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Optimization of Storage Location Allocation in Automated Warehouses Based on an Improved Spider Wasp Optimization Algorithm

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***Abstract*—Automated storage and retrieval systems (AS/RS) have been widely adopted in modern logistics systems due to their high space utilization efficiency and intelligent management capabilities. However, traditional storage location assignment strategies often fail to adequately consider factors such as rack stability, stacker crane energy consumption, and operational time, leading to reduced warehousing efficiency. Therefore, optimizing warehouse operational efficiency has become a key research focus.**

This study addresses the storage location assignment problem (SLAP) in AS/RS, aiming to optimize rack stability, stacker crane energy consumption, and operational time. An improved spider wasp optimization algorithm (SWOA) is proposed to solve this optimization problem. First, Gaussian chaotic mapping is employed to enhance initial population diversity, improving the algorithm's global search capability. Second, an adaptive weight-based Gaussian disturbance strategy is introduced to refine the population update mechanism, thereby enhancing convergence accuracy. Finally, an opposition-based learning elite retention strategy is adopted to strengthen the preservation of global optimal solutions. Experimental results demonstrate that the proposed method significantly improves the optimization performance of storage location assignment.

***Index Terms*—stacker crane energy consumption, automated warehouse, Storage location assignment, spider wasp optimization algorithm.**

I. INTRODUCTION

With the accelerated progression of global economic development, the modern logistics industry, as a vital component of global supply chains, is undergoing unprecedented transformation and upgrading. In the optimization research of automated storage and retrieval systems (AS/RS), the strategic optimization of storage location allocation under complex operational environments remains one of the key challenges affecting warehouse operational efficiency and economic performance.

The evaluation of storage location allocation schemes has been demonstrated across multiple dimensions. Jun Zhang et al.[1] investigated the item storage allocation problem in robotic mobile fulfillment systems, establishing a multi-objective optimization model that considers robotic picking efficiency and order picker energy consumption. They proposed an improved knee point-driven evolutionary algorithm to solve this model, and comparative experiments with NSGA-II and KnEA algorithms demonstrated the effectiveness of the improved algorithm and model. S. Hsieh et al.[2] introduced a bill-of-materials (BOM)-based classified storage assignment strategy. To validate its effectiveness, the researchers compared it with random storage allocation methods, confirming its capability to enhance AS/RS performance. Feng S et al.[3] developed a mathematical model for storage location allocation with the objectives of rack stability and goods arrival time, solving it via a genetic algorithm. The optimized solution significantly improved both rack stability and storage efficiency. Dong Yang et al.[4] established an automated warehouse storage model targeting rack stability and operational efficiency, which was solved using a genetic algorithm. H Li et al. [5] formulated a large-scale multi-objective optimization model for storage location allocation, focusing on efficiency, rack stability, and stacker crane load balancing. They proposed an enhanced vortex search algorithm (FDVSA) with a novel repair strategy to handle complex constraints. Validation on IEEE CEC2010 and CEC2013 benchmark sets, along with real-world case studies, demonstrated superior optimization performance in terms of solution efficiency and stability. Chen G et al. [6] aimed to improve inventory turnover and operational efficiency in power enterprise warehouses, proposing a multi-objective optimization model for storage allocation. A coefficient-of-variation-based adaptive differential evolution algorithm was applied, with simulation results showing enhanced convergence speed and improvements in turnover efficiency, rack stability, and inventory classification management.ZHANG R Q[7] introduced the Demand Correlation Pattern (DCP) to describe item correlations and constructed a dynamic storage location allocation model, solved via an enhanced simulated annealing algorithm. Mirzaei M[8] established a storage assignment model to minimize part retrieval time to the picking system by integrating product turnover rates and affinity derived from historical customer orders.

In summary, this study contributes to the field by incorporating multiple objectives—such as the dynamic acceleration/deceleration process of stacker cranes, energy consumption, and rack center of gravity—into the warehouse optimization model, while also considering humidity-sensitive material storage requirements. These advancements promote the intelligent and efficient development of AS/RS at both theoretical and practical levels, demonstrating significant academic value and broad application prospects.

