Research on the Optimization of Automated Warehouse Storage Allocation Based on Improved Whale Algorithm

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***Abstract*—In automated warehouse, the storage space allocation strategy is one of the key factors to determine the efficiency of warehouse operation. In this paper, the mathematical models of goods circulation, shelf stability and commodity classification are established, and the multi-objective model is transformed into a single-objective model by using the analytic hierarchy process. The algorithm is based on whale algorithm, introduces the crossover and mutation, and elite differential bootstrap strategy for enhancing the population diversity, overcome the problem of the whale algorithm is liable to fall into the local convergence in the early stage, and effectively improve the accuracy of the whale population optimization search. Finally, an automated warehouse of a textile manufacturing company in Tianjin was used for experimental analysis to derive the results of cargo space optimization. The results show that the improved whale algorithm has higher quality of solution set and is more effective improvement of the goods placement.**

***Index Terms*—storage location optimization; whale optimization algorithm; combinatorial optimization; automated three-dimensional warehouse**

I. INTRODUCTION

Storage of goods plays a vital role in warehouse management systems. With the continuous development of the logistics industry and the expansion of enterprises scale, the traditional way of warehouse management has been unable to meet the needs of enterprises. Therefore, automated three-dimensional warehouse plays a key position in the enterprise, can provide efficient, safe and reliable warehousing solutions, improve the competitiveness of enterprises and operational efficiency, and play an important role in supporting the development of enterprises.

In recent years, many scholars have carried out more in-depth research on the cargo location assignment problem, and proposed many solutions. For example, Yang et al. [1]used ant colony algorithm to solve the problem with the objectives of shelf-carrying capacity and stacker cranes efficiency. Shi et al. [2]mainly considered the storage efficiency of production goods, shelf stability and classification of goods as objectives, and adopted improved genetic algorithm to solve the problem. Jiao et al. [3] used multi-population genetic algorithm to solve the mathematical model of multi-objective location allocation optimization. Dai et al. [4]focused on safety, established the model according to the rule of safe distance, and used genetic algorithm to solve it. Huang et al. [5] mapped the storage allocation problem to a knapsack problem and introduced a dynamic programming algorithm to solve it. Matej et al. [6]mainly considered the energy consumption of stacker and cargo throughput, established the corresponding warehouse optimization objective, and solved it by NSGA-II algorithm. Tabatabaei et al. [7]proposed a new storage assignment optimization algorithm SAO/FEM (storage assignment optimization technique) to meet the agility aspect of storage mechanism for automated storage and retrieval process. Yuan et al. [8] used a Two-stage hybrid algorithm combining greedy algorithm and improved simulated annealing to solve the storage allocation optimization problem for RMFS, which significantly improves the efficiency of the plant operation. Yan et al. [9] mainly considered the volumetric elements such as size and shape structure of the product and used adaptive genetic algorithm to solve the problem. Pang et al. [10]used the existence of linkages between items to optimize with the objective of minimizing the total path of storage and the total path of picking for orders in order to improve the efficiency of warehouse operations. Zhang et al. [11] used a simulated annealing method algorithm to construct a commodity combination model to minimize the combination picking path. Mirzaei et al. [12] proposed a storage allocation model for minimizing the retrieval time of parts to the picking system based on the product turnover and affinity obtained from historical customer orders.

In order to solve the above problems, this paper summarizes the common goals of storage optimization through the study of the structure layout and working characteristics of automated warehouse, including the storage efficiency of goods, shelf stability, and the classification of goods, and establishes a multi-objective optimization model for these optimization goals to obtain the relative optimal solution. At the same time, an improved whale algorithm is proposed, and the crossover operator, mutation operator and elite differential guidance strategy are introduced to improve the algorithm to realize the optimization of the cargo location assignment problem. The experimental results show that the improved whale algorithm is more effective than the original whale algorithm in the cargo location assignment problem.

Manuscript received March 25, 2024.

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II. AUTOMATED WAREHOUSE STORAGE SPACE ALLOCATION MODEL

A. Problem Description

Taking the automated warehouse of a textile manufacturing enterprise as an example, the storage location allocation of the enterprise adopts the method of manual allocation. Due to the textile variety and quantity, resulting in poor efficiency of goods in and out of the warehouse, poor stability of shelves, unreasonable allocation of cargo space, increasing the difficulty of warehouse management, easy to cause waste of warehouse resources.

