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Research Article

Design of Interconnected Warehouse and Routing Optimization by BP Genetic Neural Network Algorithm

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With the continuous progress of the chemical industry, warehouse design needs to be diversified on account of the increasing complex and multitudinous perilous chemicals. In this situation, this study projects the conception of the interconnected warehouse. By taking the storage points as the quantity and the path as the variable, this study establishes a quadratic allocation model on the operations of this novel kind of warehouse. Then, an improved neural network algorithm is proposed to ascertain the optimal solution. The innovation of this study is that it releases the space resources of the classic dangerous goods warehouse and improves the operational efficiency of the dangerous goods warehouse under the premise of ensuring safety. Finally, the proposed model and algorithm is tested and verified with a data of Shanghai Lingang dangerous Material Warehouse. The empirical research demonstrates that the interconnected warehouse has ideal performance for lifting the handling efficiency on the basis of ensuring safety.

1. Introduction

Economic sectors and nearly all industries have contact with chemicals. Dangerous goods usually are combustion-supporting and harmful to human beings, facilities, or the environment. When entering the environment, dangerous goods can have a significant influence on human health and the ecosystem. In recent years, the dangerous goods warehouses have experienced a series of accidents as a result of its low operational efficiency and poor geometric design. Most Chinese dangerous goods warehouses are built with double-door structure. The advantage of the double-door warehouse is experiencing prolonged full capacity and is expecting a large volume of goods. Meanwhile, the disadvantage of this kind of warehouse is its low operational efficiency. To optimize the efficiency of the entering and exiting operation, this study projects the conception of interconnected warehouses by installing an open-isolation switch door in the conventional double-door warehouse. In the following study, to promote the reform of dangerous goods warehouse, high attention is paid to the research of warehouse management and operations, route optimization, BP neural network algorithms, and related research.

1.1. Relevant Studies. In the past decade, many scholars focused on the management and operation of dangerous goods warehouse. For example, Gaci and Mathieu [1] propose a complex adaptive system to study storage activities in a dangerous goods warehouse. However, with the continuous progress of the chemical industry, the manner of dangerous goods has changed remarkably. Such changes in management and operation challenge to the operation efficiency of the warehouse. Therefore, improving the operation efficiency of the warehouse becomes more important. Xue and Liu [2] used robot technology in warehouse to improve the efficiency of storage and retrieval. Thereafter,

Table 1: Studies on route optimization and vehicle guidance in the warehouse operation area.

Literature	Fields	Achievement
Ghazal et al. [7]	Studied rail-truck intermodal transportation of dangerous goods with terminal congestion	Proposed a nonlinear optimization model in order to improve accuracy
Cao et al. [8]	Studied the stochastic vehicle routing	Used a carnality minimization approach to find the shortest route, and proposed a partial Lagrange multiplier method to improve the efficiency of stochastic vehicle routing
Cao et al. [9]	Studied the stochastic shortest path problem in vehicle routing	Proposed a cardinality minimization approach to finding the shortest path in stochastic vehicle routing
Torabizadeh, et al. [10]	Studied the warehouse management system indicators	Proposed a model to obtain and maintain the sustainability of the operation of a large warehouse

In summary, in the field of warehouse operation, the aforementioned studies focus on the route optimization and vehicles' guidance problem with consideration of increasing operation's efficiency and promising safety.

for a kind of picker-to-part warehouses, Henn [3] used variable neighborhood descent and variable neighborhood search methods to obtain the optimization solutions of the total tardiness of a given set of customer orders. Trab et al. [4] studied a communicating object's approach for smart logistics and safety issues in the warehouse. Lee et al. [5] proposed a warehouse management system with an advanced data analysis approach using computational intelligence techniques. Besides, recently, Gerini and Sciomachen [6] studied the interactions in different components of a warehouse logistic system, which emphasized and captured the critical factors in the entire logistic chain by using Petri Nets for improving its efficiency. All the aforementioned studies have achieved good results and stimulated tour interest in the study of dangerous goods warehouses. For more results on route optimization and vehicle guidance in the warehouse operation area, please see Table 1.

In addition, recently, Li, et al. [11] proposed a kind of four-door dangerous goods warehouse, which can maximize storage space utilization and minimize the travel time of forklifts. Emde, et al. [12] proposed a routing planning model for lane-guided transport vehicles in the modern automated warehouse and introduced a mixed-integer linear programming method to solve the given model. By summarizing the aforementioned studies, it gets that the layout of the warehouse can be optimized to achieve effective use of storage space and equipment of the warehouse. Under the guidance of this thought, a novel warehouse named interchange warehouse is proposed in this study. Furthermore, a quadratic assignment model is structured for solving the route planning problem of forklifts in the process of using this novel warehouse.

Theoretically, how to find the optimal solution of the route optimization model is a difficult work for the complexity, uncertainty, randomness, and unpredictability of the operation process. Recently, many studies focus on the application of neural network and genetic algorithm in solving the optimization problem. For example, Zhang and Tao [13] designed a novel GA to optimize the parameters of a fuzzy neural network. Villarrubia et al. [14] approximated the objective function in optimization problems using artificial neural networks (ANNs). Although the aforementioned methods can achieve the objective of finding the approximate solution in an optimization problem, these methods have academic blanks of path planning problem, particularly in the fields of route planning in warehouse operation. Noting the existing defects, Colla et al. [15] proposed a simple path planning model for the navigation of mobile robots and introduced a genetic-search algorithm which improves the efficiency of iteration. Bottani et al. [16] explored the use of a genetic algorithm (GA) to optimize item allocation in a warehouse with the ultimate purpose of reducing the travel time of pickers, thus streamlining order picking operations. In addition, Verma et al. [17] proposed a biobjective model for planning and managing rail-truck intermodal transportation of dangerous goods. Thereafter, Ene, et al. [18] proposed a genetic algorithm for order execution in warehouse operations. Besides, Ansari and Nagwanshi [19] proposed a novel model to solve the shortest path optimal problem by combining the hybrid K-means with the particle swarm optimization method.

1.2. Research Framework. In the upcoming sections, Section 2 introduces the disadvantage of the current warehouse and the necessity of proposing an interconnected warehouse; In Section 3, a quadratic allocation model is structured by considering safety and efficiency; In Section 4, an improved neural network algorithm is proposed by combining of BP neural network and genetic algorithm to obtain the optimal solution; Section 5 uses data of Shanghai Lingang Port Warehouse to demonstrate the feasibility of the interconnected warehouse and analyzes the advantages of BP-Genetic ANN algorithm; Section 6 concludes this study. Specifically, the main work of this study consists of two parts. Firstly, this study analyzes the operations in the six-door (three rooms) condition and only considers the case when the volume of products stocking out is bigger than the products moving into. Secondly, this study proposes a quadratic allocation model to improve the comprehensive efficiency of warehousing operations. For more details, please see Figure 1.