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II. AUTOMATED WAREHOUSE STORAGE SPACE ALLOCATION MODEL

A. Problem Description

This chapter primarily optimizes the energy consumption of stacker cranes through three key aspects: rack stability, total stacker crane operation duration, and energy expenditure. Considering the operational realities of stacker cranes, distinct acceleration and deceleration parameters are established for both vertical and horizontal movements to accurately simulate their motion dynamics. Given the complexity of storage location optimization, the study implements the following model simplifications to better reflect real-world automated warehouse operations:

(1) Each item is stored individually in a designated rack location, with each location accommodating only one item at any given time.

(2) The stacker crane transports only one item per operation, with load weight effects on velocity being disregarded during movement.

(3) Time consumption during load handling operations is neglected.

(4) The inherent weight impact of racks on their structural stability is excluded from consideration.

B. Model symbol description

Table 1 Parameter setting of all model

Parameter	Definition
p, q, n	Number of rows, columns and levels of shelves
x, y, z	Row number, column number, floor
a_x, a_y, a_z	Triaxial acceleration parameters
d_x, d_y, d_z	Triaxial deceleration parameters
$V^x_{max}, V^y_{max}, V^z_{max}$	Maximum triaxial velocities of stacker crane
μ_x, μ_y, μ_z	Dynamic friction coefficient
S^x_a, S^y_a, S^z_a	Constant-acceleration travel distance
S^x_d, S^y_d, S^z_d	Constant-deceleration travel distance
g	Gravitational constant
M	weight of stacker crane pallet
m_i	Weight of the i-th cargo unit
i	the i-th cargo unit
(X_i, Y_i, Z_i)	Location of the i-th cargo unit
$\omega_1, \omega_2, \omega_3$	Pareto weights

C. Stability-prioritization principle

In automated warehouses, failure to adhere to the "heavy items at bottom, light items on top with balanced distribution" principle when arranging storage locations may lead to loss of rack stability and potential collapse, consequently triggering safety incidents. Therefore, to ensure rack stability, it is essential to maintain a low center of gravity with uniform load distribution. The objective function for calculating the rack's center of gravity is formulated as follows:

$$f_1 = \frac{\sum_{i=1}^{p}\sum_{j=1}^{q}\sum_{k=1}^{n} m_{ijk}{}^2 (jL_z - L_z/2)}{\sum_{i=1}^{p}\sum_{j=1}^{q}\sum_{k=1}^{n} m_{ijk}} \tag{2.1}$$

D. Principle of stacker crane runtime optimization

The motion pattern of the stacker crane in the column, tier, and row directions is determined by its travel distances along these three axes. Based on fundamental kinematic equations, the time required for the stacker crane to complete a single storage operation is calculated as follows:

$$S^x_{\lim} = \frac{(V^x_{\max})^2}{2}\left(\frac{1}{a^x} + \frac{1}{d^x}\right) \tag{2.2}$$

$$S^y_{\lim} = \frac{(V^y_{\max})^2}{2}\left(\frac{1}{a^y} + \frac{1}{d^y}\right) \tag{2.3}$$

$$S^z_{\lim} = \frac{(V^z_{\max})^2}{2}\left(\frac{1}{a^z} + \frac{1}{d^z}\right) \tag{2.4}$$

$$t^x_{\mathrm{I}} = t^x_a + t^x_d = \sqrt{\frac{2S^x d^x}{a^x(a^x + d^x)}} + \sqrt{\frac{2S^x d^x}{d^x(a^x + d^x)}} \tag{2.5}$$

$$t^y_{\mathrm{I}} = t^y_a + t^y_d = \sqrt{\frac{2S^y d^y}{a^y(a^y + d^y)}} + \sqrt{\frac{2S^y d^y}{d^y(a^y + d^y)}} \tag{2.6}$$

$$t^z_{\mathrm{I}} = t^z_a + t^z_d = \sqrt{\frac{2S^z d^z}{a^z(a^z + d^z)}} + \sqrt{\frac{2S^z d^z}{d^z(a^z + d^z)}} \tag{2.7}$$