This paper focuses on how to rationally allocate storage space, so that the goods in and out of the warehouse with the highest efficiency, the most stable shelves, goods categorized storage. The problem of storage space optimization is complex, and the following simplifications are needed to make the study convenient in order to scientifically and rationally carry out the storage operations of goods.

(1) The storage space is a cube of equal length in three directions.

(2) Each product can be stored in only one free space on a shelf, and only one product can be stored in each space.

(3) The dwell time of the stacker cranes when picking up and putting down goods is not taken into account.

(4) Any kind of goods can be stored in any available storage space.

B. Model symbol description

Table 1 Parameter setting of all model

Parameters	Definition
N_x, N_y, N_z	Number of rows, columns and levels of shelves
x, y, z	Row number, column number, floor number of the storage space.
n	Volume of all goods
N	All products totaling N categories
i	The ith cargo, $i \in [1, n]$
j	The ith of class j goods, $j \in [1, N]$
C_i, M_i, P_i	The type, weight, and turnover of the ith cargo
K_j	The number of goods in class j
V_x, V_y, V_z	Stacker transport speed along x, y, z direction
T_i	Inventory time of the ith shipment
(X_i, Y_i, Z_i)	Storage coordinates of the ith shipment
l, w, h	Length, width, height of unit storage spaces
p_j	Centering of goods in category j
S_i	Conveyor distance from the ith row of shelves to the exit
d_{ij}	Distance from the ith shipment of the jth class of goods to p_j

C. Turnover prioritization principle

Turnover rate can also be expressed as the frequency of goods in and out of the warehouse, the need for multiple entries and exits should be as small as possible from the warehouse entrance distance, which will shorten the picking time, to improve the speed and efficiency of the picking requirements. The objective function is expressed as follows:

$$f_1(x, y, z) = \sum_{i=1}^{n} (P_i \times T_i) \tag{2.1}$$

$$T_i = T_{ix} + \sqrt{(T_{iy})^2 + (T_{iz})^2} \tag{2.2}$$

$$x_i = \begin{cases} \left\lceil \left\lceil \dfrac{x}{2} \right\rceil \right\rceil \times H + (x \times w) & x \text{ is odd } number \\ \left\lceil \left\lceil \dfrac{x}{2} \right\rceil \right\rceil \times H + [(x-1) \times w] & x \text{ } is \text{ } even \text{ } number \end{cases} \tag{2.3}$$

$$T_{ix} = \frac{x_i}{v_x} \tag{2.4}$$

$$T_{iy} = \frac{y_i}{v_y} \tag{2.5}$$

$$T_{iz} = \frac{z_i}{v_z} \tag{2.6}$$

D. Principle of shelf stability

The improper distribution of total mass during the process of placing goods on shelves, resulting in an excessive bias towards one side of the center of gravity, may lead to shelf overturning. The shelf stability model is expressed as follows:

$$f_2(x, y, z) = \frac{\sum_{i=1}^{n} (M_i \times z_i \times d_z)}{\sum_{i=1}^{n} M_i} \tag{2.7}$$

E. Principle of similar products adjacency

When handling tasks, it is common for items of the same type to appear together, so shortening the distance between them reduces the time it takes for the stacker cranes to be dispatched repeatedly.

$$p_i = \frac{\sum_{j=1}^{K_i} (x_j, y_j, z_j)}{K_i} \tag{2.8}$$

$$d_{ij}^x = [x_{ij} - p_j(x)]^2 \tag{2.9}$$

$$d_{ij}^y = [y_{ij} - p_j(y)]^2 \tag{2.10}$$

$$d_{ij}^z = [z_{ij} - p_j(z)]^2 \tag{2.11}$$

$$d_{ij} = \sqrt{d_{ij}^x + d_{ij}^y + d_{ij}^z} \tag{2.12}$$

$$d = \sum_{i=1}^{N} \sum_{j=1}^{K_i} d_{ij} \tag{2.13}$$

$$f_3(x, y, z) = \sum_{i=1}^{N} \sum_{j=1}^{K_i} d_{ij} \tag{2.14}$$

F. Combinatorial optimization model

Through the analysis of the three objective models, the goods turnover model, the shelf stability model and the goods correlation model, the obtained multi-objective function no longer has the single direction optimal solution after the combination. Weight coefficients ω_1、ω_2、ω_3 are given by analytic hierarchy process[13].Combining three objective functions, we obtain the goods location assignment model as follows:

$$f(x,y,z)=\omega_1 f_1+\omega_2 f_2+\omega_3 f_3 \tag{2.15}$$

The constraint objective is as follows:

$$\begin{cases}\omega_1+\omega_1+\omega_1=1\\ 0\le\omega_1\le 1, 0\le\omega_2\le 1, 0\le\omega_3\le 1\end{cases} \tag{2.16}$$