2. Problem Analysis

According to the field investigation, Chinese dangerous goods warehouse is categorized into four different types, i.e., monolayer warehouse, tank storage warehouse, goods sheds,

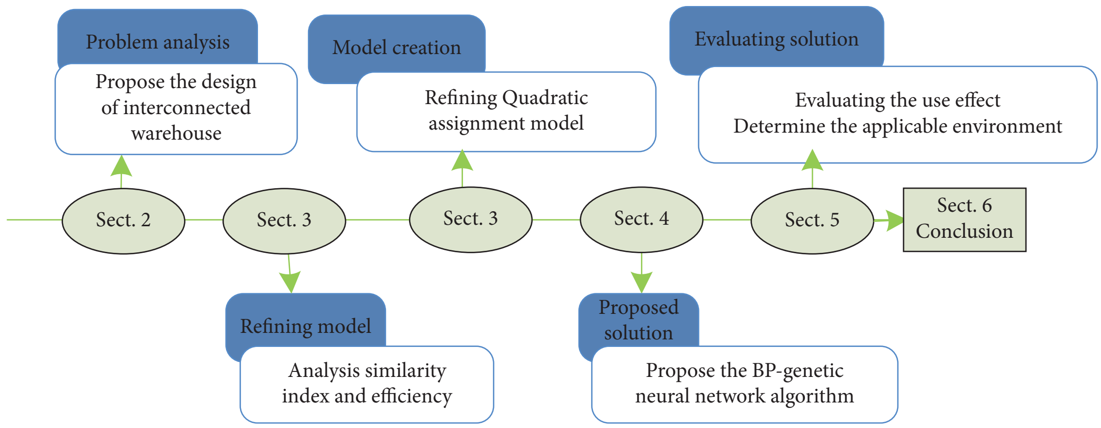

FIGURE 1: Technical roadmap.

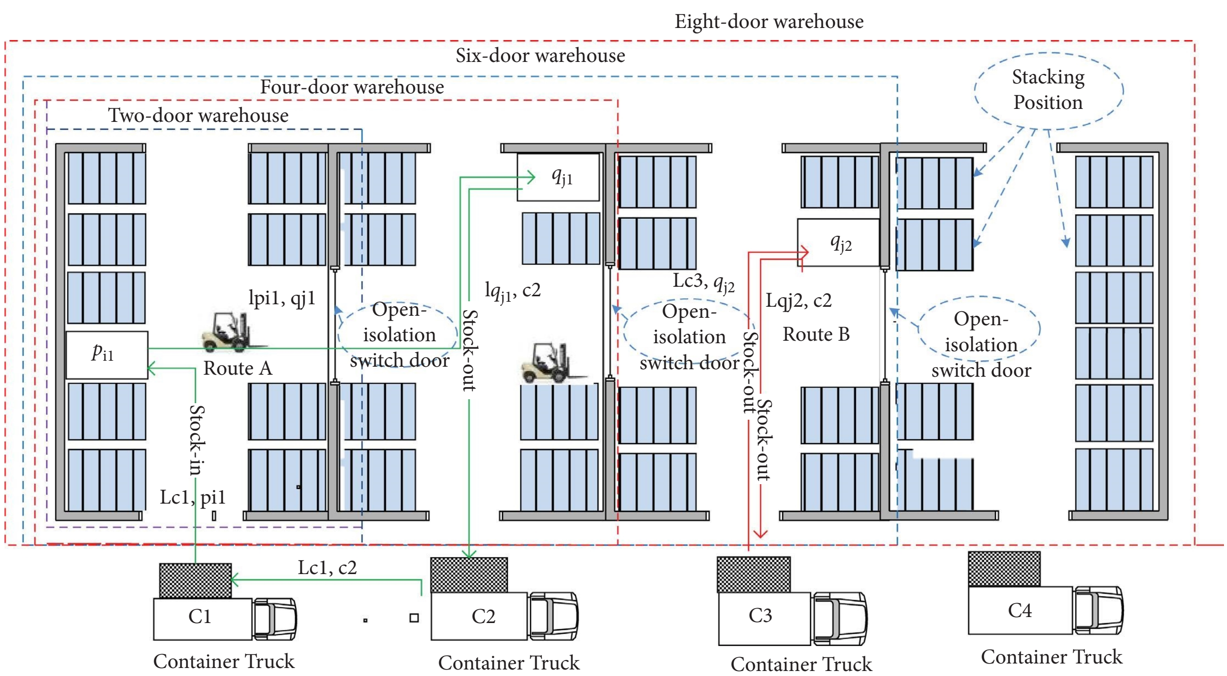

FIGURE 2: Interconnected warehouse schematic.

and freight yard [20]. Considering that conventional monolayer warehouse is of the largest proportion type in China, this study mainly focuses on this type. For the convenience of study, we take the Shanghai port dangerous goods warehouse as an example, where each storage room has only 12 cargo stacking places and there is a central passageway for the forklift to operate in the warehouse. In this kind of warehouse, the container is required to be parked outside the warehouse and the forklifts are required to proceed to the door to pick up the goods before entering the warehouse to deposit the goods. Depending on the layout and width of the warehouse, it is impossible for two forklifts to move simultaneously in the same or opposite direction. For this kind of dangerous goods warehouse, it only allows one forklift to operate in the double-door warehouse at any given time according to the present administrative provisions. Therefore, how to improve the low efficiency of inbound and outbound operation is the core question perplexing warehouse managers. Comparatively, the introduced interconnected warehouses can overcome these shortcomings. By installing an open-isolation switch door in the conventional double-door warehouse (Please see Figure 1), forklifts get more flexible options when operating, so as to improve work efficiency. Meanwhile, the construction costs of the passageway is the storage space. Overall, the two construction modes all have their own characteristics. Accordingly, they have different applicable environments.

To illustrate the warehousing operation more clearly, a green closed-loop is denoted as Route A in Figure 2. Generally, Route A indicates the inbound-outbound route, which begins from stacking the products into the warehouse and carries the outbound products out of the warehouse. Figure 2 also provides a red closed-loop, which is denoted as a process to transporting goods out of the warehouse. For convenience, this study labels the red closed-loop as Route B. According to the field investigation, the invalid running distance reduces when the forklifts run according to Route A. Moreover, field investigation also tells that the operation of the forklifts should follow two principles. The first one is the number of the storage points. If the inbound point is larger than the outbound point, the forklifts would take stock in operating first. Otherwise, it would take stocking out operation first. In addition, the operation would follow the requirement of the customer. If the customers prefer stocking in first, the forklifts would carry the stocking in operation first.

In the interconnected warehouse, it allows multiple forklifts to operate simultaneously in the interconnected warehouse. The container truck would park in the nearest door of the inbound-outbound point, and the warehouse operator adjusts the order of each stack according to the job requirements on-site. Depending on the layout and width of the warehouse, it is possible for two forklifts to move simultaneously in the same or opposite direction. Warehouse management regulations just only allow one forklift to operate in the double-door warehouse at any given time and in any case to be as safe as possible. Therefore, outbound and inbound routes should be planned with as many options as possible. Diversification of line length can reduce the possibility of line overlap when conducting line scheduling. Furthermore, when the length of the path is diverse enough, the warehouse operator can adjust the order of each stack according to the requirements of the field work. It also makes the process more coordinated, smoother, and as safe as possible. In addition, the total length of forklifts is also a key which can issue in determining the efficiency of storage. When the forklifts' speed is given as a fixed value, the smaller is the total length of the routes covered by the forklifts, and the higher efficiency is in the warehousing operation. Therefore, we construct a quadratic assignment model to minimize the similarity index and the length of the inbound and outbound operation. Meanwhile, it is noteworthy that the core task of this study is to propose a method for planning the forklifts' routing lines, while the routing order is dependent on the operators on-site. Besides, it is noteworthy that this principle is to ensure the effectiveness of the forklift operations and to give autonomy to the operators.