$$t^x_{\mathrm{II}} = t^x_a + t^x_d + t^x_{\text{匀速}} = \frac{V^x_{\max}}{a^x} + \frac{V^x_{\max}}{d^x} + \frac{S^x - S^x_{\lim}}{V^x_{\max}} \tag{2.8}$$

$$t^y_{\mathrm{II}} = t^y_a + t^y_d + t^y_{\text{匀速}} = \frac{V^y_{\max}}{a^y} + \frac{V^y_{\max}}{d^y} + \frac{S^y - S^y_{\lim}}{V^y_{\max}} \tag{2.9}$$

$$t^z_{\mathrm{II}} = t^z_a + t^z_d + t^z_{\text{匀速}} = \frac{V^z_{\max}}{a^z} + \frac{V^z_{\max}}{d^z} + \frac{S^z - S^z_{\lim}}{V^z_{\max}} \tag{2.10}$$

$$t^x = \begin{cases} t^x_{\mathrm{I}}, S^x < S^x_{\lim} \\ t^x_{\mathrm{II}}, S^x \geqslant S^x_{\lim} \end{cases} \tag{2.11}$$

$$t^y = \begin{cases} t^y_{\mathrm{I}}, S^y < S^y_{\lim} \\ t^y_{\mathrm{II}}, S^y \geqslant S^y_{\lim} \end{cases} \tag{2.12}$$

$$t^z = \begin{cases} t^z_{\mathrm{I}}, S^z < S^z_{\lim} \\ t^z_{\mathrm{II}}, S^z \geqslant S^z_{\lim} \end{cases} \tag{2.13}$$

$$f_2 = \sum_{i=1}^{n} (t^x_i + \max(t^y_i + t^z_i)) \tag{2.14}$$

E. Stacker crane energy optimization principle

Under the law of conservation of energy, the energy consumed by the stacker crane during storage operations is converted into: 1) the energy required for uniformly accelerated motion, 2) the energy needed to overcome frictional forces, and 3) the energy required to counteract gravitational forces. The formula for calculating the energy consumption per unit weight during the stacker crane's operation is presented below.

$$e_1^x = \frac{2S^x a^x d^x}{a^x + d^x} + \mu^x g S_a^x + \min[(\mu^x g S_d^x - \frac{1}{2}(V_1^x)^2), 0] \quad 2.15$$

$$e_1^y = \frac{S^y a^y d^y}{a^y + d^y} + \mu^y g S_a^y + \min[(\mu^y g S_d^y - \frac{1}{2}(V_1^y)^2), 0] \quad 2.16$$

$$e_{\text{II}}^x = a^x S_a^x + d^x S_d^x + \mu^x g S^x \quad 2.17$$

$$e_{\text{II}}^y = a^y S_a^y + d^y S_d^y + \mu^y g S^y \quad 2.18$$

$$e^{z1} = (1+\mu^z) g S^z \quad 2.19$$

$$e^{z2} = (1-\mu^z) g S^z \quad 2.20$$

$$e^{z1} = (1+\mu^z) g S^z \quad 2.21$$

$$e^{z2} = (1-\mu^z) g S^z \quad 2.22$$

$$f_3 = \sum_{i=1}^{N} [2M(e^x + e^y) + M(e^{z1} + e^{z2}) + m_i(e^x + e^y + e^{z1})] \quad 2.23$$

F. Combinatorial optimization model

Through the analysis of three objective models—shelf stability, stacker crane operation duration, and energy consumption—the resulting multi-objective function no longer possesses a single-direction optimal solution after integration. The weighting coefficients were determined via the Analytic Hierarchy Process (AHP) [9].Combining three objective functions, we obtain the goods location assignment model as follows:

$$F = \omega_1 f_1 + \omega_2 f_2 + \omega_3 f_3 \quad 4.24$$

$$\omega_1 + \omega_2 + \omega_3 = 1 \quad 4.25$$

III. ALGORITHM DESIGN

A. Spider Wasp Optimizer

The Spider Wasp Optimization (SWO) algorithm is a metaheuristic optimization approach proposed by Mohamed Abdel-Basset et al. This biologically inspired algorithm emulates the behavioral patterns exhibited by female spider wasps during species propagation, including: foraging behavior, pursuit-evasion dynamics, nest-building strategies, and mating mechanisms.