III. ALGORITHM DESIGN

A. Whale Optimization Algorithm

Whale optimization algorithm (WOA) [14] is a swarm intelligence optimization algorithm proposed by Australian scholar Mirjalili et al. The core of the algorithm mainly contains three aspects as follows: encompassing contraction stratagem, bubble-net assaulting stratagem and random hunting stratagem.

(1) Encompassing Contraction Strategy

In the process of feeding, the whale first looks for the prey to determine its location, and when it is close to the prey, it contracts and surrounds the prey. The location is communicated as follows:

$$\vec{D}=\left|\vec{C}\times\overrightarrow{X_t^*}-\overrightarrow{X_t}\right| \tag{3.1}$$

$$\overrightarrow{X_{t+1}}=\overrightarrow{X_t^*}-\vec{A}\times\vec{D} \tag{3.2}$$

$$\vec{A}=2\vec{a}\vec{r}-\vec{a} \tag{3.3}$$

$$\vec{C}=2\vec{r} \tag{3.4}$$

$$\vec{a}=2-2\times\frac{t}{T_{\max}} \tag{3.5}$$

where t denotes the current iteration number; A 和 C are distance adjustment parameters; $\overrightarrow{X_t}$ denotes the current position vector, $\overrightarrow{X_t^*}$ denotes the optimal position vector obtained so far, and $\vec{r}$ denotes random number vector between 0 and 1; $\vec{a}$ is an arbitrary value that diminishes gradually from 2 to 0; T_{max} is the maximum number of iterations.

(2) Bubble-Net Assaulting Strategy

The whale moves upstream in a spiral path, updating its position, spitting bubbles of different sizes, and narrowing the enclosing circle to capture prey. Assume that the shrinking bounding mechanism and the spiral updating each have a 50% chance of updating the position of the whale search individual. The location is communicated as follows:

$$\overrightarrow{X_{t+1}}=\begin{cases}\overrightarrow{X_t^*}-\vec{A}\times\vec{D} & p<0.5\\ \overrightarrow{D'}\times e^{bl}\times\cos(2\pi l)+\overrightarrow{X_t^*} & p\ge 0.5\end{cases} \tag{3.6}$$

where p denotes an arbitrary value between 0 and 1, $\overrightarrow{D'}$ denotes the length between the existing whale and the target prey, l denotes an arbitrary value $[-1,1]$, and b denotes a logarithmic spiral value.

(3) Random Hunting Strategy

During hunting, whales also randomly change their position based on the positions of other whales, thus expanding the search range for better prey. The location is communicated as follows:

$$\vec{D}=\left|\vec{C}\times\overrightarrow{X_{rand}}-\overrightarrow{X_t}\right| \tag{3.7}$$

$$\overrightarrow{X_{t+1}}=\overrightarrow{X_{rand}}-\vec{A}\times\vec{D} \tag{3.8}$$

where $\overrightarrow{X_{rand}}$ denotes an arbitrary location vector or search agent.

B. Improved whale algorithm for location assignment

(1) Coding

The article employs a decimal encoding method and devises a three-dimensional mapping coding approach to effectively illustrate the solution. In computations, Gaussian rounding is employed for any encountered floating-point numbers. The positional structure of i whales is $X_i=\{T_1,T_2,T_3,\dots,T_n\}$, Cargo sequence order fixed is $S=\{S_1,S_2,S_3,\dots,S_n\}$,Cargo position sequence is $L=\{L_1,L_2,L_3,\dots,L_n\}$, each whale represents a specific scenario for depot allocation.

(2) Crossover and mutation

In the flow of the whale algorithm, as the number of iterations increases, the proportion of $|A|>1$ is decreasing, which leads to a decreasing global search capability of the whale population thus making the algorithm converge prematurely[15]. The objective of this paper is to enhance the global search range and population diversity in the later stage of the whale algorithm by incorporating the crossover and mutation strategies from genetic algorithms[16, 17], thereby mitigating the issue of getting trapped in local optima.