3. Interconnected Warehouse Route Modeling

3.1. Basic Terminologies. With the continuous progress of the chemical industry, compared with the traditional two-door warehouse, the interconnected warehouse can improve the handling efficiency, reduce the cost, and increase the efficiency. On the basis of the interconnection warehouse framework, the traditional two-door warehouse can be transformed into an interconnection warehouse through the isolation door. In this section, the way to achieve the optimal warehousing operation under the condition of the novel interconnected warehouse is studied. For convenience, this study analyzes the operations in the six-door (three rooms) condition and only considers the case when the volume of products stocking out is bigger than the products moving into. A similar process can be described when the stocking out products are less than or equal to the stocking in products.

For convenience, denote C_1 as the container truck for inbound operation, and C_2, C_3 as two container trucks are used for the outbound operation of the dangerous products. Assume that C_1 has m inbound points, which are denoted as $p_1, p_2, \cdots, p_m$. C_2, C_3 having n outbound points, which are denoted as $q_1, q_2, \cdots, q_n$, where $m < n$. Denote= $\{1, 2, \cdots, m\}$, $N = \{1, 2, \cdots, n\}$, then, there are m closed-loop routes available for Routes A and $n - m$ routes for route B. For any given $i \in M$, $j \in N$, if a forklift starts to C_1, through the path l_{C_1,p_i} to deliver the products to the position $p_i\,(i \in M)$, then follow the path $l_{p_i,qj}$ to pick up the outbound products in $q_j\,(j \in N)$ and send it to $C_t\,(t = 2, 3)$. Finally, the forklift goes back to C_1 along the path l_{C_t,C_1}. Such a close-loop can be denoted as L_{p_i,q_j}, which is the green close-loop (Route A) in Figure 3. The distance of Route A can be calculated as $L_{p_i,q_j} = l_{C_1,p_i} + l_{p_i,q_j} + l_{q_j,C_1} + l_{C_1,C_2}$. Assume that a forklift travel from $C_t\,(t = 2, 3)$ along the path l_{C_t,q_s} to the outbound point q_s, after the dangerous products are loaded, the forklift along path l_{q_s,C_t} return to C_t. Such a route is marked as a Route B and denoted as L_{C_t,q_s}, which is the red close loop in Figure 3. The distance of Route B can be calculated as $L_{C_3,q_s} = l_{C_3,p_s} + l_{p_s,C_3}$.

Thereafter, the core work is transferred to construct a quadratic aassignment model with consideration on safety and efficiency of warehouse operation. In essence, the question is to select the best route which is of the shortest operating distance while promising safety. When it comes to the safety, it should select the different closed-loops route that varies significantly in the distance. In this situation, it is possible to enable more forklifts to operate together and give the operators more time for selection.

3.2. Quadratic Assignment Model. On the basis of the above-given research, we propose a quadratic allocation model to minimize the similarity index and the length of loading and unloading operation routes. This is based on existing procedures for loading, stacking, and unloading of dangerous goods in a conventional warehouse.

Firstly, we normalize the distance between the original inbound and outbound points, which is denoted as follows:

$$l'_{p_{i_k},q_{j_k}} = \frac{l_{p_{i_k},q_{j_k}} - \min\limits_{s\in M, f\in N} l_{p_{i_s},q_{j_f}}}{\max\limits_{s\in M, f\in N} l_{p_{i_s},q_{j_f}} - \min\limits_{s\in M, f\in N} l_{p_{i_s},q_{j_f}}}. \tag{1}$$

Next, we select two points from both pairs of final inbound and outbound points and denote as $l'_{p_{i_k},q_{j_k}}$ and $l'_{p_{i_k},q_{j_k}}$. Then, we denote r as the similarity index between $l_{p_{i_s},q_{j_s}}$ and $l_{p_{i_k},q_{j_k}}$, where

$$r\left(l'_{p_{i_k},q_{j_k}}, l'_{p_{i_k},q_{j_k}}\right) = 1 - \frac{\left|\left(l'_{p_{i_k},q_{j_k}} - l'_{p_{i_k},q_{j_k}}\right)\right|}{\max\left\{l'_{p_{i_k},q_{j_k}}, l'_{p_{i_k},q_{j_k}}\right\}}. \tag{2}$$

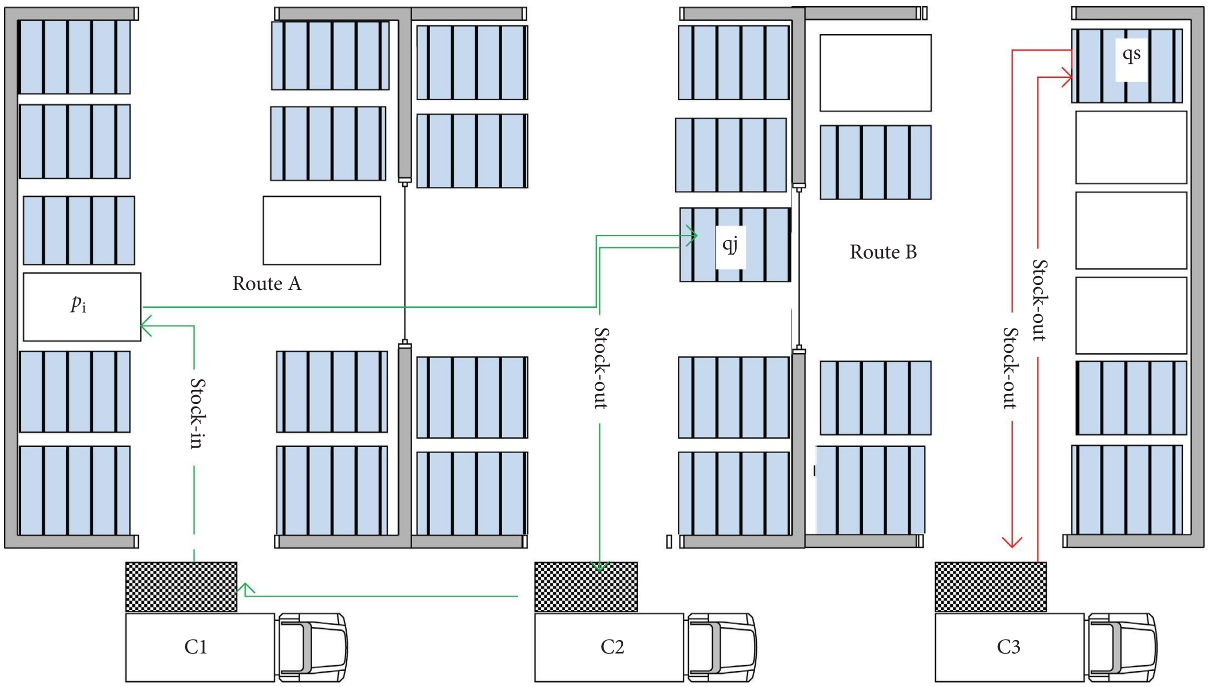

FIGURE 3: The six-door interconnected warehouse.