(1) Search Behavior

This phase emulates the female spider wasp's stochastic search behavior within the solution space, employing either fixed-step or adaptive-step strategies to locate optimal host spiders for larval parasitism. The position update mechanism governing this randomized search paradigm is formulated as follows:

$$SW_i^{t+1} = SW_i^t + \mu_1 \times (SW_a^{\ t} - SW_b^{\ t}) \quad 3.1$$

$$\mu_1 = r_n \times r_1 \quad 3.2$$

$$SW_i^{t+1} = SW_c^{\ t} + \mu_2 \times (L + r_2 \times (H - L)) \quad 3.3$$

$$\mu_2 = B \times \cos(2\pi l) \quad 3.4$$

$$B = \frac{1}{1+e^l} \quad 3.5$$

(2) Pursuit and Evasion Behavior

This phase simulates the relative motion dynamics between a female spider wasp and its designated prey. During the pursuit behavior, the spider wasp continuously updates its position through active chases of the prey. When the prey initiates an evasive maneuver, the spider wasp adjusts its pursuit strategy accordingly to accommodate the dynamic environment. Two distinct methods for updating the position during this process are outlined below.

$$SW_i^{t+1} = \begin{cases} SW_i^t + C \times |2 \times r_5 \times SW_a^{\ t} - SW_i^t| & r_3 < r_4 \\ SW_a^{\ t} * vc & otherwise \end{cases} \quad 3.6$$

$$C = (2 - 2 \times (\frac{t}{t_{\max}})) \times r_6 \quad 3.7$$

$$k = 1 - (\frac{t}{t_{\max}}) \quad 3.8$$

(3) Nest Behavior

During this process, the nest-building behavior of female spider wasps is abstracted into two strategies. In the first strategy, the spider wasp drags captured prey to an optimal location based on the positional characteristics of the prey and establishes a nest there to ensure the best growth environment for its offspring. The second strategy involves randomly selecting a position from the female spider wasp population for nest-building, introducing randomness and diversity to avoid becoming trapped in local optima,the position update formula is formulated as follows:

$$SW_i^{t+1} = SW^* + \cos(2\pi l) \times (SW^* - SW_i^t) \quad 3.9$$

(4) Meting Behavior

In the Spider Wasp Optimization algorithm, mating behavior is simulated through uniform exchange operators between female and male wasps to generate offspring. The wasp eggs are abstracted as new potential solutions. To characterize sexual dimorphism, male wasps are generated differently from females, as formulated below.

$$SW_i^{t+1} = Crossover(SW_i^t, SW_m^{\ t}, CR) \quad 3.10$$

$$SW_m^{\ t+1} = SW_i^t + e^l \times |\beta| \times v_1 + (1-e^l) \times |\beta_1| \times v_2 \quad 3.11$$

$$v_1 = \begin{cases} x_a - x_i, & f(x_a) < f(x_i) \\ x_i - x_a, & otherwise \end{cases} \quad 3.12$$

$$v_2 = \begin{cases} x_b - x_c, & f(x_b) < f(x_c) \\ x_c - x_b, & otherwise \end{cases} \quad 3.13$$

B. Improved SWO for location assignment

(1) Gaussian chaotic mapping

Unlike conventional random initialization, Gaussian chaotic mapping produces initial populations with concentrated edge distribution in the solution space. While maintaining the randomness of initial spider wasp individuals, it generates solutions better suited for storage location allocation problems, thereby improving both initial solution quality and convergence rate. The Gaussian chaotic mapping is formulated as follows:

$$X_n = \mathrm{mod}(m * X_{n-1} * (1 - X_{n-1}), 1) \quad 3.14$$

(2) Adaptive weight-based Gaussian perturbation

The adaptive Gaussian perturbation strategy dynamically adjusts disturbance magnitude based on generation count, balancing exploration (early stage) and convergence (late stage). Its formulation is shown below.