(a) Crossover operator

The crossover step in genetic algorithms refers to the selection of two good parents for the crossover operation, which has a chance of generating even better offspring. However, partial matching crossover in genetic algorithm is to randomly select two bodies from the parent, randomly select two points and extract the part between the two points, and put them in the same position of the offspring respectively. This does generate new children, but it is not clear whether all the nodes in the child still satisfy the constraint[18]. To improve the genetic operator, the specific steps are as follows:

Step1: Two parents are randomly drawn from the generated current population, named parent P1 and parent P2.

Step2: Check if the crossover of two parents yields a valid zygote chromosome, after the crossover if there is a duplicate number in the chromosome it is an invalid solution. If it is an invalid zygotic chromosome, this crossover is ignored.

Step3: If parent crossover to get valid zygotic chromosomes and the zygotic chromosomes all satisfy the constraint relationship, then a random starting position i between 0 and n is given, which corresponds to exchanging the positions of the two sets of genes in the group of $[i,n]$ to ensure that the new pair of zygotic genes formed is free of conflict.

(b) Mutation operator

The mutation operation is inspired by the phenomenon of genetic mutation, through which it can enable the algorithm to search towards a new solution space, which facilitates the global search of the algorithm [19]. The general mutation method is to randomly select gene loci for mutation, but considering the possibility of gene loci duplication, the mutation arithmetic is improved as follows:

Step1: Randomly select a location $L1$, which has a current value of m, to generate a random number r in the range $[1, n]$.

Step2: If there does not exist a gene encoding r in this chromosome except for the gene at L1 position, the gene at L1 position is directly replaced by r. Otherwise, the interval $[m, n]$ or $[m, n]$ is formed according to the interval, and the interval random search value replacement is performed on it.

(3) Elite differential guidance strategy

In the WOA algorithm, the generation of the global optimal position depends on the current best individual of the whale swarm after multiple iterations. The population continuously moving closer to the prey position, but neglects the influence of other individuals on the globally optimal solution and has difficulty escaping in the face of local extremes[20, 21]. Therefore, in order to effectively improve the accuracy of whale population optimization, this paper proposes an information-guided strategy to improve the determination of the global optimal position. As shown in equations (3.9), (3.10), and (3.11):

$$\overrightarrow{X_{t1}} = \overrightarrow{X_t^*} + F \times (\overrightarrow{X_m} + \overrightarrow{X_n}) \tag{3.9}$$

$$\overrightarrow{X_{t2}} = \overrightarrow{X_t} + F \times (\overrightarrow{X_m} + \overrightarrow{X_n}) \tag{3.10}$$

$$F = \omega \times (1 - \frac{t}{T_{\max}}) \tag{3.11}$$

The variation factor F determines the population individual difference step size and affects the search for the optimal solution of the algorithm. To avoid the premature convergence characteristic of the whale algorithm, an adaptive scaling factor is used. Increasing the solution space of the algorithm in the pre iteration period increases the population diversity and facilitates the algorithm to search for the optimal solution, and increasing the development capability of the algorithm in the late iteration period increases the convergence speed of the algorithm. $\overrightarrow{X_t^*}$ represents the optimal position of whales so far, $\overrightarrow{X_l}$ 、 $\overrightarrow{X_m}$ 、 $\overrightarrow{X_n}$ denote the optimal position, the suboptimal position, and the optimal position of the current population, respectively. Although the elite differential bootstrapping strategy maximizes the mining of prey positions and effectively reduces the possibility of premature maturation of the algorithm in the later stages of the iteration, it is not possible to determine whether the new position obtained after information bootstrapping is better than the fitness value of the original position. Therefore, the greedy rule is introduced[22], as shown in Equation (3.12).

$$\overrightarrow{X_t^*} = \begin{cases} \overrightarrow{X_t^*}, \max(F(\overrightarrow{X_t^*}), F(\overrightarrow{X_{t1}}), F(\overrightarrow{X_{t2}})) \\ \overrightarrow{X_{t1}}, \max(F(\overrightarrow{X_t^*}), F(\overrightarrow{X_{t1}}), F(\overrightarrow{X_{t2}})) \\ \overrightarrow{X_{t2}}, \max(F(\overrightarrow{X_t^*}), F(\overrightarrow{X_{t1}}), F(\overrightarrow{X_{t2}})) \end{cases} \tag{3.12}$$