The operational safety corresponds to the similarity index, and the total distance of the route corresponds to the operational efficiency. A multi-target model is designed to achieve the target of reducing the total similarity index r and keep the total length of the closed-loop L' to the shortest as follows:

$$\begin{cases} \min \gamma = w_1 \sum_{i_s, i_k}^{m} \sum_{j_t, j_f}^{n} \left(x_{i_s j_t} x_{i_k j_f} r \left(l'_{p_{i_s}, q_{j_t}}, l'_{p_{i_k}, q_{j_f}} \right) \right) + w_2 \sum_{i_s=1}^{m} \sum_{j_t=1}^{n} x_{i_s j_t} L'_{p_{i_s}, q_{j_t}} \\ + w_1 \sum_{i,j=2}^{3} \sum_{j_t, j_f}^{n-m} \left(x_{C_i j_t} x_{C_j j_f} r \left(l'_{C_i, q_{j_t}}, l'_{C_j, q_{j_f}} \right) \right) + w_2 \sum_{i=2}^{3} \sum_{j_t=1}^{n-m} x_{C_i j_t} L'_{C_i, q_{j_t}} \\ s.t. \sum_{i_s=1}^{m} x_{i_s j_t} = 1, \quad \sum_{j_t=1}^{n} x_{i_s j_t} = 1, \; x_{i_s j_t} \in \{0,1\}, x_{i_k j_f} \in \{0,1\}, x_{C_i j_t} \in \{0,1\}, \end{cases} \tag{3}$$

where$w_1 \in (0,1)$, $w_2 \in (0,1)$, and $w_1 + w_2 = 1$, whereas $\sum_{i_s,i_k}^{m} \sum_{j_t,j_f}^{n} (x_{i_s j_t} x_{i_k j_f} r(l'_{p_{i_s}, q_{j_t}}, l'_{p_{i_k}, q_{j_f}}))$ represents the similarity between the inbound-outbound closed-loop routes. Besides, $\sum_{i_s=1}^{m} \sum_{j_t=1}^{n} x_{i_s j_t} L'_{p_{i_s}, q_{j_t}}$ refers to the total distance between all closed-loops in the warehouse. Here, the sum of $\sum_{i,j=2}^{3} \sum_{j_t,j_f}^{n-m} (x_{C_i j_t} x_{C_j j_f} r(l'_{C_i, q_{j_t}}, l'_{C_j, q_{j_f}}))$ is defined as the similarity between the outbound routes, the sum of $\sum_{i=2}^{3} \sum_{j_t=1}^{n-m} x_{C_i j_t} L'_{C_i, q_{j_t}}$ refers to the total distance of the outbound routes.

This model quantifies the correlation and the weight preceding the distance and further analyzes the operations of the forklifts by adjusting the weights of w_1 and w_2. When $w_1 = 0$, the objective function in the model (3) involves only the similarity between routes. When $w_2 = 0$, the model (3) refers only to the minimization of the route distance. Since the similarity corresponds to the operational safety and the route distance refers to the operating efficiency. As the number of forklifts increases, more emphases are placed on the operational safety, and the value of w_1 can be used to measure the impacts on the similarity on the model. The total number of feasible solutions in the model (3) is $C_n^m m!$. Since each operation consists of multiple steps, the calculation time will increase significantly with the increase of storage products. Therefore, a heuristic algorithm is used to solve the aforementioned model when the number of the inbound and outbound points is large. However, the traditional heuristic allocation algorithm is a trend to fall into the local optimal shortcoming, in addition, the search speed is slow. Therefore, we propose an improved version of the neural network based on the BP neural network and genetic algorithm.

4. BP-Genetic Neural Network Algorithm

In recent years, ANNs have been widely used in system identification, pattern identify, and other fields. The standard BP algorithm is conducted using the gradient decent method. Then, the error of the BP algorithm is decreased in the inverse gradient direction. Therefore, the local optimum is a result that often appears in this algorithm. Many scholars have done some improvement in BP neural network. For example, Zhao et al. [21] proposed some improved approaches to the network design problem in regional dangerous waste management systems. When the number of training samples is large, the relationship of input and output is complicated and the convergence rate of the network becomes slow. Considering these shortcomings of neural network algorithms, we propose an improved neural network algorithm by combining the genetic algorithm, which can optimize the initial value of the BP neural network structure in a random point set. The structure of a BP neural network is determined by the input and output parameters of the fitting function. The genetic algorithm is used to optimize the weights and thresholds of the BP neural network. Subsequently, the genetic algorithm finds the best fitness value corresponding to the individual by means of the selection, crossover, and mutation. Next, the BP neural network obtains the optimal initial weights and threshold provided by the genetic algorithm and predicts the function output after the network has been trained. In the genetic-BP neural network algorithm, the individual encoding is real encoded and each individual is a real string which consists of connection weights of the input layer and the hidden layer, the threshold of the hidden layer, connection weights of the hidden layer and output layer, and the threshold of the output layer. The individual contains all weights and thresholds of the neural network. We can form a neural network with the determined structure, weights, and thresholds under the conditions of the network structure being known.

The weight w and threshold θ of the neural network are generally initialized by random numbers in $[-0.5, 0.5]$. Since this parameters have a great impact on network training, but it cannot be accurately obtained. Therefore, a genetic algorithm is used to optimize the initial weight distribution and locates better search spaces in the solutions. The basic idea of the BP-genetic algorithm is that the first can solve the problem of optimizing the weights and thresholds by genetic algorithm. So after several evolution of a certain calculation, we can get the optimal weight and thresholds. Starting from these optimal points, and using the neural network to solve, and then we obtain the global optimal solution. The structure of the BP neural network is determined according to the input and output parameters. So the number of optimization parameters of the genetic algorithm can be determined. The meaning of the notation in this algorithm is as Table 2.

Table 2: The notation of genetic-BP neural network algorithm.

Notations	Meaning
X	Network input
Y	Estimated output
O	Ground truth output
$T_{\max}$	Maximum iteration
N	Group size
P_c	Crossover rate
P_m	Mutation rate
P_s	Selection rate
C	Value for the hidden layer
$g(x_{ij})$	Activation function for hidden layer
w	Weight in the neural network
$f(x_{ij})$	Output transfer function
θ	Threshold in the neural network

In this section, a three-layer BP neural network is introduced where the input layer, hidden layer, and output layer nodes are, respectively, p, n, p. Given the sample set $\{X_j, O_j\}$, $j = 1, 2, \cdots, p$. Then, the input of the network is denoted as $X_j = (x_{j1}, x_{j2}, \cdots, x_{jp})$, and the ground truth output is denoted as $O_j = (O_{j1}, O_{j2}, \cdots, O_{jp})$, where $O_{ji} \in (0, 1)$, whereas Y_j is the estimated output, which is a vector corresponding to the ground truth output O_j. To calculate the fitness value, it gets $E = 1/2 \sum_{j=1}^{p} (O_j - y_j)^2$ as the output of the objective function.