$$SW_i^t = SW_i^t * (1 + \gamma * randn) \quad 3.15$$

(3) Opposition-based elite retention strategy

In population-based algorithms, late-stage iterations often exhibit clustered solutions in localized search spaces, reducing diversity and slowing convergence. The opposition-based learning strategy counters this by generating opposing populations, expanding search coverage and enhancing global exploration to mitigate premature convergence. This approach simultaneously improves solution quality and diversity, as formulated below.

$$\overline{SW_i^t} = L + H - SW_i^t \quad 3.16$$

To preserve elite individuals from the opposition population, this study introduces an elite retention strategy that merges opposition-generated and original populations, selecting superior solutions for the next iteration to prevent loss of high-quality candidates. The hybrid integration of opposition-based learning and elite retention enhances the SWO algorithm's ability to escape local optima while improving population diversity and convergence efficiency.

C. *ISWO Algorithm Procedure*

Step 1: Initialize the algorithm parameters, including initial population size, minimum population size, maximum number of iterations, trade-off rate, and crossover rate.

Step 2: Employ the Gaussian chaotic mapping strategy to initialize the population and evaluate the fitness values of the population. Update the position of the optimal individual in the population and its fitness value based on each individual's fitness.

Step 3: Perform iterative optimization according to the behaviors of the original Spider-Wasp Optimization Algorithm (SWO), including searching, chasing, escaping, nesting, and mating.

Step 4: At the end of each iteration, use the Gaussian perturbation strategy for local search to help individuals escape from local optima. Additionally, generate an opposing population using an opposition-based learning strategy, evaluate the fitness values of the mixed population, and apply the elite retention strategy to select outstanding individuals from the mixed population to form the next generation population, updating the position of the optimal individual in the population and its fitness value.

Step 5: Determine whether the maximum number of iterations has been reached. If not, return to Step 3 and continue optimization; if so, output the global optimal solution and plot the convergence curve.

IV. EXPERIMENT SIMULATION AND ANALYSIS

A. *Simulation Analysis*

To minimize the influence of software and hardware variations on experimental results, all simulations in this study were conducted on the same computational device with consistent software and hardware configurations throughout the experimental procedures. The software environment comprised MATLAB 2020b running on the Windows 11 operating system, while the hardware configuration utilized an Intel® Core™ i5-9300H CPU @ 2.40 GHz processor with 16 GB of RAM.

B. *Cargo data*

This study, by analyzing the inbound data of a specific enterprise over a defined period, extracted a dataset of goods. From this dataset, 70 representative items were selected to serve as simulated data for the experiment. The detailed dataset is presented in Table II.

C. *Simulation results of products assignment*

This study proposes an improved spider wasp optimization algorithm (ISWO) that addresses the limitations of the conventional spider wasp optimization (SWO) algorithm through the incorporation of multiple enhancement strategies. To validate the efficacy of ISWO, comparative analyses were conducted using the grey wolf optimizer (GWO), whale optimization algorithm (WOA), subtractive-average-based optimizer (SABO), original SWO, and the hybrid-enhanced ISWO for solving the automated warehouse storage location allocation model. Parameter configurations for all algorithms are detailed in Table III.

For enhanced visualization of optimization results, the storage location allocation schemes derived from each algorithm were converted into schematic diagrams (Figures 1 to 5). In these schematics, each block represents a cargo unit, with color-coded blocks indicating distinct mass categories: red, pink, yellow, and blue, corresponding to a four-tier mass classification system.

Table IV presents the objective function values of the allocation schemes derived from each algorithm. Figures 6 to 9 comparatively analyze the convergence curves generated during the iterative processes of the algorithms, evaluated from the perspectives of distinct objective functions.