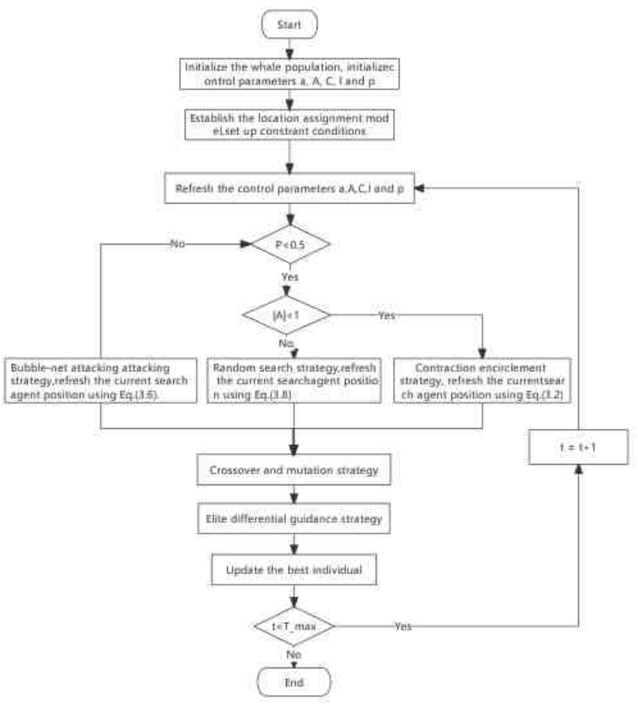


Fig.1 Algorithm flowchart of GDWOA

IV. EXPERIMENT SIMULATION AND ANALYSIS

A. Simulation Analysis

In this paper, the improved whale algorithm is simulated with MATLAB2022b on Intel (R) Core (TM) i5-13500H CPU @ 2.30GHz processor. In order to verify the effectiveness and stability of the model and algorithm, the system parameters are set as follows: the capacity of the warehouse is 400 fixed cargo grids, the length, width and height of the storage position are 1m, and the running speed of the stacker in the x axis, y axis and z axis is $2m/s$, $1m/s$ and $0.6m/s$, respectively.

B. Cargo data

The experiment selected a textile manufacturing enterprise of a certain order warehousing task information, the order information is a total of 11 categories of goods, a total of 60 to be warehoused goods, the initial information shown in Table II.

C. Simulation results of products assignment

In this paper, Genetic Algorithm (GA), Differential Evolution algorithm (DE) [23], Grey Wolf Algorithm (GWO) [24], Whale Algorithm (WOA) and Improved whale Algorithm (GDWOA) are implemented for the storage location assignment problem, and the parameters are optimized, and then used to solve the problem. The parameters of the algorithm are shown in Table I. Each optimization direction can be used as three performance indexes to verify the optimization degree of the model. The data in Table II are optimized by GA, DE, GWO, WOA and GDWOA respectively, and the 3D simulation results and the values of each index are given. From Figures 2 to 6, it can be seen that the positions of goods calculated by GDWOA are more in line with the arrangement rule of "upper light and lower weight". Goods of the same type are scattered in different rows of shelves, and in the same row of shelves, they are arranged more closely and orderly in a clustered state. Table III shows the solution results of each objective function of each algorithm, and Figs. 8, 9, and 10 show the algorithm iteration diagrams of the three performance indicators of each algorithm.

Table I Parameter setting of all algorithms

Algorithms	Optimization parameters	Values
GA	Initial population size	50
	Iteration number of GA	500
	Crossover probability	[0.5,0.8]
	Mutation probability	[0.01,0.1]
DE	Initial population size	50
	Iteration number of GA	500
	Crossover probability	[0.5,0.8]
	Mutation probability	[0.01,0.1]
GWO	Convergence factor a	[0,2]
	An arbitrary number $r1$	[0,1]
	An arbitrary number $r2$	[0,1]
WOA	An arbitrary number r	[0,1]
	Convergence factor a	[0,2]
	Constant coefficient b	1
	An arbitrary number l	[-1,1]
	An arbitrary number p	[0,1]
GDWOA	An arbitrary number r	[0,1]
	Convergence factor a	[0,2]
	Constant coefficient b	1
	An arbitrary number l	[-1,1]
	An arbitrary number p	[0,1]
	Crossover probability	[0.5,0.8]
	Mutation probability	[0.01,0.1]