To begin this algorithm, the initial weights and thresholds of the BP neural network are given randomly; then, the output is predicted after the BP neural network has been trained with the training data. Denote the fitness function as follows:

$$E = \frac{1}{2} \sum_{j=1}^{p} \left(O_j - y_j\right)^2. \tag{4}$$

Then, the selection probability of each individual is obtained as $p_s = f_i / \sum_{j=1}^{p} f_j$, where $f_i = k/E_i$ and k is the coefficients. The crossover rate P_c and mutation rate P_m are constant in value.

In addition, the algorithm randomly selects samples from the set, that is, it adopts no-return policy. For convenience, denote

$$g\left(x_{ij}\right) = \tan sig(x) = \frac{2}{((1 + \exp(-2x)) - 1)}, \tag{5}$$

then, it gets the output of the hidden layer as follows:

$$C_j = g\left(w_1 \times r\left(x_{ij}\right) + w_2 \times L\left(x_{ij}\right) + \theta\right). \tag{6}$$

Furthermore, denote

$$f\left(x_{ij}\right) = \log sig\left(x_{ij}\right) = \frac{1}{\left(1 + \exp\left(-x_{ij}\right)\right)}, \tag{7}$$

then, the output is obtained as $Y = f(\sum_{j=1}^{n} C_j)$.

On the basis of the aforementioned analysis, the proposed BP-Genetic neural network algorithm is used to solve the given model. Specific steps are as follows:

Step 1 Construct a three-layer BP neural network of the initial state.

Step 2 Construct the initialized population. The initial group is randomly generated according to the encoding method, and each individual in the group represents an initial parameter.

Step 3 According to the no-return strategy, a sample set is established for the input layer of the BP network, and the output error of the neural network is calculated.

Step 4 Genetic algorithm is used to determine the optimal connection weight, threshold, and learning rate of the neural network.

Step 5 Determine whether all samples have been trained and calculate the total error based on the fitness function $E = 1/2 \sum_{j=1}^{p} (O_j - y_j)^2$ and determine whether the total error of the network satisfies the condition where $E < e$. If satisfied, terminate the training. If the result is unsatisfactory, we calculate the selection rate P_s and return to Step 3.

It is noteworthy that the input of the network is the distance between inbound and outbound point. In the estimated output Y, the value approaches 1 means that the outbound point is the optimal solution. For more details of the proposed model, please see Figure 4.

5. Empirical Example

5.1. Preliminaries. In this section, we draw the data from the dangerous chemical warehouse in Shanghai port. By conducting a field investigation in a dangerous goods warehouse in Shanghai Port, the paper concludes that the usual width of the warehouse is 17.5 meters, and the length is 48 meters, and the width of the warehouse door is 4 meters, and the distance between container trucks is 12 meters and the distance from the container trucks to the warehouse is 2 meters. The length of the container truck can be neglected. Under the above-given conditions, this study provides a route optimization scheme for forklift operation. Assume that C_1 has 12 inbound points and C_2, C_3 have the total of 16. Therefore, the whole operation process includes 12 inbound and outbound routes and 3 outbound routes, and the forklift can make a variety of choices according to the needs. It is noteworthy the warehouse operation diagram is shown in Figure 3. Multiple forklifts can carry out dangerous goods in and out of the warehouse at the same time and an alternative one is prepared too. The distances of closed-loop routes between inbound and outbound point are recorded as $L = (l_{ij})_{12\times 15}$, $i = 1, 2, \cdots, 12$; $j = 1, 2, \cdots, 15$, where the rows in L corresponds to the inbound point, and the column corresponds to the outbound point. The matrix L is obtained by actual measurement. For example, the distance of a inbound-outbound route is obtained as follows:

$$l_{2,5} = l_{C_1,p_2} + l_{p_2,q_5} + l_{q_5,C_2} + l_{C_2,C_1}, \tag{8}$$

and the distance of a outbound route is obtained as follows:

$$l_{C_4,16} = l_{C_4,q_{16}} + l_{q_{16},C_4}, \tag{9}$$

where

$$L = \begin{bmatrix}
85.8 & 71.7 & 80.3 & 85.8 & 80.3 & 99.75 & 102.6 & 71.7 & 99.7 & 71.7 & 72.5 & 53.1 & 71.5 & 114 & 99.7 \\
70.5 & 64.8 & 67.6 & 70.5 & 64.8 & 87.1 & 87.1 & 61.9 & 87.1 & 64.8 & 59.9 & 96.8 & 59.1 & 98.5 & 87.1 \\
71.7 & 66.1 & 57.5 & 71.7 & 66.1 & 79.8 & 88.3 & 54.6 & 82.6 & 66.1 & 55.4 & 60.3 & 54.6 & 99.7 & 62.6 \\
72.1 & 66.1 & 57.5 & 72.0 & 66.05 & 85.5 & 88.3 & 57.5 & 82.6 & 66.3 & 55.4 & 54.65 & 57.3 & 99.7 & 85.5 \\
85.8 & 71.7 & 80.3 & 85.8 & 80.3 & 99.7 & 102.6 & 71.7 & 99.7 & 71.7 & 72.5 & 53.1 & 71.5 & 114 & 99.7 \\
71.7 & 106 & 106 & 71.7 & 66.1 & 94.1 & 94.1 & 66.1 & 94.1 & 112.1 & 98.8 & 112.3 & 66.1 & 105.4 & 94.1 \\
77.4 & 103.7 & 103.7 & 77.5 & 71.7 & 88.3 & 94.1 & 54.6 & 91.2 & 103.7 & 93.1 & 103.7 & 54.6 & 105.4 & 88.3 \\
83.2 & 109.4 & 109.4 & 83.2 & 77.4 & 94.1 & 87.7 & 60.3 & 94.1 & 109.4 & 98.8 & 112.1 & 54.6 & 110.9 & 96.9 \\
109.4 & 135.7 & 135.7 & 109.4 & 103.7 & 94.1 & 94.1 & 95.2 & 94.1 & 135.7 & 130.8 & 141.4 & 98.1 & 99.7 & 94.1 \\
118 & 138.6 & 138.6 & 118 & 96.3 & 99.7 & 99.7 & 103.7 & 99.75 & 141.4 & 136.5 & 147.1 & 103.5 & 99.7 & 99.7 \\
112.3 & 138.5 & 138.5 & 112.3 & 103.7 & 93.4 & 82.62 & 98.05 & 94.1 & 135.8 & 130.8 & 141.4 & 98.1 & 99.7 & 94.1 \\
103.7 & 130.1 & 130.1 & 130.1 & 103.7 & 98.05 & 88.35 & 86.6 & 82.6 & 130.1 & 119.4 & 130.1 & 86.6 & 99.7 & 82.6
\end{bmatrix}. \tag{10}$$