Table III Parameter Configuration Table

Algorithms	parameters	Values
GWO	T_{max}	1000
	N_{max}	50
SABO	T_{max}	1000
	N_{max}	50
WOA	T_{max}	1000
	N_{max}	50
SWO	T_{max}	1000
	N_{max}	50
	TR	0.5
	CR	0.9
	N_{min}	20
ISWO	T_{max}	1000
	N_{max}	50
	TR	0.5
	CR	0.9
	N_{min}	25

Table II Cargo Data

number	weight(kg)	number	weight(kg)	number	weight(kg)	number	weight(kg)	number	weight(kg)
1	92.5	15	50	29	59.1	43	59.4	57	86.2
2	60.8	16	69.3	30	65.3	44	41	58	72.8
3	68	17	82.6	31	93.7	45	57	59	62.3
4	76.7	18	86.3	32	42	46	90.3	60	73
5	93.1	19	41.1	33	45	47	88.7	61	72.1
6	71	20	50.2	34	75.3	48	91.9	62	63
7	39	21	56.8	35	53	49	53	63	78.7
8	46	22	36	36	95.5	50	70.8	64	29.9
9	30.9	23	46	37	64.3	51	88.3	65	52.4
10	99.6	24	46	38	42	52	34.1	66	70
11	96.7	25	92.6	39	55	53	70	67	44.1
12	33	26	65	40	96.4	54	99.1	68	89
13	39.2	27	69.3	41	71.2	55	40.9	69	100
14	37	28	96.5	42	60.1	56	64.1	70	63