Table II Storage task information

No.	M	P	C	No.	M	P	C	No.	M	P	C
1	48	0.83	1	21	50.3	0.85	4	41	70.5	0.35	8
2	43	0.67	1	22	53.7	0.94	4	42	76.7	0.85	8
3	41.2	0.92	1	23	16.3	0.21	4	43	80.7	0.34	8
4	45	0.48	1	24	39.3	0.77	4	44	90	0.13	9
5	53	0.61	1	25	19	0.95	5	45	92.3	0.65	9
6	71.5	0.92	1	26	13	0.88	5	46	95.5	0.48	9
7	50.7	0.66	2	27	39	0.46	6	47	34	0.77	9
8	64.2	0.75	2	28	56.6	0.33	6	48	43.8	0.66	9
9	51	0.91	2	29	37.6	0.94	6	49	29.3	0.59	9
10	68.9	0.47	2	30	38.5	0.65	6	50	9.5	0.74	10
11	27.5	0.61	3	31	46	0.45	7	51	4.3	0.34	10
12	31	0.72	3	32	77	0.57	7	52	18	0.13	10
13	36.7	0.65	3	33	57.2	0.92	7	53	14.3	0.11	10
14	57	0.95	3	34	84.5	0.78	7	54	37.3	0.77	10
15	38.8	0.75	3	35	42	0.31	7	55	98	0.35	10
16	34.5	0.78	3	36	62.5	0.76	8	56	51	0.78	11
17	41	0.75	3	37	64.7	0.93	8	57	59	0.46	11
18	51.8	0.64	3	38	68.2	0.64	8	58	14.8	0.33	11
19	67.3	0.51	4	39	71	0.91	8	59	94.5	0.94	11
20	37.5	0.84	4	40	73.2	0.34	8	60	70.5	0.85	11

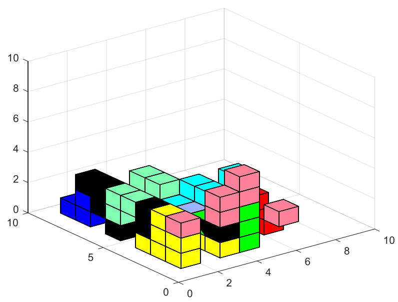


Fig.3 Optimized storage state of GDWOA

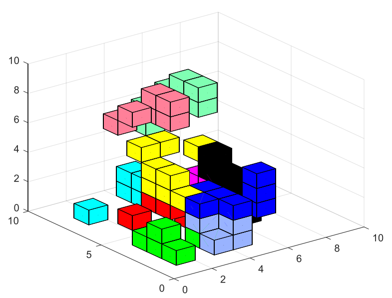
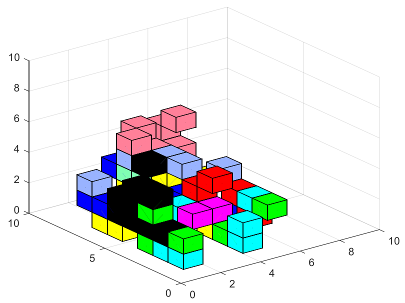


Fig. 4 Optimized storage state of WOA



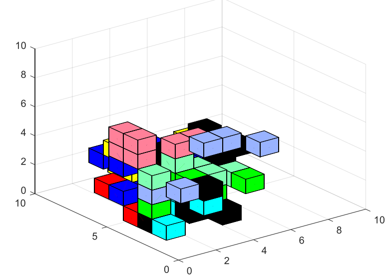


Fig. 5 Optimized storage state of GWO Fig. 6 Optimized storage state of GA

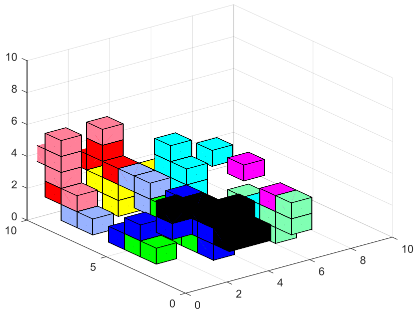


Fig. 6 Optimized storage state of DE

Table III Solution results

functions	GA	DE	GWO	WOA	GDWOA
f	133.9	144.9	135.5	133.9	102.6
f_1	292.4	339.1	287.5	296.2	259.2
f_2	122	144	121	134	41
f_3	77.5	74.5	83	74.9	58.3