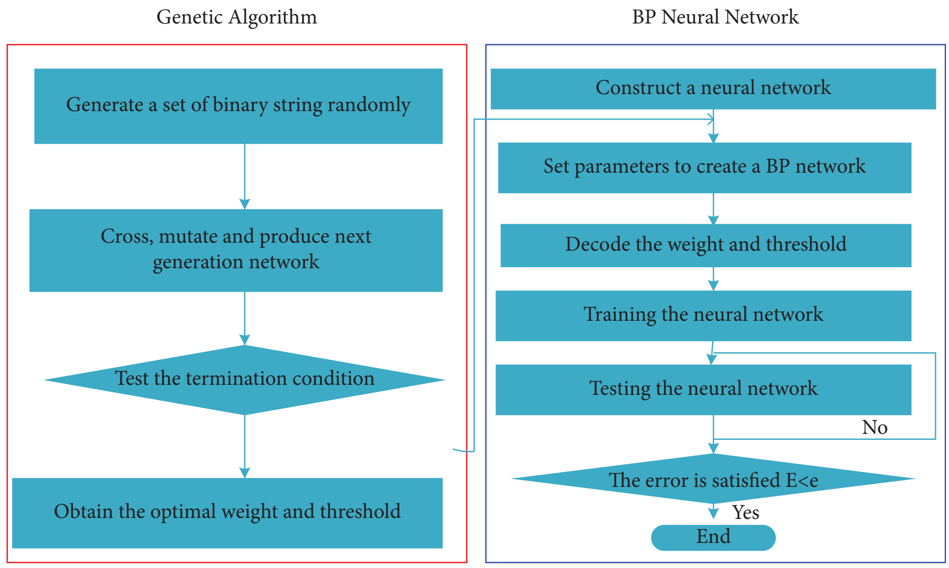

FIGURE 4: The algorithm flowchart.

From (1), it obtains the standard matrix L'. The similarity index can be calculated by (2). Hence the quadratic assignment model is obtained as follows:

$$\% \begin{cases} \min \gamma = w_1 \sum_{i_s,i_k}^{12} \sum_{j_t,j_f}^{15} \left(x_{i_s j_t} x_{i_k j_f} r\left(l'_{p_{i_s},q_{j_t}}, l'_{p_{i_k},q_{j_f}} \right) \right) + w_2 \sum_{i_s=1}^{12} \sum_{j_t=1}^{15} x_{i_s j_t} L'_{p_{i_s},q_{j_t}} \\ +w_1 \sum_{i,j=2}^{3} \sum_{j_t,j_f}^{3} \left(x_{C_i j_t} x_{C_j j_f} r\left(l'_{C_i,q_{j_t}}, l'_{C_j,q_{j_f}} \right) \right) + w_2 \sum_{i=2}^{3} \sum_{j_t=1}^{3} x_{C_i j_t} L'_{C_i,q_{j_t}} \\ s.t. \sum_{i_s=1}^{12} x_{i_s j_t} = 1, \ \sum_{j_t=1}^{15} x_{i_s j_t} = 1, x_{i_s j_t} \in \{0,1\}, x_{i_k j_f} \in \{0,1\}, x_{C_i j_t} \in \{0,1\}. \end{cases} \tag{11}$$

Under the above-given conditions, our primary research objective is to use the improved BP neural network algorithm to solve the allocation model. On the basis of the model, the performance of the newly designed warehouse is compared with the existing conventional warehouse to verify its effectiveness and safety.

5.2. Data Analysis. Let $X = L$, so $X_j = (x_{j1}, x_{j2}, \cdots, x_{jp})$ refers to the distance from the i-th inbound point to the outbound. O_j is a 0-1 vector corresponding to real output y_j. We use the data of $L' = (L_1, L_2, \cdots, L_{10})$ as the training set, and $L = (L_1, L_2, \cdots, L_{12})$ as the testing set. The performance of the network can be determined by the test error. The smaller the error is, the better the network structure is. Then, we select a three-layer BP neural network, since there are 12 input variables, so $p = 12$. The approximate relationship of n and p is $n = 2p + 1$, so $n = 25$. So the overall BP neural Network is 12-25-12. The activation function in the hidden layer is tansig (x), the function in output layer is logsig (x). The BP algorithm has a training frequency of 5000, training target is 0.0001, and learning rate is 0.01. Given that the initial population is 50, the maximum number of iterations is 100, the crossover rate is $p_c = 0.6$, and the selection rate is $p_m = 0.001$.

Firstly, we consider the condition of $w_1 = w_2 = 0.5$. Figure 5 shows the optimal fitness value curve in the iterative process. The fitness value of each operation has a significant declining trend as the iteration number increases. It suggests that this algorithm converges smoothly to the minimum error which means that the BP-genetic algorithm can find the optimal solution successfully. Furthermore, the optimal solution can help the manager to decide on the order of the forklift. Using the BP-genetic algorithm, we can obtain the optimal solution as follows:

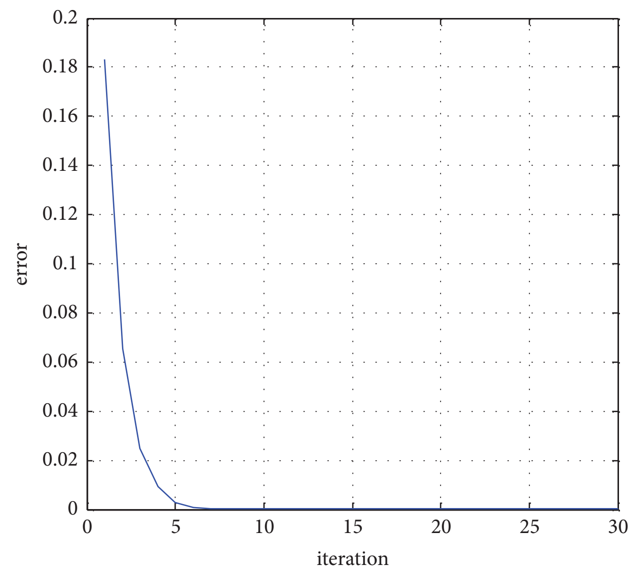

Figure 5: The trend of BP-genetic training error.

$$l^* = \begin{pmatrix} C_1 & C_1 & C_1 & C_1 & C_1 & C_1 & C_1 & C_1 & C_1 & C_1 & C_1 & C_1 \\ 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 \\ 10 & 11 & 8 & 3 & 2 & 1 & 5 & 7 & 9 & 6 & 14 & 15 \\ C_2 & C_2 & C_2 & C_2 & C_2 & C_2 & C_2 & C_3 & C_3 & C_3 & C_3 & C_3 \end{pmatrix}, \quad (12)$$

where the first row represents the inbound container truck, the second row shows the inbound position, the third row signifies the corresponding outbound position, and the last row expresses the outbound container truck. As the use of the BP-genetic neural network algorithm can obtain a solution. To further determine q_4, q_{12}, q_{13}, we measured the distance between the outbound points to the container truck, from the result. Hence, the overall running route of the forklift is

$$l^* = \begin{pmatrix} C_1 & C_1 & C_1 & C_1 & C_1 & C_1 & C_1 & C_1 & C_1 & C_1 & C_1 & C_1 & C_2 & C_2 & C_2 \\ 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 & C_2 & C_2 & C_2 \\ 10 & 11 & 8 & 3 & 2 & 1 & 5 & 7 & 9 & 6 & 14 & 15 & 4 & 12 & 13 \\ C_2 & C_2 & C_2 & C_2 & C_2 & C_2 & C_2 & C_3 & C_3 & C_3 & C_3 & C_3 & C_2 & C_2 & C_2 \end{pmatrix}. \quad (13)$$

To provide more choices to managers, it is necessary to vary the weight of different closed-loop route similarity index. Parts of the calculation results are shown in Figure 6.

It should be noted that in the process of warehousing operations, due to the high number of job orders, real-time data and contextual information are highly required. Since orders change frequently based on business needs, warehouse managers need to adjust orders on-site with reference to our solution to ensure that orders are completed on time. Next, we consider the situation of $w_1 \neq w_2$. The fitness values under different weights are obtained by adjusting the weights of route similarity and the route distance and then analyzing the overall trend. To further analyze Equation (11) with different weights, we calculate the fitness values under different value in $w_i \in (0, 1)$, $(i = 1, 2)$. The error trend sees Figure 7.

Figure 7 suggests that with the increase of w_1 and decrease of w_2, the value of error has a a declining trend. Since w_1 reflects the importance of the similarity index, w_2 reflects the importance of the route length. This shows that in the warehousing operation, and the similarity index plays an important role in the route optimization. Therefore, more attention is paid to operational safety in the warehousing management. In order to provide more choices to on-site managers, it is necessary to increase the weight of different closed-loop route similarity index in the (11). Not only it would improve the operation safety and coordinate, but also enhance the efficiency.

In this study, the effectiveness of the proposed method can be further demonstrated by adjusting the training time, and the new BP-genetic algorithm is compared with the traditional BP algorithm. The two network training results are shown in Figure 8. It can be concluded that for the same amount of training, Compared with the traditional BP network structure, the new BP-genetic network structure has the advantages of higher convergence accuracy and faster convergence speed. The results have greatly improved after using the BP neural network based on the genetic algorithm.

In conventional operation environments, considering the situation forklifts carry dangerous goods where no room can accommodate two or more forklifts, as long as safety is ensured. We assign a forklift in each warehouse to operate the materials. Therefore, there is no possibility of

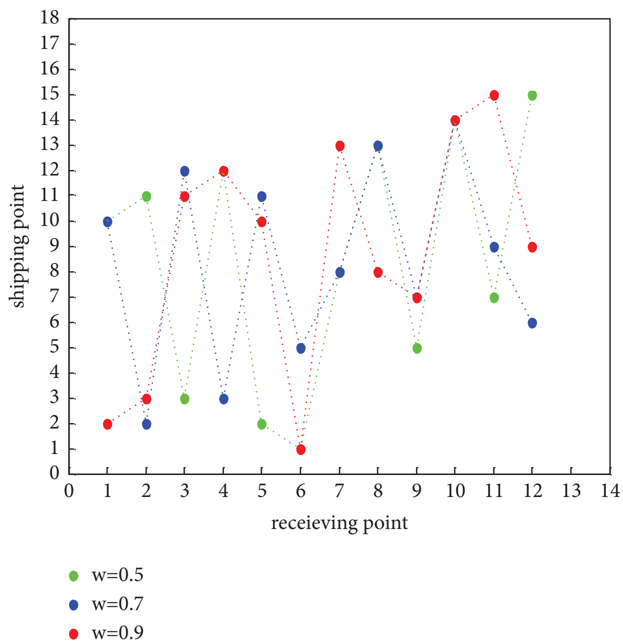

Figure 6: The shipping point of different w_1.

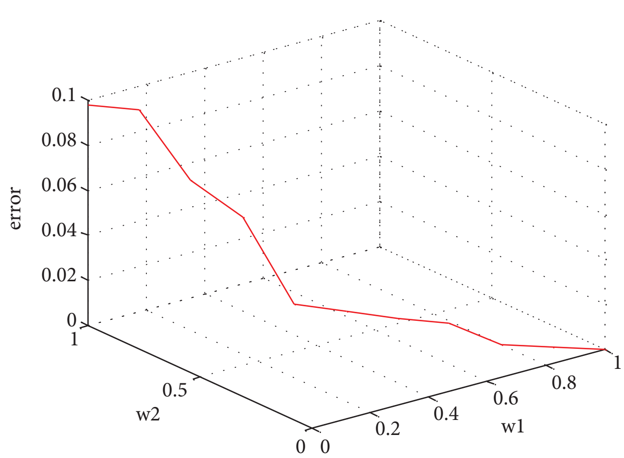

Figure 7: GA-BP training error with different weights.

overlap between forklift paths. The allocation of storage points is shown in Figure 9. The container truck would move to another convenient door after a warehousing operation finished. We assume that the forklifts would not interact with each other in a conventional double-door warehouse and interconnected warehouse. So the level of security is equal. As for the efficiency, we compared the total running time in the whole process. In the conventional warehouse, the total distance traveled by the forklift is $L = 1377$m, and the total distance traveled by the container trucks is $l'_{C_i,C_j} = 24$m. Field investigation recommends that, the speed of forklift is $v_1 = 15$km/h, and the speed of the container truck is $v_2 = 5$km/h. The number of forklifts in conventional warehouse is $e_1 = 1$. Then, it gets the time as follows:

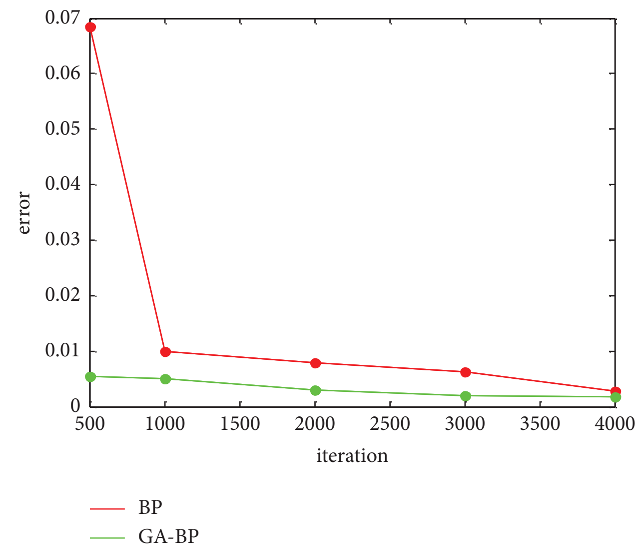

Figure 8: GA-BP VS. BP.

$$t_1 = e_1^{-1}\left(v_1^{-1}L + v_2^{-1}l_{C_i,C_j}\right) = 0.0966\text{h}. \quad (14)$$

Meanwhile, the running distance in an interconnected warehouse is obtained as $L' = 1006$m, and the total distance traveled by the container trucks is obtained as $l^*_{C_i,C_j} = 24$m, the number of forklifts in an interconnected warehouse is obtained as $e_2 = 2$. Then, it gets $t_2 = e2_1^{-1}v_1^{-1}L' = 0.068$h. Since $t_1 > t_2$, we conclude that the interconnected warehouse could increase the efficiency with ensuring operational safety.