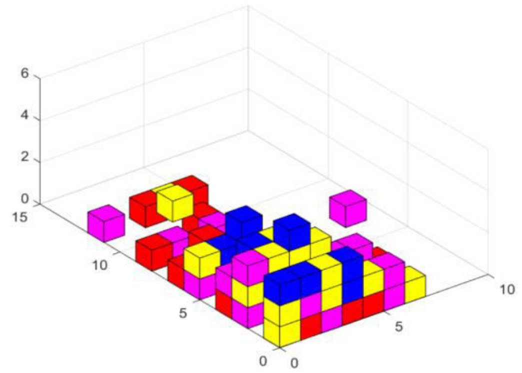

Fig.1 GWO Optimization Result

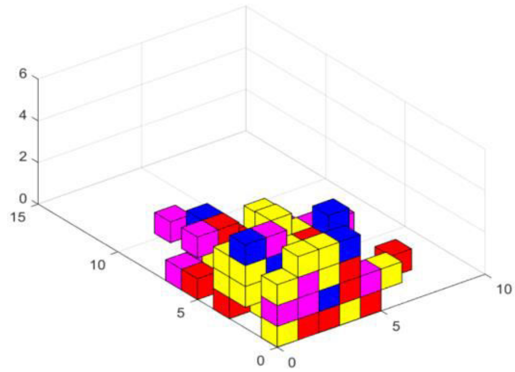

Fig.2 SABO Optimization Result

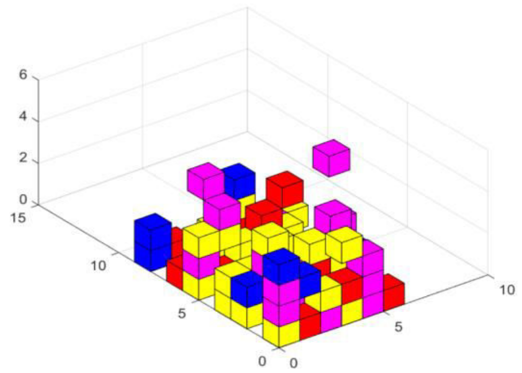

Fig.3 WOA Optimization Result

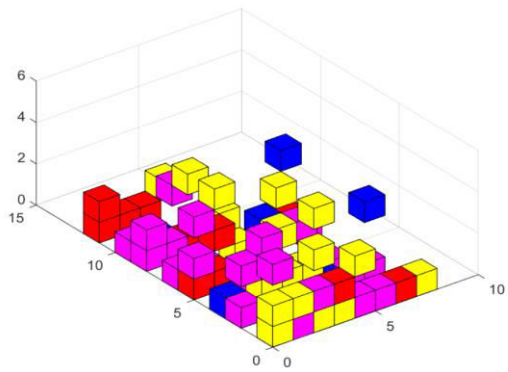

Fig.4 SWO Optimization Result

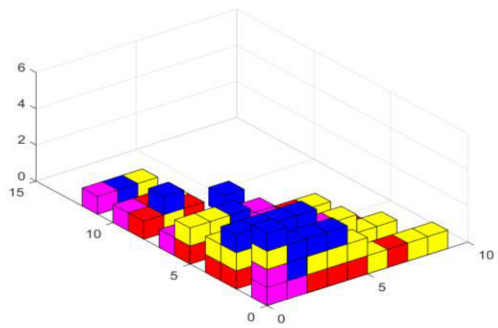

Fig.5 ISWO Optimization Result

Table IV Algorithmic Optimization Performance

Functions	GWO	SABO	WOA	SWO	ISWO
F	208.8850	235.6139	252.0178	220.5590	162.3052
f1	94.3955	147.9084	147.6140	127.0910	76.0743
f2	749.5389	715.0780	806.5315	713.0106	578.2242
f3	82.0790	95.5613	95.9711	83.4720	61.0617

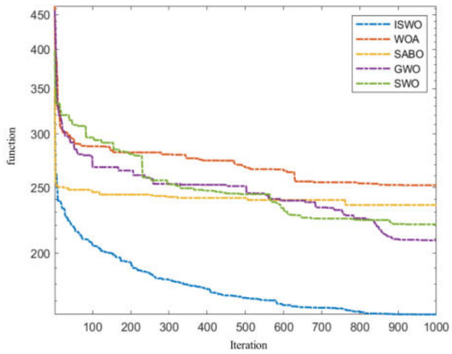

Fig.6 Convergence Curve of F

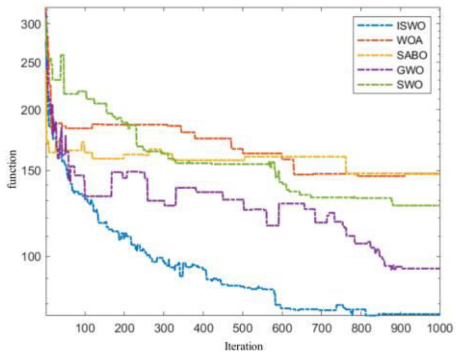

Fig.7 Convergence Curve of f1

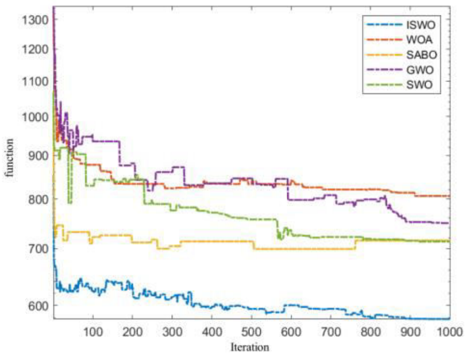

Fig.8 Convergence Curve of f2

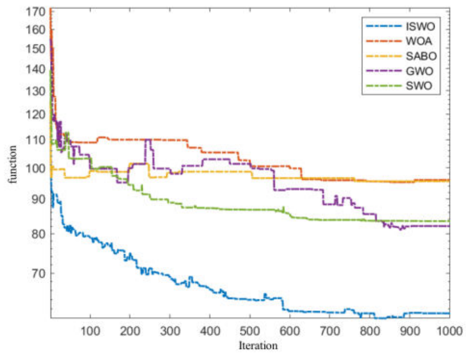

Fig.9 Convergence Curve of f3

V. CONCLUSION

This study investigates the storage location allocation problem in an automated warehouse of a manufacturing enterprise, establishing a mathematical model with three objective functions to evaluate allocation schemes: rack stability, time consumption, and energy expenditure during storage/retrieval operations by stacker cranes. To rationally determine the weighting coefficients of these objectives, the Analytic Hierarchy Process (AHP) was employed, transforming the multi-objective optimization problem into a single-objective formulation.

Under identical experimental conditions, comparative simulations were conducted across five optimization algorithms. Analysis of convergence curves and storage location allocation schematics demonstrates that the improved spider wasp optimization (ISWO) algorithm exhibits superior convergence rate and optimization performance compared to baseline methods.

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