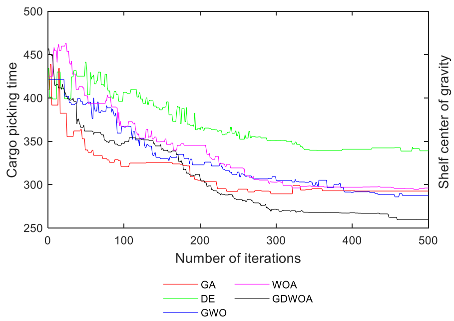


Fig.8 Cargo picking time iteration

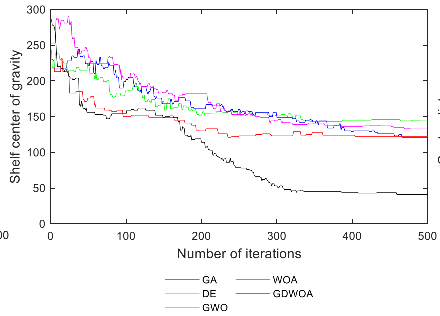


Fig.9 Shelf center of gravity iteration

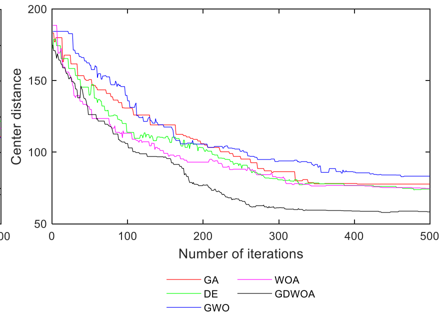


Fig.10 Cargo center distance iteration

The non-uniqueness of the whale algorithm's result necessitates conducting experiments to assess its stability and prevent exceptional cases. The optimization solution was performed 20 times for the above warehousing task, and the mean value of f was calculated every 5 experiments, and the test results are shown in Table IV.

Table IV Algorithm mean values for different number of experiments

Number	GA	DE	GWO	WOA	GDWOA
5	133.4	131.8	132.5	121.5	105.6
10	133.1	136.3	135.4	123.1	105.8
15	135.4	128.9	133.6	124.8	105.5
20	132.4	132.2	133.9	125.7	104.9

Table V Standard deviation of the algorithm for different number of experiments

Number	GA	DE	GWO	WOA	GDWOA
5	3.1	2.5	3.4	2.1	1.9
10	3.7	4.1	4.7	2.8	2.5
15	4.5	6.4	5.8	4.7	4.1
20	6.1	7.8	6.2	5.9	5.3

It is clear from Table IV and Table V that GA, DE, GWO, WOA and GDWOA can obtain the following conclusions after different times of experiments: GDWOA has the lowest average value, the lowest standard deviation, and the best comprehensive performance.

The accuracy of the algorithm solution is paramount in the field of engineering. When comparing the performance of the three algorithms throughout the experiment, GDWOA demonstrates.

V. CONCLUSION

This paper studies the storage location allocation problem of automated warehouse, and establishes a joint model optimization based on improved whale algorithm with the goal of goods turnover rate, shelf stability and goods classification status. In the process of problem optimization, this paper proposes an improved whale algorithm, which discretized the problem, and introduced the crossover mutation and elite differential guidance strategy to improve the population diversity and overcome the problem of local convergence in the early stage of whale algorithm. The algorithm comparison experiment demonstrates, through stereo simulation, index data analysis, and iterative curve evaluation, that the improved whale algorithm exhibits superior optimization effects compared to other algorithms. It significantly enhances the efficiency of goods in and out of storage while improving shelf stability by arranging similar goods adjacent to each other. The aforementioned method demonstrates its capability to fulfill the requirements of intelligent distribution in automated warehouses, thereby facilitating the overall development of enterprise operations and enabling modern management.