5.3. Concluding Analysis. From the research results obtained, the effective hybrid of the genetic algorithm and BP neural network algorithm can make up for the randomness flaws from selecting the weights and thresholds in the BP model. Through fully utilizing the genetic algorithm's advantage on a global search capability and the BP's local search capabilities, the improved algorithm helps to improve the overall smart searching capacity in the network.

Overall, compared with conventional neural network algorithm, the BP-Genetic neural network algorithm converges more rapidly with higher accuracy. The disadvantages of the standard BP algorithm, including easy falling into local optimal, slowed convergence rate and caused oscillation, and so on. The genetic algorithm has a strong global search capability, so using it to complete the research algorithm can overcome the shortcoming of the BP neural network. On the other hand, until now, there are few studies using neural network algorithms to solve the quadratic assignment problem. In such a context, a novel geometric-design of the interconnected dangerous chemical warehouse is proposed, and a quadratic allocation model is constructed by considering the high level of safety and operation efficiency. Furthermore, to solve the introduced problem, a BP-Genetic neural network is proposed. Finally, the empirical study demonstrates the proposed BP-Genetic neural

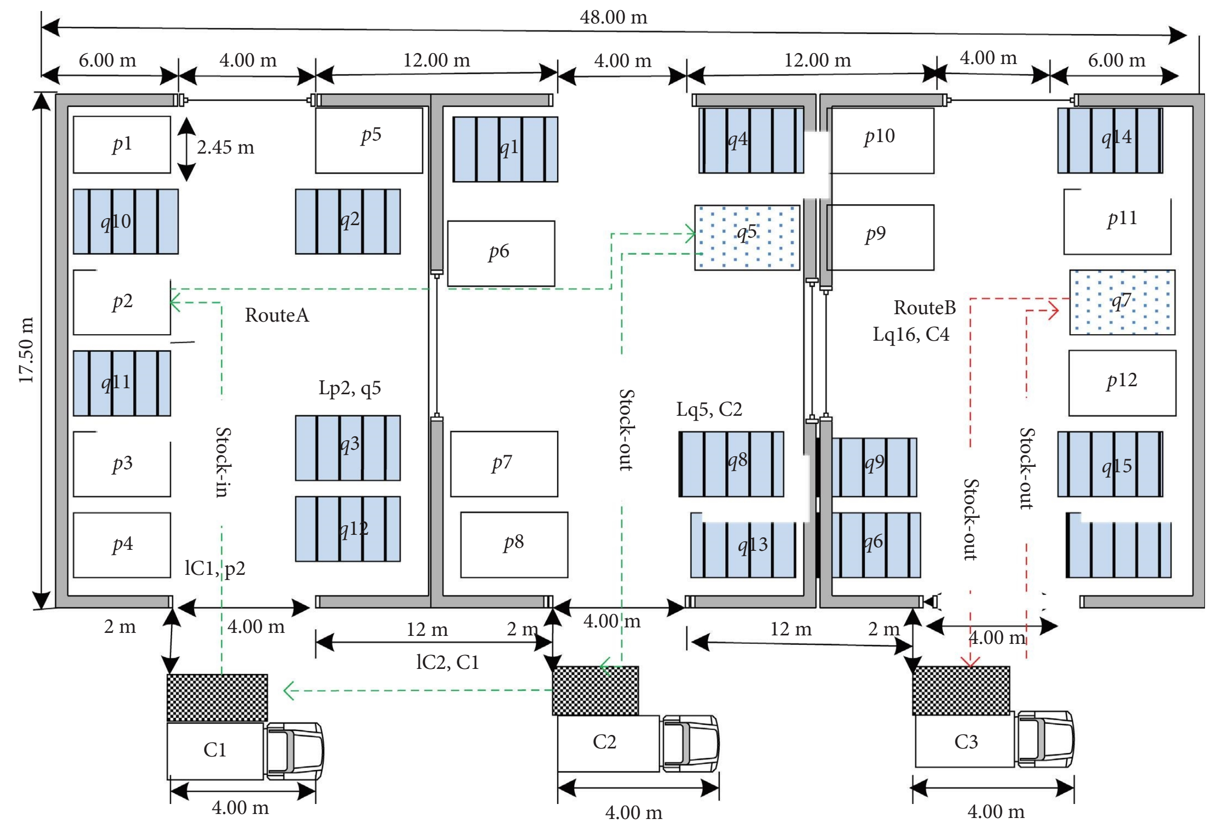

Figure 9: Schematic diagram of geometric structure of the warehouse.

network algorithm has a satisfactory performance for solving the given quadratic assignment model.

6. Conclusions

With the continuous progress of the chemical industry, the existing warehouse structure is difficult to meet the needs of the logistics industry in China. In order to provide better service to customers, and ensure the safety of the warehouse, Zhang et al. [22] proposed the interconnected dangerous goods warehouse by using an isolated door. However, the problem of operation optimization and the balance between operation cost, safety, and efficiency of interchangeable dangerous goods warehouse have not been studied at that time. Considering that this optimization problem is critical to the realistic profitability of enterprises, this study proposes a BP-genetic neural network algorithm to solve the aforementioned optimal problem. The main contributions of this study are as follows:

(1) Under the background of interconnected dangerous goods warehouse, this study puts the efficiency, cost, and safety of storage operation into a unified research framework, and abstractions a kind of multiobjective optimization problem in this novel warehouse.

(2) In order to improve operation efficiency while ensuring safety, a quadratic assignment model of path planning is constructed. This model has also considered different weights of similar index and distance and did a series of sensitivity analyses, which indicate that the similarity index plays an important role in this model.

(3) This study has considered different forklift's routes and concluded that the use of closed-loops provides the best solution, where the order of operations of the closed-loops is decided by the management team on-site. This means that the implementation of the paper's model requires better human-to-machine interactions.

(4) The study uses a BP-genetic neural network algorithm, which is simple, practical and has wide applications for future references.

(5) Based on the actual database of Shanghai Lingang Dangerous Chemicals Logistics Co., Ltd., the model is simulated in this study. The simulation results verify the validity and feasibility of the model, and the model can be widely used in the modern warehousing operation of traditional double-door warehouse with high labor intensity and large variability.

Finally, it is noteworthy that by using the proposed BP-genetic algorithm, one can get an approximate optimal solution for a path optimization problem. When one wants to generalize the proposed algorithm in other situation, the algorithm must be compared with the classical optimization algorithm in the future.

Data Availability

The data that support the findings of this study are available from the first author upon reasonable request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

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