times 2l_2+l_2+l_4, & X_i \text{ is located in aisles 3 to 8;}\end{cases}$$

2). $15m/20+1 \le c_i \le m$:

$$d_{ij}=\begin{cases}\left(c_i-\frac{10m}{20}\right)\times l_1+\frac{l_5}{2}+(T_i-1)\times(2l_2+l_3)+l_2, & X_i \text{ is located in aisles 1 to 3;}\\ \left(c_i-\frac{10m}{20}\right)\times l_1+\frac{l_5}{2}+(T_i-2)\times l_3+(T_i-1)\times 2l_2+l_2+l_4, & X_i \text{ is located in aisles 3 to 8;}\end{cases}$$

5.2. Problem Statement and Description

Optimizing picking paths is crucial for improving warehouse efficiency. Currently, most companies rely on the intuition and experience of employees for picking. This section aims to improve the picking efficiency of YY's through scientific planning.

YY's Warehouse Overview: The warehouse is divided into two levels, with 16 rows of shelves on each level, numbered 1-16; each column in the north and south areas has 20 storage locations, numbered 1-20; the aisles are numbered 1-8, close to the In/Out gate. The storage compartments are quadrilaterals with dimensions of 2.4m×1m, with a length ($\boldsymbol{l_1}$) of 2.4m, a width ($\boldsymbol{l_2}$) of 1m, an aisle width ($\boldsymbol{l_3}$) of 4m, a middle passage width ($\boldsymbol{l_4}$) of 5.6m, and a main passage width ($\boldsymbol{l_5}$) of 6m.

The problem addressed in this paper is similar to the Vehicle Routing Problem (VRP), which is to choose the best path from the In/Out gate to minimize the picking distance under given constraints.

5.3. Model Construction

5.3.1. Model Assumptions

(1) The source point (the In/Out gate), and the storage locations of the goods to be picked are known;
(2) The cost of the cart and the number of times the cart is used are not considered;
(3) In the same aisle, it is allowed to pick goods from both sides of the storage locations simultaneously;
(4) The order requires y trips to pick, and all y trips start from the In/Out gate.

5.3.2 Symbols and Variables Description

(1) Q_{yz} : The quantity of goods picked from the zth storage location on the yth trip's sub-circuit;
(2) C_{yz} : The zth storage location on the yth trip's sub-circuit;
(3) C_y : The path corresponding to the yth trip's cart;
(4) l_y : The number of storage locations on the yth sub-circuit;
(5) Q (K) : The total weight of the goods to be picked in the order;
(6) y : The corresponding serial number of the cart; Wi : The max of load capacity of the cart ;
(7) D : The total distance to be traveled;
(8) t0 : In/Out gate ; S : The number of cart trips required;
(9) m : The number of storage locations for the goods in the order;

(10) $d_{y(z-1)z}$: In the y[th] trip's corresponding route, the shortest picking distance between the (z-1)[th] storage location and the z[th] storage location;

(11) $d_{y(l_y)(0)}$: The shortest picking distance between the l_y[th] storage location in the y[th] trip's corresponding route and the warehouse in/Out gate t0.

5.3.3. Model Construction

In multiple trips, each trip forms a separate circuit, and the path planning and scheduling of the cart within each circuit are determined to minimize the total travel distance D of the entire circuit.

$$\min D = \sum_{y=0}^{S}[\sum_{z=1}^{l_y} d_{y(z-1)z} + d_{y(l_y)(0)} \times sign(l_y)] \quad (5\text{-}1)$$

$$s.t. \quad sign(l_y) = \begin{cases} 1, & l_y > 0 \\ 0, & \text{else} \end{cases} \quad (5\text{-}2)$$

$$\sum_{y=1}^{S}\sum_{z=1}^{l_y} Q_{yz} = \mathrm{Q(K)} \quad (5\text{-}3)$$

$$\sum_{z=1}^{l_y} Q_{yz} \leq Wi \quad (5\text{-}4)$$

$$0 \leq y \leq S \quad (5\text{-}5)$$

$$\sum_{y=1}^{S} l_y = m \quad (5\text{-}6)$$

$$C_y = \{C_{yz} | C_{yz} \in \{S_1, S_2, \ldots, S_m, Z = 1,2, \ldots, l_y\} \quad (5\text{-}7)$$

$$C_y \cap C_z = \emptyset, \forall y \neq z \quad (5\text{-}8)$$

In the above model, the objective optimization function is the shortest total walking distance; Table 5-2 indicates whether the yth cart is assigned to the picking task; Table 5-3 indicates that all goods required for the order must be picked; Table 5-4 represents the capacity constraints of the transport tool (handcart), meaning the total quantity of goods picked from each sub-circuit by the handcart must not exceed the maximum load capacity of the handcart; Table 5-5 indicates that the handcart's identification number must be constrained within the required number of trips; Table 5-6 indicates that the sum of storage locations on the y sub-circuit must equal the number of storage locations for the goods in the order; Table 5-7 to Table 5-8 indicate that in each storage location to be picked, goods can only be picked once.

5.4. Model Solution Based on Genetic Algorithm

5.4.1. Algorithm Flow

Based on the introduction of the improved genetic algorithm and considering YY's actual situation and the above mathematical model, the algorithm flowchart for the picking path optimization problem is shown in Figure14:

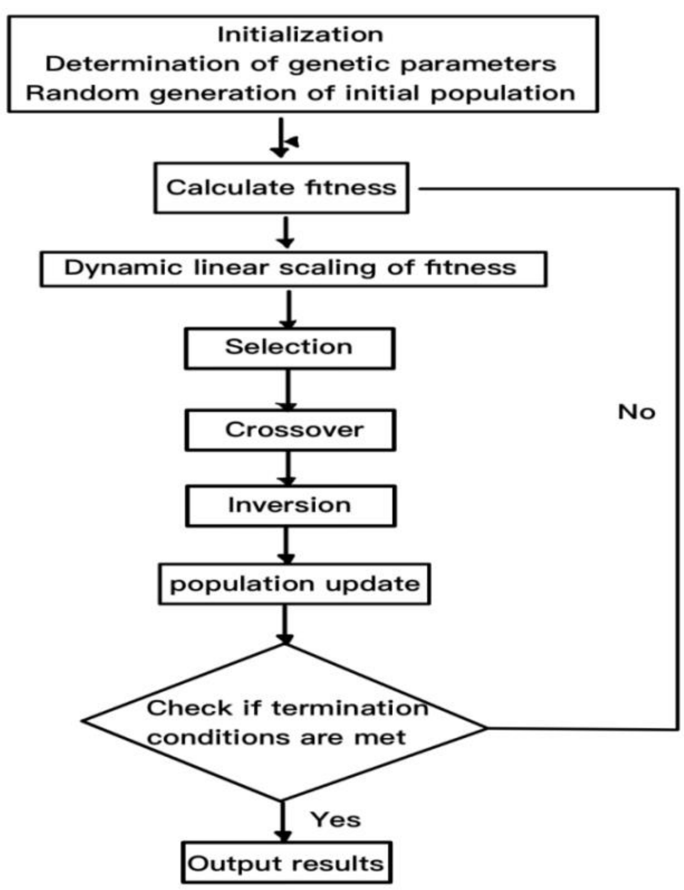

Figure 14. Algorithm Process.

5.4.2. Specific Steps in Algorithm Flow Design

Based on the algorithm flowchart, the specific algorithm steps are as follows:

(1) Determine Encoding: Use natural number encoding. For multi-cart goods picking in a single order, this paper inserts the corresponding 0 in the natural number sequence, with the specific method as follows:

Assume in order A, there are 8 types of goods to be picked, and all 8 types of goods are distributed in different 8 storage locations. Based on the above content, 0 can be used to represent the warehouse's In/Out gate, and the natural numbers 1 to 8 can be used to represent individual storage locations. Now, let's set the picking path for this order as follows:

Path 1 : In/Out gate 0→Location 1→Location 4→Location 8→Location 5→In/Out gate 0
Path 2 : In/Out gate 0→Location 2→Location 3→Location 6→Location 7→In/Out gate 0
The natural number sequence represented by the genetic algorithm is: {0 1 4 8 5 0 2 3 6 7 0}.

To better encode the data, the storage locations required for the order are now transformed into a coordinate axis, with the specific positions of the storage locations represented by x and y coordinates, as shown in Figure 15:

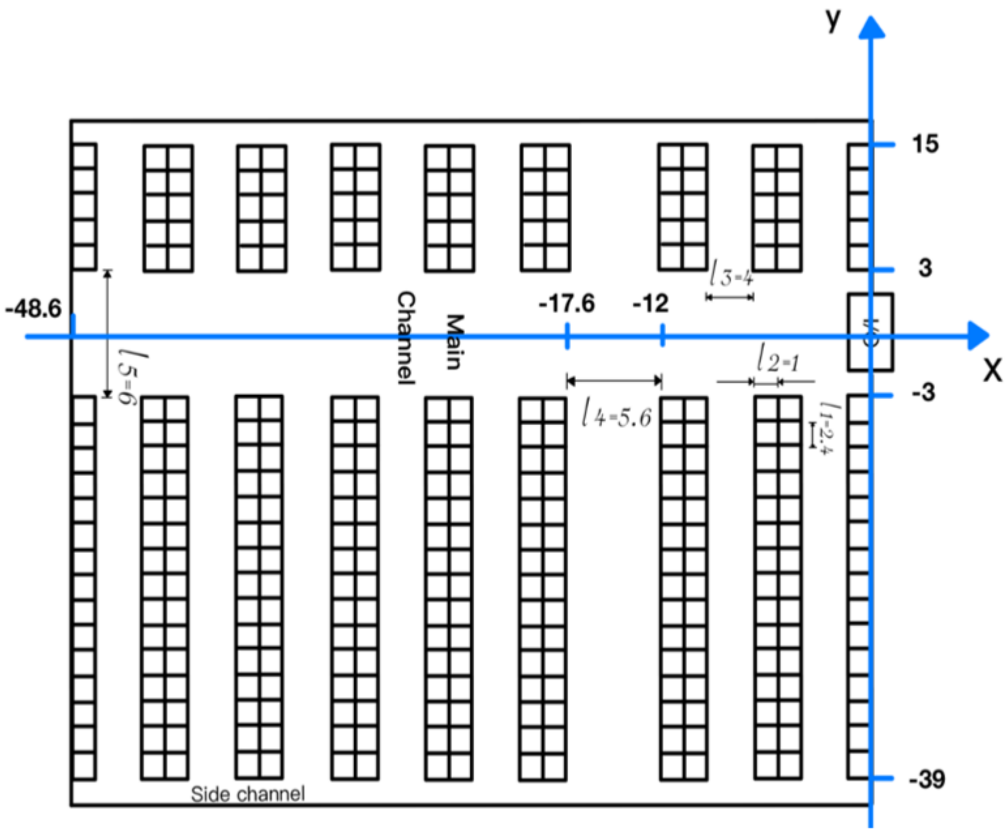

Figure 15. Storage Location Coordinate Axis.

(2) Determine Fitness Function: In this paper, the fitness function is represented by $r = 76.2 * maxD * N^{0.5}$ to form a new fitness function $Fix(x) = r|X$.

Where max D is the maximum distance between the storage locations of the goods to be picked in the customer order, N is the length of the chromosome, which is the number of storage locations passed through in the picking path (including the In/Out gate), and X is the length of the picking path.

(3) Selection and Crossover Operator Design: Based on the basic principles of the improved genetic algorithm described earlier, this paper uses a random generation method to produce the initial solution population. Then, using the random traversal sampling method, two individuals are selected from the parent generation each time, and crossover and mutation are performed with a set probability.

In the random traversal sampling method, individuals are selected through multiple nodes, with equal distances between nodes. The expression for equal distance is as follows:

$$Dis = F_t/N$$

$$r\epsilon[0, \frac{F_t}{N})$$

Dis represents the equal distance between nodes, F_t represents the cumulative fitness of the individual, Num represents the number of individuals to be selected, and r represents the position of the starting point in the node, which is randomly generated within the range$[0, \frac{F_t}{N})$.

The specific crossover steps are as follows:

In the initial OX crossover method, if the randomly selected gene segments of the two parent individuals are the same, new child individuals cannot be generated. In this case, the crossover method can be improved: First, randomly select two nodes in the two parent individuals (the positions of the two nodes must be the same), and extract the gene segments (crossover sub-path); Second, place the extracted two gene segments in front of and behind the originally selected parent individuals; Finally, based on the second step, delete the duplicate gene segments to obtain new individuals. The specific process is shown in Figure 16:

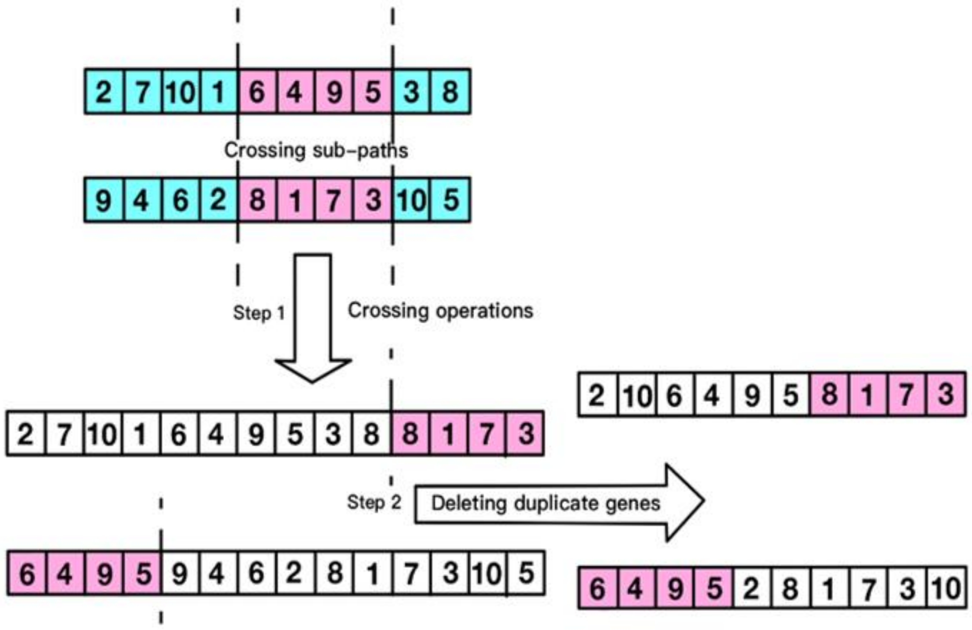

Figure 16. Crossover Process.

(4) Mutation Operation: Employ a continuous and multiple swap mutation technique to significantly adjust the order of feasible solutions, thereby suppressing the homogenizing effect in "evolutionary reversal".

5.4.3. Analysis and Comparison of Optimization Results

(1) Optimization Results: Similar to storage location optimization, path optimization also uses software for simulation calculations, with the following specific settings (Tables12):

Table 12. Algorithm Parameter

Parameter	Definition	Value
NIND	Population Size	100
MAXGEN	Maximum Iteration Number	200
P_c	Crossover Probability	0.05
P_m	Mutation Probability	0.03

Due to space constraints, only a portion of the data is displayed. Based on the above parameter settings, a random order is selected, and the order data is shown in Tables 13 and 14. The data is input into the algorithm, and the optimized route is calculated, with the iterative results shown in Figure 17:

Table 13. Customer Order.

Product	**Storage**	**Goods Weight (kg**
1	9	56
2	13	13
3	35	47
4	43	53
5	50	45
6	66	47
7	80	31
8	91	6
9	98	32
10	117	12
11	139	29
12	152	47
13	175	62
14	179	19
15	184	46
16	208	58
17	227	41
18	254	42
19	259	7
20	262	57
21	273	15
22	280	46
23	295	34
24	307	44
25	315	11

Table 14. Order Required Goods Storage Coordinates.

Storage Number	Coordinate Position
9	(0, -19.8)
13	(0, -10.2)
35	(-4, -5.4)
43	(-6, -34.2)
50	(-6, -17.4)
66	(-10, -27)
80	(-10, 15)
91	(-11, -15)
98	(-11, 10.2)
117	(-17.6, 7.8)
139	(-18.6, 12.6)
152	(-22.6, -12.6)
175	(-23.6, -5.4)
179	(-23.6, 12.6)
184	(-27.6, -31.8)
208	(-28.6, -22.2)
227	(-32.6, -24.6)
254	(-33.6, -7.8)
259	(-33.6, 12.6)
262	(-37.6, -36.6)
273	(-37.6, -10.2)
280	(-37.6, 15)
295	(-38.6, -5.4)
307	(-42.6, -24.6)
315	(-42.6, -5.4)

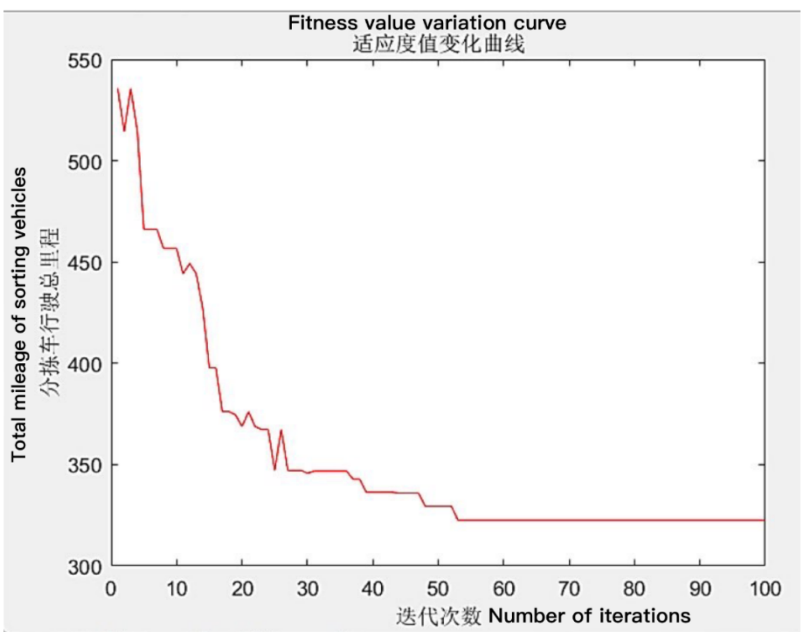

Figure 17. Iteration Number Diagram.

In summary, based on the above parameter settings and optimization model, the specific optimized vehicle picking sequence and the total running distance of the sorting vehicle are as follows:

The path of 1st cart n11= (0 3 2 1 6 8 12 13 23 25 24 0) ;

The path of 2nd cart n22= (0 16 17 15 20 4 5 0) ;

The path of 3rd n33= (0 7 9 10 11 14 19 22 18 21 0) ;

The total running distance of the three sorting carts is: 435.431486m.

(2) Comparative analysis: To demonstrate the effectiveness of the improved genetic algorithm in solving the storage location optimization problem, a comparison is made between the path distances before and after storage location optimization, with the comparison results shown in Tables 15 and 16:

Table 15. Algorithm Effect Comparison (S-shaped Path).

Order	S-shaped Path (m)	Optimized Path (m)	Difference value (m)	Path Distance Savings (%)
1	603.2	351.55	251.65	41.7%
2	538.19	329.46	208.73	38.8%
3	504.01	306.57	197.44	39%

Table 16. Algorithm Effect Comparison (U-shaped Path).

Order	U-shaped Path (m)	Optimized Path（m）	Difference value (m)	Path Distance Savings（%）
1	560.6	351.55	208.45	37.1%
2	518.62	329.46	189.16	36.4%
3	502.41	306.57	195.84	38.9%

Storage location and path optimization play a significant role in improving the efficiency of picking operations. This paper first places high-association goods near the warehouse entrance and exit based on the outbound rate of storage locations, thereby reducing the picking time and distance for pickers. As shown in the table, the differences before and after optimization are 167.77, 126.36, 117.78, 125.17, 100.81, and 105.40, with the path savings ratio concentrated between 20% and 25%, indicating a significant path optimization effect.

6. Summary and Recommendations

6.1. Storage Location Optimization for YY's

To achieve storage location optimization, the following measures are necessary:

(1) Develop a detailed plan and coordinate with all departments to ensure the continuity of warehouse operations. The plan should be flexible to accommodate unexpected events.

(2) Consider the weight and quantity of goods, employ suitable equipment, and augment personnel to streamline the storage location adjustment process.

(3) Enhance staff training to minimize errors and omissions during the storage location optimization process, with experienced personnel overseeing the implementation.

6.2. YY's Path Optimization

To optimize picking paths, the following measures are recommended:

(1) Offer operational guidance and training to assist employees in adapting to the new picking paths, thereby reducing error rates.

(2) Update picking labels to facilitate efficient picking by employees according to the new paths.

(3) Utilize the logistics system to monitor and evaluate the implementation of the new paths, and make real-time adjustments based on feedback to maintain picking efficiency and accuracy.

References

Bortolini, M., Botti, L., Cascini, A., Gamberi, M., Mora, C., & Pilati, F. (2015). Unit-load storage assignment strategy for warehouses in seismic areas. *Computers & Industrial Engineering*, 87, 481–490. https://doi.org/10.1016/j.cie.2015.05.023bancadellesoluzioni.org+1docente.unife.it+1

Chen, F., Wang, H., Qi, C., & Xie, Y. (2013). An ant colony optimization routing algorithm for two order pickers with congestion consideration. *Computers & Industrial Engineering*, 66(1), 77–85. https://doi.org/10.1016/j.cie.2013.06.006

Chou, Y. C., Chen, Y. H., & Chen, H. M. (2012). Recency-based storage assignment and warehouse configuration for recurrent demands. *Computers & Industrial Engineering*, 62(4), 880–889. https://doi.org/10.1016/j.cie.2011.12.013

Li, Y., & Qin, H. (2024). Dynamic slot optimization in warehouses using reinforcement learning techniques. *Journal of Intelligent & Robotic Systems.*

Note: As of now, a DOI for this article is not available. Please check the journal's official website or databases like CrossRef for updates.

Liu, X. (2020). Cargo space optimization and picking path optimization based on immunogenetic algorithm [Doctoral dissertation, Anhui University of Technology].

Note: Doctoral dissertations typically do not have DOIs. You may access this dissertation through the university's repository or contact the university library for assistance.

Wang, J., & Xu, H. (2023). Simultaneous optimization of storage layout and picking paths in warehouses with machine learning and optimization algorithms. *Expert Systems with Applications.*

Note: The DOI for this article is not available in the provided information. Please consult the journal's website or academic databases for the most recent updates.

Xu, X., & Ma, Z. (2021). RMFS order picking system dynamic cargo space reassignment research. *Computer Integrated Manufacturing Systems*, 27(4), 1146–1154.

Note: This article appears to be published in a Chinese journal. For access and DOI information, please refer to the journal's official website or contact the publisher directly.

Xu, X., & Ren, C. (2021). Vehicle path optimization method considering vehicle restriction and packing constraints. *Journal of Transport Information and Safety*, 39(3), 77–84. https://doi.org/10.3963/j.jssn.1674-4861.2021.03.010jtxa.net+1jtxa.net+1

Zhang, L., & Li, S. (2022). Automated warehouse slot optimization using deep learning and genetic algorithms. *International Journal of Logistics Management.*