REFERENCES

[1] YANG D, WU Y, MA W J M, et al. Optimization of storage location assignment in automated warehouse [J]. 2021, 80: 103356

[2] SHI W, TIAN Y, WANG S, et al. Research on Storage Allocation Strategy of Automated Warehouse Based on Improved Genetic Algorithm; proceedings of the 2022 11th International Conference of

Information and Communication Technology (ICTech)), F, 2022 [C]. IEEE.
[3] JIAO Y-L, XING X-C, ZHANG P, et al. Multi-objective storage location allocation optimization and simulation analysis of automated warehouse based on multi-population genetic algorithm [J]. 2018, 26(4): 367-77.
[4] DAI B, LI Y F, REN H S, et al. Research on Optimization for Safe Layout of Hazardous Chemicals Warehouse Based on Genetic Algorithm; proceedings of the 10th IFAC Symposium on Advanced Control of Chemical Processes (ADCHEM), Shenyang, PEOPLES R CHINA, F Jul 25-27, 2018 [C]. 2018.
[5] HUANG Q, XIE S, LIU G. Storage Allocation Algorithm with Multi-Objective Optimization in High-Density Tridimensional Warehouse; proceedings of the 2019 6th International Conference on Systems and Informatics (ICSAI), F, 2019 [C]. IEEE.
[6] BOROVINŠEK M, EKREN B Y, BURINSKIENĖ A, et al. Multi-objective optimisation model of shuttle-based storage and retrieval system [J]. 2017, 32(2): 120-37.
[7] TABATABAEI S-K, VALILAI O F, ABEDIAN A, et al. A novel framework for storage assignment optimization inspired by finite element method [J]. 2021, 7: e378.
[8] YUAN R, LI J, WANG W, et al. Storage Assignment Optimization in Robotic Mobile Fulfillment Systems [J]. 2021, 2021: 1-11.
[9] YAN B, YAN C, LONG F, et al. Multi-objective optimization of electronic product goods location assignment in stereoscopic warehouse based on adaptive genetic algorithm [J]. 2018, 29: 1273-85.
[10] PANG K-W, CHAN H-L J I J O P R. Data mining-based algorithm for storage location assignment in a randomised warehouse [J]. 2017, 55(14): 4035-52.
[11] ZHANG R-Q, WANG M, PAN X J C, et al. New model of the storage location assignment problem considering demand correlation pattern [J]. 2019, 129: 210-9.
[12] MIRZAEI M, ZAERPOUR N, DE KOSTER R J T R P E L, et al. The impact of integrated cluster-based storage allocation on parts-to-picker warehouse performance [J]. 2021, 146: 102207.
[13] KORDOS M, BORYCZKO J, BLACHNIK M, et al. Optimization of warehouse operations with genetic algorithms [J]. 2020, 10(14): 4817.
[14] MIRJALILI S, LEWIS A J A I E S. The whale optimization algorithm [J]. 2016, 95: 51-67.
[15] MOSTAFA BOZORGI S, YAZDANI S J J O C D, ENGINEERING. IWOA: An improved whale optimization algorithm for optimization problems [J]. 2019, 6(3): 243-59.
[16] KATOCH S, CHAUHAN S S, KUMAR V J M T, et al. A review on genetic algorithm: past, present, and future [J]. 2021, 80: 8091-126.
[17] WANG W, GAO J, GAO T, et al. Optimization of automated warehouse location based on genetic algorithm; proceedings of the 2017 2nd International Conference on Control, Automation and Artificial Intelligence (CAAI 2017), F, 2017 [C]. Atlantis Press.
[18] HASSANAT A, ALMOHAMMADI K, ALKAFAWEEN E A, et al. Choosing mutation and crossover ratios for genetic algorithms—a review with a new dynamic approach [J]. 2019, 10(12): 390.
[19] LIM S M, SULTAN A B M, SULAIMAN M N, et al. Crossover and mutation operators of genetic algorithms [J]. 2017, 7(1): 9-12.
[20] CHAKRABORTY S, SAHA A K, SHARMA S, et al. A hybrid whale optimization algorithm for global optimization [J]. 2023, 14(1): 431-67.
[21] ABD ELAZIZ M, LU S, HE S J E S W A. A multi-leader whale optimization algorithm for global optimization and image segmentation [J]. 2021, 175: 114841.
[22] CHAKRABORTY S, SAHA A K, CHAKRABORTY R, et al. An enhanced whale optimization algorithm for large scale optimization problems [J]. 2021, 233: 107543.
[23] ALI M, SIARRY P, PANT M J E J O O R. An efficient differential evolution based algorithm for solving multi-objective optimization problems [J]. 2012, 217(2): 404-16.
[24] LIU J, YANG Z, LI D J E S W A. A multiple search strategies based grey wolf optimizer for solving multi-objective optimization problems [J]. 2020, 145: