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RESEARCH ARTICLE

Optimization of Storage and Retrieval Strategies in Warehousing Based on Enhanced Genetic Algorithm

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ABSTRACT The Shuttle-Based Storage and Retrieval System (SBS/RS) faces challenges of low efficiency due to the constraints of single outbound or inbound operations. To overcome this limitation, a scheme enabling simultaneous outbound and inbound operations has been proposed. This involved developing a physical model that incorporates costs related to outbound cargo urgency, shelf stability, time, and warehouse busyness. The model was solved using a Genetic Algorithm with priority selection, adaptive operators, and a decay factor (GA-DF). Experimental results, validated across various environments, demonstrate that the proposed GA-DF algorithm achieves 50% higher efficiency compared to the IOSA algorithm when the shelf occupancy rate is 50% and multiple cost environments are considered. Additionally, GA-DF outperforms the Simulated Annealing algorithm, traditional Genetic Algorithm, and IOSA algorithm in optimizing storage and retrieval locations, significantly enhancing system optimization. This provides a crucial reference for optimizing such systems, particularly in dynamic and complex warehousing environments. The GA-DF algorithm's applicability and advantages have been widely recognized through further validation, highlighting its potential to drive improvements in warehousing system efficiency and optimization strategies.

INDEX TERMS Shuttle-based storage and retrieval system, physical model, genetic algorithm.

I. INTRODUCTION

With the rapid development of internet and artificial intelligence technologies, the smart warehousing industry is experiencing significant growth. The dramatic increase in the number of orders and the scale of data has made efficient automated storage systems the optimal choice for enhancing logistics operation efficiency. Applying cross-aisle multi-tier shuttle systems in e-commerce environments is of great significance for achieving rapid order picking of massive orders. The order picking system mainly includes Shuttle-Based Storage and Retrieval System (SBS/RS) and automated storage and retrieval systems (AS/RS) [1], [2]. Currently, optimization algorithms for warehouse systems include genetic algorithms (GA), simulated algorithms (SA), particle swarm algorithms (PSO), and others [3], [4], [5].

Regarding SBS/RS systems, current research focuses on two main aspects. The first aspect is the development of analytical and simulation models to evaluate the performance of SBS/RS. The second aspect is the design of storage and scheduling strategies to optimize the performance and energy consumption of SBS/RS. In the following, this paper will review the literature on these two aspects.

Regarding analytical and simulation models, Rizqi et al. [2] introduced a simulation optimization (SO) framework for integrated AS/RS planning. However, the flexibility of the AS/RS framework is inferior to that of SBS/RS. Andrea and Giulio [6] studied the development trends of warehouse models, confirming that the SBS/RS model has been increasingly utilized by scholars in the past decade,

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particularly for efficient scheduling purposes. Teck et al. [7] and Ekren [8] identified factors affecting the performance metrics of SBS/RS, such as time and energy consumption, using the Tukey test to determine the optimal levels of these metrics, with the cost of outbound travel distance as the criterion. Yang et al. [9], based on the SBS/RS model, improved the PSO algorithm using the total order outbound time as the cost function, determining the appropriate number of lifts and the number of shelf levels for the warehouse. SBS/RS is an automated shuttle that runs along aisles and works with lifts to complete cross-level storage and retrieval tasks. Based on the above analysis, SBS/RS was developed as a replacement for AS/RS based on small loading cranes, designed to complete small orders within short response times. Therefore, this paper will use SBS/RS as the model for study.

Regarding storage and scheduling strategies, Cergibozan and Tasan [10] proposed two methods for the order batching problem: a local search genetic algorithm and a hybrid algorithm based on interactions between different populations. However, they only considered time as the cost and did not comprehensively address the warehouse. Lin et al. [11] built on this by proposing a double-deep SBS/RS model with single and dual lifts, with a cost function including shuttle waiting time, elevator idle time, and total outbound time. They improved the Non-dominated Sorting Genetic Algorithm-II (NSGAII) based on this model to achieve the shortest outbound time, but did not consider multiple application scenarios. Mrad et al. [12] proposed two collaborative scenarios and a Clarke and Wright heuristic genetic algorithm to solve different scenarios, using a genetic algorithm to address the integrated warehouse location problem. Liyun et al. [13], based on the Tier-to-tier Four-way Shuttle Warehousing system, used the total outbound time as the cost function and provided a new crossover improved genetic algorithm, ultimately achieving the optimal scheduling scheme, but did not consider the number of shuttles. Mao et al. [14] established an SBS/RS model based on the optimization of inbound and outbound operations and path scheduling of four-way shuttles. They used an improved genetic algorithm for task planning and an improved A* algorithm for solving the internal path of shelves, enhancing the efficiency of shuttle inbound and outbound operations. Wu et al. [15] established an SBS/RS model considering the acceleration and deceleration characteristics of equipment, and proposed an improved genetic algorithm based on double-layer coding to solve the scheduling problem, validating its effectiveness through large-scale practical experiments. However, the operation modes in the literatures [10], [11], [12], [13], [14], and [15] are single command modes for inbound or outbound operations, without discussing the dual command mode for simultaneous inbound and outbound operations.

Regarding the selection and improvement of genetic algorithms, [11] and [15], genetic algorithms are compared with hybrid algorithms, first come first serve, enumeration method, and ant-colony optimization. It is found that genetic algorithms converge earlier and are more efficient. Hu and Chuang [16] optimized the layout of e-commerce warehouses, established a nonlinear programming model, and used a GA to solve the model, demonstrating that GA has better convergence compared to PSO and SA. This provides an important reference for the selection of algorithms in this paper. Lu et al. [17] applied GA to the field of ship optimization, embedding GA into the solution model and utilizing the algorithm more flexibly, which inspired the better application of GA in the SBS/RS system in this paper. Koohestani [18] conducted in-depth research on GA and proposed using a new coding method that significantly improves the efficiency of GA. This finding inspired the design of the genetic algorithm coding in this paper.

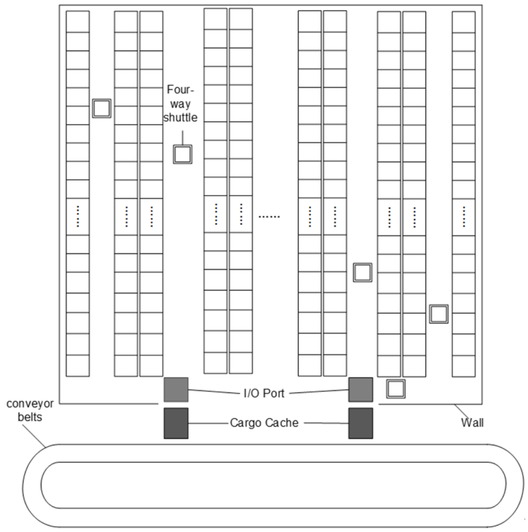
Based on the above study of the existence of a single task in and out of the warehouse, this paper introduces a dual-task model of goods in and out of the warehouse. For the SBS/RS, the introduction of the cost of the urgency of the goods out of the warehouse, the urgent need for the goods in order to get out of the warehouse as soon as possible. The introduction of the cost of the stability of the shelves, so that the stability of the warehouse better. The introduction of the cost of the time, the overall goods can be quickly out of the warehouse. The introduction of the busyness of the warehouse, the shuttle can be run in an orderly fashion. To address the issues of low warehouse access efficiency described above, this paper proposes the genetic algorithm with decay factor (GA-DF). This algorithm employs a genetic algorithm framework incorporating preferential selection, adaptive operators, and a decay factor to optimize the warehouse operations. The approach involves utilizing actual enterprise data to validate the effectiveness and feasibility of both the model and the algorithm. Finally, the paper concludes by summarizing the research outcomes and results obtained through this approach.

II. PHYSICAL MODELING OF SBS/RS

This chapter systematically describes the physical modeling of the SBS/RS. It begins by detailing the system layout, including shelf setup, shuttle car plan, and a three-dimensional schematic of the enterprise. The operation flow is then outlined, describing the steps in dual-task mode and providing a system operation flow diagram. Finally, assumptions and definitions of the model are listed to ensure the rationality and efficiency of system scheduling. In summary, the SBS/RS model is designed to provide a basis for optimizing the warehousing system, considering system layout, operation flow and scheduling framework.

A. LAYOUT INTRODUCTION

The SBS/RS is engineered to enhance warehousing efficiency. In this system, each aisle features shelves on both sides, with multiple cargo spaces arranged on each level. Goods of the same type are stored together in designated areas. Shuttles within the system are propelled and positioned using electric drives on rails or guided by infrared signals, among other methods. Additionally, the SBS/RS system facilitates convenient access between shelves and elevators,



(a) Top view of SBS/RS

(b) SBS/RS Enterprise Stereo Warehouse

FIGURE 1. SBS/RS position chart.

allowing shuttles to be transported to any level within the warehouse. This design optimizes storage and retrieval processes, enhancing overall operational efficiency within the warehouse environment.

Fig. 1(a) illustrates the top view of the SBS/RS. The system's I/O port is positioned at the front of the warehouse, where an elevator transports the four-way shuttle to the designated level. On one side of the I/O port, there is an aisle port for goods incoming and outgoing, while the other side connects to the goods caching area for temporary storage of goods. Fig. 1(b) presents a three-dimensional depiction of the enterprise warehouse. This layout includes an elevator, aisle shuttle, multi-level shelves, box conveyor, and goods temporary storage area. The visualization uses blue and orange colors to distinguish between two different types of goods, each stored separately according to type. These illustrations provide a clear representation of the SBS/RS system's layout and operational components, emphasizing efficient organization and segregation of goods within the warehouse environment.

B. OPERATIONAL PROCESSES

The SBS/RS operates in two modes: traditional single-task mode and the newly proposed dual-task mode. The single-task mode handles either incoming or outgoing operations separately, which can lead to inefficiencies in large warehouses requiring simultaneous goods movement. To address this limitation, this paper focuses on studying scheduling problems under the dual-task mode. This mode allows for concurrent goods entering and leaving the warehouse, aiming to optimize operational efficiency. By examining dual-task scheduling, this research aims to enhance the effectiveness of the SBS/RS system, particularly in large warehouse settings.

A complete goods I/O operation encompasses multiple inbound and outbound operations, each involving a series of coordinated steps. Typically, a single inbound and outbound operation within a warehouse requires the execution of three fundamental steps. Firstly, the inbound instruction is initiated to bring goods into the warehouse, where the goods are identified and prepared for storage. Subsequently, a search instruction is executed to locate the specific goods within the warehouse efficiently. Finally, the outbound instruction is carried out to retrieve and dispatch the goods from the warehouse as required. These instructions work together seamlessly to facilitate the smooth movement of goods, ensuring efficient handling and delivery. By implementing this systematic approach, warehouses can optimize operational efficiency and effectively manage the flow of goods in and out of the facility.

In the SBS/RS, when issuing inbound, search, or outbound instructions, the system determines whether a hoist is required based on the location of goods or I/O ports relative to the shuttle. If goods or I/O ports are on the same level as the shuttle, the hoist is engaged to transport the goods to the specified location or conveyor, completing the operation efficiently. Conversely, if goods or I/O ports are not on the same level, the hoist is not used, and goods are

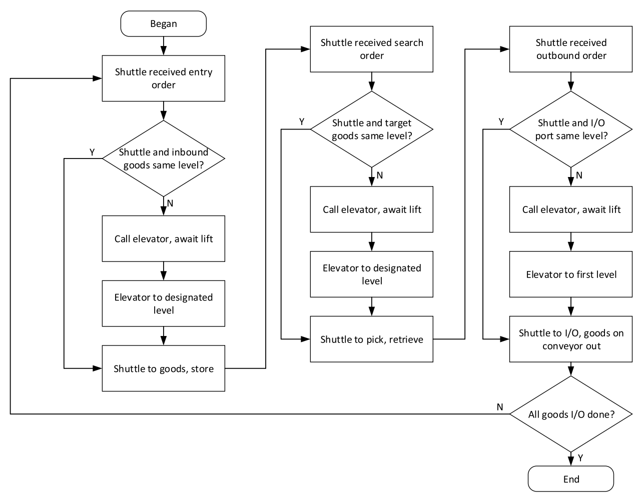


FIGURE 2. SBS/RS operation flowchart.

transported directly to the designated location or conveyor to finalize the operation. The operation flow of SBS/RS is illustrated in Fig. 2, outlining the sequence of actions involved in issuing instructions, utilizing hoists as needed, and completing inbound, search, and outbound operations within the warehouse environment. This operational framework ensures streamlined goods handling and efficient logistical operations within the SBS/RS system.

C. MODEL ASSUMPTIONS AND DEFINITIONS

To establish a reasonable scheduling framework for the SBS/RS and optimize cargo handling processes while improving system throughput and resource utilization, the following assumptions are proposed:

- Each four-way shuttle can transport only one cargo at a time, ensuring focused handling and efficient movement of goods within the system.
- The hoist is capable of serving only one four-way shuttle at a time, preventing resource conflicts and optimizing hoist utilization.
- Multiple four-way shuttles are allowed to occupy the same location between lanes, facilitating concurrent operations and efficient goods handling.
- The speed and acceleration of both the four-way shuttle and the hoist remain consistent, whether loaded or unloaded, ensuring predictable and reliable performance.
- Goods of the same type are stored together in designated areas, streamlining retrieval processes and optimizing storage efficiency.
- The hoists at both ends of the I/O port operate on a first-come-first-served basis, ensuring fair and orderly service for shuttle operations.
- In cases where both outgoing and incoming tasks are present, the shuttle prioritizes bringing goods into the warehouse before handling goods to be transported out, optimizing workflow and minimizing delays.

III. MATHEMATICAL MODELING OF SBS/RS

Chapter 3 details the mathematical model of the cross aisle multilevel shuttle system, focusing on four essential cost functions: outbound cargo urgency cost, shelf stability cost, inbound and outbound time cost, and warehouse busyness cost. These functions provide a comprehensive mathematical framework for optimizing warehouse operations. The outbound cargo urgency cost prioritizes urgent deliveries, minimizing delays. The shelf stability cost ensures safe and organized storage. The time cost optimizes efficiency for both inbound and outbound operations. The warehouse busyness cost manages operational flow to minimize congestion. This mathematical model facilitates systematic evaluation and task prioritization, enhancing operational performance within the warehouse environment.

A. COST OF URGENCY OF OUTGOING SHIPMENTS

In the competitive landscape with evolving customer demands, warehouses must remain agile to swiftly respond to emergencies, meet customer needs, and uphold efficient supply chain operations. Implementing an urgency classification system based on product characteristics, customer demand, and supply chain dynamics is essential for optimizing outbound processes.

This system allows users to define urgency coefficients for warehouse inventory, assigning higher values to goods with greater outbound urgency. The cost of urgency $O(\mathrm{i})$ for goods leaving the warehouse is calculated using equation (1):

$$O(i) = \frac{i * U(i)}{n} \tag{1}$$

where i represents the cargo number, U(i) denotes the urgency coefficient assigned to the i-th cargo, and n represents the total number of outgoing cargoes.

B. COST OF SHELF STABILITY

Inbound goods placement directly impacts shelf stability, warehouse space utilization, and outbound efficiency. To enhance shipping efficiency and facilitate warehouse management, goods of the same type are stored on different layers of shelves. This storage strategy not only improves shipping efficiency but also simplifies warehouse management during operational challenges. In the context of storage operations using a four-way shuttle, the selection of shelf levels is critical. Placing heavier goods on lower shelf levels can enhance shelf stability and prolong shelf service life. The cost associated with inbound goods placement M(i) is defined by equation (2):

$$M(i) = \left| \frac{W(i)}{L} - q \right| \tag{2}$$

where W(i) represents the mass of the i-th shipment, L denotes the total number of layers in the warehouse, and q indicates the number of layers on which the incoming shipment will be placed.

C. COST OF ACCESS TIME

In the operations of the SBS/RS, the criticality of time management cannot be overlooked. The strategic arrangement of inbound and outbound timing directly impacts the efficiency and cost-effectiveness of warehouse operations. Timely delivery of goods is essential for customer satisfaction during outbound processes, while efficient storage of goods is crucial for warehouse functionality. Improper timing arrangements can lead to resource wastage, increased costs, and operational inefficiencies. Therefore, effective warehouse management requires optimizing timing schedules, streamlining processes, and leveraging advanced technologies to enhance efficiency. By focusing on efficient storage and retrieval timing, warehouses can boost operational effectiveness and competitiveness in today's dynamic marketplace. This strategy also raises service levels to meet evolving customer demands.

Assuming n is the number of outbound goods, m is the number of inbound goods, and b is the number of hoists at the I/O port, the coordinate information matrices for outbound goods MT_{out}, inbound goods MT_{in}, and hoists MT_{io} are defined by equation (3):

$$MT_{out} = \begin{bmatrix} A_1Q_1L_1 \\ A_2Q_2L_2 \\ \cdots\cdots \\ A_nQ_nL_n \end{bmatrix} \quad MT_{in} = \begin{bmatrix} C_1D_1F_1 \\ C_2D_2F_2 \\ \cdots\cdots \\ C_mD_mF_m \end{bmatrix} MT_{io} = \begin{bmatrix} E_1J_1G_1 \\ E_2J_2G_2 \\ \cdots\cdots \\ E_bJ_bG_b \end{bmatrix} \tag{3}$$

where $[A_n, Q_n, L_n]$ represents the coordinate of the n-th outbound cargo, $[C_m, D_m, F_m]$ represents the coordinate of the m-th inbound cargo, and $[E_b, J_b, G_b]$ represents the coordinate of the b-th hoist at the I/O port.

Assume that the maximum speed of the four-way shuttle is V_t and the acceleration is a_t; the speed of the elevator is V_e and the acceleration is a_e, and the coordinates of the i-th goods out are (A_i, Q_i, L_i), the coordinates of the i-th incoming goods are (C_i, D_i, F_i), and the coordinates of the i-th I/O port are (E_i, J_i, G_i). the running times for the three steps described are determined based on the given coordinates:

1) The time $T^{i/o-in}$ for a four-directional shuttle to transport goods from the I/O port to the shelf depends on the type of task. If the shuttle is performing a non-interlayer task, $T^{i/o-in}$ is calculated as shown in equation (4); if the shuttle is performing an interlayer task, $T^{i/o-in}$ is calculated as shown in equation (5).

(1) When $MT_{in}(F_i) = MT_{io}(G_i)$, the shuttle carries out a non-cross-layer task operations.

$$T_{sa}^{i/o-in}(i) = \begin{cases} \frac{4V_t}{a_t} + \frac{\left(|E_i - C_i| + |J_i - D_i| - \frac{2V_t^2}{a_t}\right)}{V_t} & |E_i - C_i| > \frac{V_t^2}{2a_t}, |J_i - D_i| > \frac{V_t^2}{2a_t} \\ \frac{2V_t}{a_t} + \frac{\left(|E_i - C_i| - \frac{V_t^2}{a_t}\right)}{V_t} + 2\sqrt{\frac{2|J_i - D_i|}{a_t}} & |E_i - C_i| > \frac{V_t^2}{2a_t}, |J_i - D_i| < \frac{V_t^2}{2a_t} \\ \frac{2V_t}{a_t} + \frac{\left(|J_i - D_i| - \frac{V_t^2}{a_t}\right)}{V_t} + 2\sqrt{\frac{2|E_i - C_i|}{a_t}} & |E_i - C_i| < \frac{V_t^2}{2a_t}, |J_i - D_i| > \frac{V_t^2}{2a_t} \\ 2\sqrt{\frac{2|J_i - D_i|}{a_t}} + 2\sqrt{\frac{2|E_i - C_i|}{a_t}} & |E_i - C_i| < \frac{V_t^2}{2a_t}, |J_i - D_i| < \frac{V_t^2}{2a_t} \end{cases} \tag{4}$$

(2) When $MT_{in}(F_i) \neq MT_{io}(G_i)$, the shuttle carries out cross-level task operations.

$$T_{di}^{i/o-in}(i) = \begin{cases} T_{sa}^{i/o-in} + \frac{2V_e}{a_e} + \frac{\left(|G_i - F_i| - \frac{V_e^2}{a_e}\right)}{V_e} & |G_i - F_i| > \frac{V_e^2}{2a_e} \\ T_{sa}^{i/o-in} + 2\sqrt{\frac{2|G_i - F_i|}{a_e}} & |G_i - F_i| < \frac{V_e^2}{2a_e} \end{cases} \tag{5}$$

2) The time T^{in-out} for a four-directional shuttle to travel from the unloading location to the loading location depends on the type of task. If the shuttle is performing a non-interlayer task, T^{in-out} is calculated as shown in equation (6); if the shuttle is performing an interlayer task, T^{in-out} is calculated as shown in equation (7).

(1) When $MT_{in}(F_i) = MT_{out}(L_i)$, the shuttle carries out no cross-layer task operations.

$$T_{sa}^{in-out}(i) = \begin{cases} \frac{4V_t}{a_t} + \frac{\left(|A_i - C_i| + |Q_i - D_i| - \frac{2V_t^2}{a_t}\right)}{V_t} & |A_i - C_i| > \frac{V_t^2}{2a_t}, |Q_i - D_i| > \frac{V_t^2}{2a_t} \\ \frac{2V_t}{a_t} + \frac{\left(|A_i - C_i| - \frac{V_t^2}{a_t}\right)}{V_t} + 2\sqrt{\frac{2|Q_i - D_i|}{a_t}} & |A_i - C_i| > \frac{V_t^2}{2a_t}, |Q_i - D_i| < \frac{V_t^2}{2a_t} \\ \frac{2V_t}{a_t} + \frac{\left(|Q_i - D_i| - \frac{V_t^2}{a_t}\right)}{V_t} + 2\sqrt{\frac{2|A_i - C_i|}{a_t}} & |A_i - C_i| < \frac{V_t^2}{2a_t}, |Q_i - D_i| > \frac{V_t^2}{2a_t} \\ 2\sqrt{\frac{2|Q_i - D_i|}{a_t}} + 2\sqrt{\frac{2|A_i - C_i|}{a_t}} & |A_i - C_i| < \frac{V_t^2}{2a_t}, |Q_i - D_i| < \frac{V_t^2}{2a_t} \end{cases} \tag{6}$$

(2) When $MT_{in}(F_i) \neq MT_{out}(L_i)$, the shuttle carries out cross-layer task operations.

$$T_{di}^{in-out}(i) = \begin{cases} T_{sa}^{in-out} + \frac{2V_e}{a_e} + \frac{\left(|L_i - F_i| - \frac{V_e^2}{a_e}\right)}{V_e} & |L_i - F_i| > \frac{V_e^2}{2a_e} \\ T_{sa}^{in-out} + 2\sqrt{\frac{2|L_i - F_i|}{a_e}} & |L_i - F_i| < \frac{V_e^2}{2a_e} \end{cases} \tag{7}$$

3) The time $T^{i/o-out}$ for a four-directional shuttle to transport goods from the loading location to the I/O port depends on the type of task. If the shuttle is performing a non-interlayer task, $T^{i/o-out}$ is calculated as shown in equation (8); if the shuttle is performing an interlayer task, $T^{i/o-out}$ is calculated as shown in equation (9).

(1) When $MT_{in}(L_i) = MT_{io}(G_i)$, the shuttle carries out a non-cross-tier mission task operation.

$$T_{sa}^{i/O-out}(i) = \begin{cases} \frac{4V_t}{a_t} + \frac{\left(|E_i - A_i| + |J_i - Q_i| - \frac{2V_t^2}{a_t}\right)}{V_t} & |E_i - A_i| > \frac{V_t^2}{2a_t}, |J_i - Q_i| > \frac{V_t^2}{2a_t} \\ \frac{2V_t}{a_t} + \frac{\left(|E_i - A_i| - \frac{V_t^2}{a_t}\right)}{V_t} + 2\sqrt{\frac{2|J_i - Q_i|}{a_t}} & |E_i - A_i| > \frac{V_t^2}{2a_t}, |J_i - Q_i| < \frac{V_t^2}{2a_t} \\ \frac{2V_t}{a_t} + \frac{\left(|J_i - Q_i| - \frac{V_t^2}{a_t}\right)}{V_t} + 2\sqrt{\frac{2|E_i - A_i|}{a_t}} & |E_i - A_i| < \frac{V_t^2}{2a_t}, |J_i - Q_i| > \frac{V_t^2}{2a_t} \\ 2\sqrt{\frac{2|E_i - A_i|}{a_t}} + 2\sqrt{\frac{2|J_i - Q_i|}{a_t}} & |E_i - A_i| < \frac{V_t^2}{2a_t}, |J_i - Q_i| < \frac{V_t^2}{2a_t} \end{cases} \tag{8}$$

(2) When $MT_{in}(L_i) \neq MT_{io}(G_i)$, the shuttle carries out cross-level task operations.

$$T_{di}^{i/O-out}(i) = \begin{cases} T_{sa}^{i/O-out} + \frac{2V_e}{a_e} + \frac{\left(|G_i - L_i| - \frac{V_e^2}{a_e}\right)}{V_e} & |G_i - L_i| > \frac{V_e^2}{2a_e} \\ T_{sa}^{i/O-out} + 2\sqrt{\frac{2|G_i - L_i|}{a_e}} & |G_i - L_i| < \frac{V_e^2}{2a_e} \end{cases} \tag{9}$$

In summary, the total time $T(i)$ for the four-way shuttle to complete the i-th operational task involves the cumulative running times of the three steps described earlier:

$$T(i) = T^{i/o-in}(i) + T^{in-out}(i) + T^{i/o-out}(i) \tag{10}$$

D. COST OF WAREHOUSE BUSYNESS

In SBS/RS operations, goods movement within the warehouse relies primarily on four-way shuttles and hoists. The utilization rates of these systems indicate the current warehouse activity level and directly affect the efficiency of inbound and outbound operations. Unlike the hoists, which only operates upon receiving a request from a four-way shuttle and thus does not accurately reflect overall warehouse activity, the busyness of the warehouse is predominantly measured by the efficiency of the four-way shuttle transportation. Based on the above analysis, the total transportation time Tsum p of the p-th four-way shuttle is (11), the maximum value of the time spent by the shuttle T_{max} is (12), and the warehouse busyness R is (13).

$$T_p^{sum} = \sum_{i=1}^{H} T(i) \tag{11}$$

$$T_{max} = max(T_p^{sum})p \in [1, S] \tag{12}$$

$$R = \frac{\sum_{p=1}^{S} \frac{T_P^{sum}}{T_{max}}}{S} \times 100\% \tag{13}$$

where H represents the number of operational tasks that the p-th four-way shuttle is required to transport goods in and out of the warehouse. S denotes the total number of four-way shuttles operating within the warehouse system.

IV. GENETIC ALGORITHM DESIGN FOR SBS/RS

Chapter 4 presents the genetic algorithm design tailored for SBS/RS. GA excel in handling goods allocation and scheduling due to their ability to explore a wide solution space effectively, adapt to complex constraints, and optimize multiple objectives simultaneously. They offer robustness, scalability, and the capability to find near-optimal solutions in challenging logistics scenarios. Therefore, GA was chosen to deal with the SBS/RS problem. Initially, the genetic algorithm with decay factor (GA-DF) algorithm is introduced with a novel encoding method aimed at simplifying problem by representing various aspects of access and egress operations. Subsequently, individual fitness functions undergo normalization to facilitate effective evaluation. Detailed operations within the GA-DF algorithm are elaborated, encompassing key aspects such as the selection operator, preferred selection strategy, adaptive operator, crossover approach, mutation approach and the design of a decay factor. The comprehensive flow of the GA-DF algorithm is then delineated to optimize the scheduling of inbound and outbound operations using genetic algorithms, ultimately aiming to enhance the efficiency and cost-effectiveness of warehouse operations.

A. DESIGN OF CODING METHODS

The optimal solution for SBS/RS operations is achieved through the application of GA-DF, leveraging an effective coding method to streamline problem-solving. A comprehensive four-way shuttle cargo in/out operation entails several critical components, including arranging and combining inbound and outbound cargo, selecting appropriate hoists, determining inbound cargo levels, and choosing cargo batches for delivery by the shuttle. These elements are strategically integrated and optimized within the genetic algorithm framework to enhance operational efficiency and maximize warehouse throughput.

The GA-DF coding method, as illustrated in Fig. 3, employs a structured chromosome representation to optimize the sequence and selection of operations within the SBS/RS. Each chromosome corresponds to a specific aspect of the operational workflow:

- Chromosome 1: Sequence of inbound operations.
- Chromosome 2: Sequence of outbound operations.
- Chromosome 3: Selection of the cargo elevator.
- Chromosome 4: Selection of the level for inbound cargo placement.
- Chromosome 5: Selection of the shuttle for completing an inbound and outbound operation.

Together, these chromosomes form a complete chromosome that represents the solution for executing the entire operation. The depicted workflow outlines a series of actions, such as selecting specific shuttles, goods, and I/O ports for inbound and outbound operations, optimizing the process to enhance efficiency and effectiveness in the warehouse operations. Each step is orchestrated based on the encoded genetic algorithm solution derived from the GA-DF method.

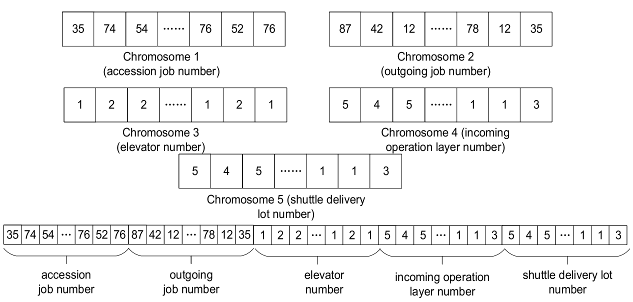


FIGURE 3. GA-DF coding method.

B. ADAPTATION FUNCTION DESIGN

In the SBS/RS operation, the objective function integrates incoming goods urgency O, shelf stability M, in and out of warehouse time T, and warehouse busyness R to determine its value. Due to potential large variations in the objective function values, normalization is applied as a preprocessing step. The processed objective function F is defined by the equation:

$$O_{new} = \frac{(O - O_{min})}{(O_{max} - O_{min})} \tag{14}$$

$$M_{new} = \frac{(M - M_{min})}{(M_{max} - M_{min})} \tag{15}$$

$$T_{new} = \frac{(T - T_{min})}{(T_{max} - T_{min})} \tag{16}$$

$$R_{new} = \frac{(R - R_{min})}{(R_{max} - R_{min})} \tag{17}$$

where O_{new}, M_{new}, T_{new} and R_{new} is the new cost function after normalization, O_{max}, M_{max}, T_{max} and R_{max} is the maximum value in the iterative process, and O_{min}, M_{min}, T_{min} and R_{min} is the minimum value in the iterative process.

In this study, the fitness function F is designed such that lower values indicate higher probability of selection for the next generation. However, since busyness R is inversely related, the cost value here is set as the reciprocal. The modified fitness function F is expressed as:

$$F = \left(O_{new} + M_{new} + T_{new} + \frac{1}{R_{new}}\right) \tag{18}$$

C. GA-DF GENETIC MANIPULATION

In this subsection, a GA-DF genetic operation is designed to solve the optimization problem of a cross-aisle multilevel shuttle system. The approach integrates several key genetic algorithm components to enhance efficiency and convergence. First, a tournament selection operator is employed to maintain population diversity by randomly selecting multiple groups of individuals and choosing the one with the highest fitness function F as a candidate for the next generation. Second, a preferential selection design is introduced to prioritize urgent incoming goods, speeding up the search for optimal solutions. An adaptive operator dynamically adjusts crossover and mutation probabilities based on the fitness values of the current population, optimizing exploration and exploitation. Two-point crossover and mutation operations are tailored to the specific chromosome coding method used in this study, maintaining genetic diversity and exploring potential solutions effectively. Finally, a decay factor design facilitates multi-point mutation on chromosomes, allowing the algorithm to escape local optima when fitness functions remain unchanged. By integrating these genetic operations, the efficiency and convergence of the genetic algorithm are improved to better solve the optimization problem of the cross-aisle multilevel shuttle system.

1) CHOOSING AN OPERATOR DESIGN

In genetic manipulation, tournament selection is employed as a selection method in this paper. This approach involves randomly selecting multiple groups of individuals, and from each group, the individual with the highest fitness function F is chosen as a candidate for parent selection or the next generation. Tournament selection helps maintain genetic diversity by considering multiple individuals in each selection round and prioritizing those with the best fitness for further evolutionary processes.

Tournament selection involves randomly selecting individuals in each round of tournaments, allowing even lower-fitness individuals a chance to win in some rounds despite the presence of higher-fitness competitors. This approach helps maintain diversity in the population by giving all individuals a chance to contribute to the next generation. However, there is a risk of local convergence because individuals with higher fitness are more likely to prevail in the tournaments, potentially leading to a narrowing of genetic diversity over successive generations. This balance between exploration (through inclusion of lower-fitness individuals) and exploitation (favoring higher-fitness individuals) is a critical aspect of genetic algorithm design to ensure effective optimization and prevent premature convergence to suboptimal solutions.

To prevent local convergence, this paper employs a strategy where individuals with the top and bottom 5% of fitness values are directly selected into the new population, while the remaining individuals are selected using tournaments. This method helps maintain population diversity and mitigates the risk of falling into local optimal solutions by ensuring a mix of high- and low-fitness individuals in each generation. By incorporating this selective approach, the genetic algorithm can explore a broader range of potential solutions and avoid premature convergence to suboptimal outcomes.

2) PREFERRED DESIGN

When working with genetic algorithms, each chromosome contains numerous genes, with each segment representing a potential solution to the problem. However, if the chromosome is excessively long, certain segments may reach optimal solutions while the overall chromosome does not. This scenario can hinder progress because operations like crossover and mutation on problematic segments can disrupt their order, delaying the emergence of an optimal solution.

To expedite the optimal solution of SBS/RS operations using genetic algorithms, this paper implements a strategy. Initially, the urgency degree O of incoming goods is calculated to prioritize finding the optimal solution efficiently. Once the optimal solution based on urgency O is stabilized, subsequent segments of chromosomes are then optimized to finalize the overall solution. This sequential approach focuses on addressing critical aspects first to accelerate the convergence towards an optimal solution for the SBS/RS operation.

The speed of finding the optimal solution can be accelerated through the preferential selection method, which prioritizes solving the urgency of incoming goods. By addressing this critical aspect first, the genetic algorithm gains a solid foundation for optimizing the overall problem. This approach enhances algorithm efficiency and reduces computation time by focusing on key factors that significantly impact the solution quality.

3) ADAPTIVE OPERATORS

Well-configured adaptive operators for crossover and mutation probabilities can enhance the convergence speed of genetic algorithms.GA-DF incorporates the adaptive operator described in [13], as shown in the following equation.

$$P_c = \begin{cases} \dfrac{k_1\left(f_m - f'\right)}{f_m - f_a}, f \geq f_a \\ k_2, \qquad\qquad\qquad f < f_a \end{cases} \tag{19}$$

$$P_m = \begin{cases} \dfrac{k_3\left(f_m - f'\right)}{f_m - f_a}, f \geq f_a \\ k_4, \qquad\qquad\qquad f < f_a \end{cases} \tag{20}$$

where k_1, k_2, k_3, k_4 are constants, f_m denotes the maximum fitness value of an individual in the current population, f' denotes the larger fitness value of the two individuals to be crossed over, f_a denotes the average fitness value of the current population, f denotes the fitness value of an individual to be mutated, P_c denotes the crossover probability, and P_m denotes the mutation probability.

4) CROSS-MODAL DESIGN

Due to a different encoding approach compared to traditional genetic algorithms, this study employs a two-point crossover method with randomly selected crossover positions. Two positions p_1 and p_2 are randomly chosen from parent2 with values v_1 and v_2, which are then copied to the child. The values v_1 and v_2 are located in parent1 and removed, with the remaining values copied sequentially to the child. The chromosome encompasses five distinct genetic characteristics, each undergoing crossover operations separately for individual genetic traits as shown in Fig. 4.

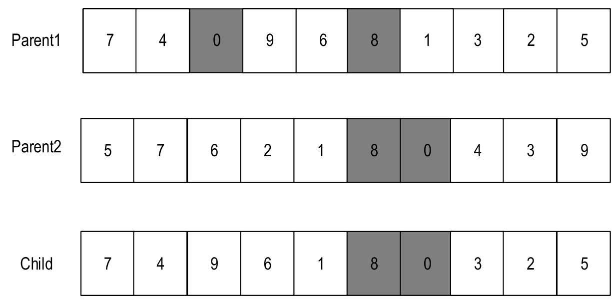


FIGURE 4. GA-DF crossover mode.

5) MUTATION APPROACH DESIGN

In chromosomal mutation routines, bitwise variation is commonly used for binary coding problems. However, in this paper with a special encoding method, a two-point mutation with permutation is employed. During this mutation operation, two random positions $p1$ and $p2$ are selected from the parent chromosome, and their values $v1$ and $v2$ are exchanged to produce the offspring chromosome, denoted as Child. The chromosome comprises five gene characteristics, and the mutation process is applied independently to each characteristic. The method for mutating a single gene characteristic is illustrated in Fig. 5.

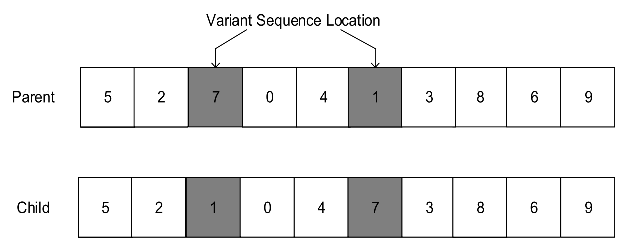


FIGURE 5. GA-DF variation approach.

6) DECAY FACTOR DESIGN

Adaptive decay is a crucial method for parameter tuning in genetic algorithms, enabling dynamic adjustment of the decay factor's value during runtime. This adaptive approach allows the algorithm to balance diversity and convergence based on its performance, ultimately enhancing algorithm performance.

The traditional genetic algorithm is prone to getting stuck in local optimal solutions, and the introduction of a decay factor can help to escape these local optima more effectively. For a decay factor Decay ∈ [4], [6], a multi-point mutation operation is conducted on the chromosome. The multi-point mutation is depicted in Model 1 in Fig. 6. The number of mutation points X is determined by the following equation:

$$X = 8 - \text{Decay} \qquad 4 \leq \text{Decay} \leq 6 \tag{21}$$

where Decay denotes the decay factor, and the decay factor begins to take effect when the fitness F remains constant for 2 consecutive generations.

When Decay ∈ [1], [3], the chromosome undergoes Model1 and Model2 operations to facilitate a rapid escape from local optimal solutions.

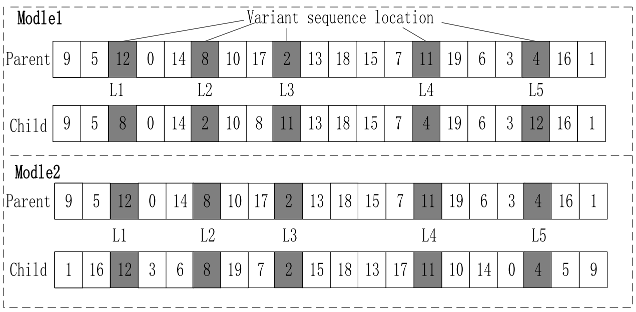


FIGURE 6. Multi-point mutation manipulation.

D. ALGORITHM FLOW DESIGN

Step 1: Generate D individuals randomly, set the total number of iterations to C. Initialize the iteration count d for the preferred selection section to I, the iteration count E for the remaining section to I, and initialize the decay factor Decay to 6.

Step 2: Calculate O using the preferred selection strategy.

Step 3: Apply adaptive operator crossover and genetic probability. The GA-DF crossover and mutation methods are employed to perform crossover and mutation operations on the genetic segments of outbound goods.

Step 4: Check if three consecutive generations of O are equal. If true, proceed to Step 5; otherwise, return to Step 2.

Step 5: Transfer the optimal solution O from the preferred segment to the new population.

Step 6: Check if E is less than $C-d$. If true, proceed to Step 7; otherwise, Otherwise, the goal is to find the optimal solution and fitness F.

Step 7: Apply adaptive operator crossover and genetic probability. Use GA-DF crossover and mutation to perform crossover and mutation operations on the genes related to inbound cargo, inbound cargo layer, hoist number, and shuttle number segments, and calculate the fitness F.

Step 8: Check if the maximum fitness F is unchanged for two consecutive generations. If true, proceed with Step 9.; otherwise, return to Step 6.

Step 9: Check if Decay is in the interval [4], [6]. If true, perform model1 mode mutation; otherwise, perform model1 and model2 mode mutation.

Step 10: Check if Decay is 1. If true, set Decay = 6; otherwise, decrement Decay by 1. Return to Step 6.

Algorithm flow chart 7 shows.

V. SIMULATION VERIFICATION

To verify the performance of the GA-DF, the software simulation platform used in this paper is Matlab R2020a, and the hardware specifications include an Intel(R) Core(TM) i5-8300H CPU running at 2.30GHz with 16GB of RAM. According to the SBS/RS (Shuttle-Based Storage and Retrieval Systems) models referenced in literatures [9], [11], [13], and [19], the integration of parameters like shelf configurations, shuttle cars, and lift machines forms a cornerstone in designing efficient and effective storage and retrieval systems across various industrial applications. These models are pivotal in modern logistics and warehouse management, aiming to optimize space utilization, enhance operational efficiency, and improve overall supply chain dynamics. The parameters used in the simulation are summarized in the Table 1:

In the subsequent experiments, this paper compares the performance of the GA-DF algorithm proposed in this study with the Simulated Annealing Algorithm (SA), Classical Genetic Algorithm (GA), and Improved Genetic Algorithm (IOSA) from [20].

To enhance the comprehensiveness and robustness of the algorithm, this paper chooses four environmental scenarios to validate the superiority of the GA-DF algorithm. The four scenarios include: considering only the stability of shelves, considering only the urgency of outgoing goods, comprehensive consideration of warehouse in/out times, shelf stability, and warehouse busyness, and considering all cost functions. In these scenarios, three order quantities (50, 250, 350) are set for inbound and outbound goods, with goods randomly distributed on shelves accounting for 10%, 50%, and 70% of total warehouse locations. Due to the larger quantity of orders (350*350), 800 iterations are selected, while for 250*250 orders, 500 iterations are used, and for 50*50 orders, 200 iterations are used. Each scenario is simulated 20 times to record average results. The efficiency improvements presented in this paper are compared with the IOSA algorithm as described in [20]. Simulation graphs that best represent the performance of each algorithm are selected for comparison.

Fig. 8 illustrates the scenario where goods urgently need to be dispatched from the warehouse, focusing solely on the urgency of outbound goods. It's evident from the figure that GA-DF outperforms the other three algorithms across all three scales. From Table 2, it can be observed that for 50*50 orders, the average urgency of outbound goods managed by GA-DF is 0.678, compared to 0.682 for the IOSA algorithm proposed in [20], resulting in a 0.59% improvement in efficiency with GA-DF. For 250*250 orders, the average urgency of outbound goods managed by GA-DF is 0.571, while IOSA's is 0.692,

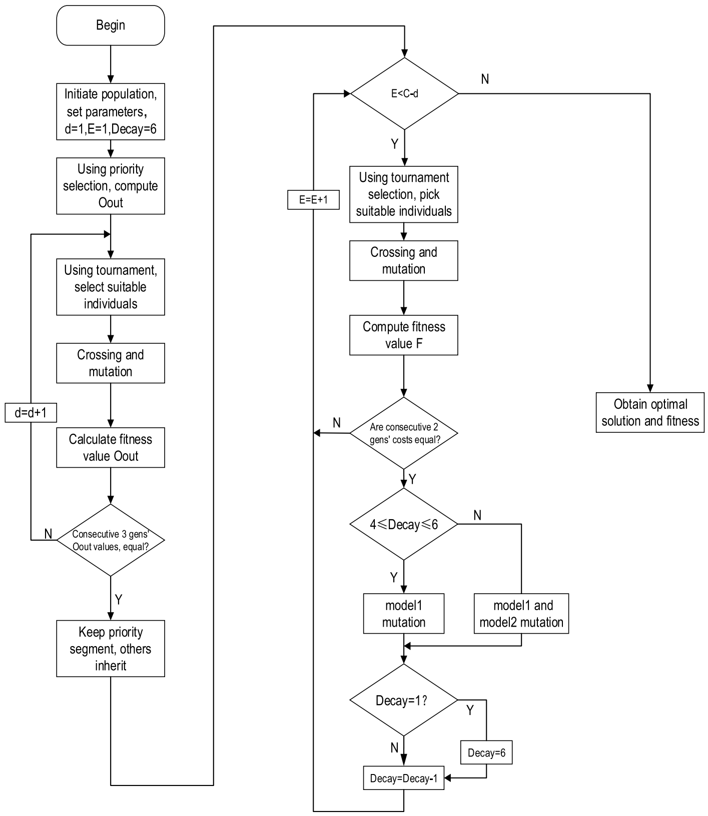


FIGURE 7. Flowchart of GA-DF design.

TABLE 1. SBS/RS physical model parameters.

parameters	value	unit	parameters	value	unit
Number of Lanes	10	\	Population size	300	\
Number of racks	10	\	initial temperature	100	\
Number of rows	20	\	temperature attenuation	0.98	\
Number of shelves	5	\	crossover probability	0.2	\
Number of hoists	2	\	probability of mutation	0.05	\
Number of AGVs	5	\	Cargo urgency	1-10	\
AGV Maximum Speed	3	m/s	K1	2	\
AGV acceleration	1	m/s^2	K2	0.3	\
Maximum speed of hoist	2	m/s	K3	1.5	\
Elevator acceleration	0.75	m/s^2	K4	0.2	\
Quality of goods	1-20	Kg	\	\	\

resulting in a 17.49% efficiency improvement with GA-DF. For 350*350 orders, the average urgency of outbound goods managed by GA-DF is 0.687 compared to 0.719 for IOSA, leading to a 4.45% improvement in efficiency with GA-DF. In summary, the improvement effect is more significant when goods occupy 50% of the total shelf space.

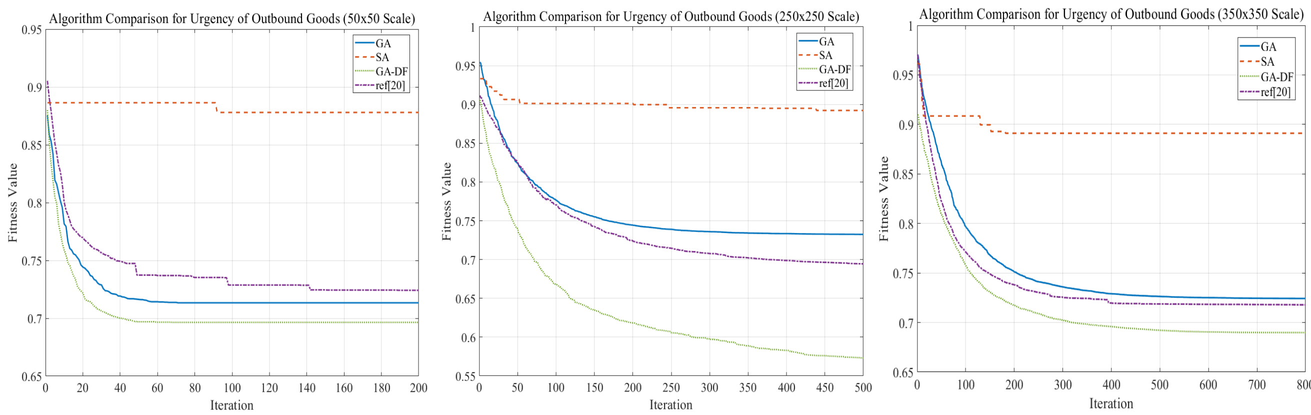
Fig.9 considers only the stability of the shelves, focusing on the stability and longevity of warehouse shelving. The figure shows that GA-DF outperforms the other three algorithms across all three scales. According to Table 2, for 50*50 orders, the average shelf stability managed by GA-DF is 0.168, compared to 0.181 for the IOSA algorithm proposed in [20], resulting in a 7.18% improvement in efficiency with

GA-DF. For 250*250 orders, the average shelf stability managed by GA-DF is 0.261, while IOSA's is 0.304, leading to an 14.14% efficiency improvement with GA-DF. For 350*350 orders, the average shelf stability managed by GA-DF is 0.207 compared to 0.297 for IOSA, resulting in a 30.30% improvement in efficiency with GA-DF. In summary, the improvement effect is more significant when goods occupy 70% of the total shelf space.

Fig.10 considering task time, shelf stability, and warehouse busyness, there are no urgently needed outbound goods in this scenario. The figure illustrates that GA-DF outperforms the other three algorithms across all three scales. According to Table 2, for 50*50 orders, the average multi-cost managed by GA-DF is 1.212, compared to 1.553 for the IOSA algorithm proposed in [20], resulting in a 21.96% improvement in efficiency with GA-DF. For 250*250 orders, the average multi-cost managed by GA-DF is 0.501, while IOSA's is 1.883, leading to a 73.39% efficiency improvement with GA-DF. For 350*350 orders, the average multi-cost managed by GA-DF is 0.876 compared to 1.003 for IOSA, resulting in a 12.66% improvement in efficiency with GA-DF. In summary, the improvement effect is more significant when goods occupy 50% of the total shelf space.

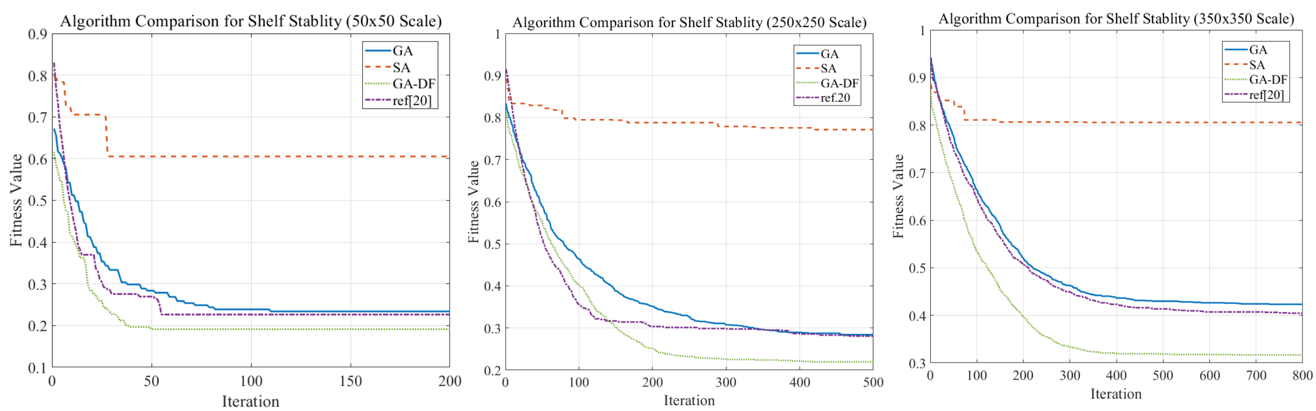
Fig. 11 presents a comparison of overall cost algorithms. The figure indicates that GA-DF outperforms the other three algorithms across all three scales. In this environment, GA-DF adopts a priority selection approach. It first conducts genetic operations on urgency, finding the optimal solution, and then continues genetic operations on the remaining segments of chromosomes. According to Table 2, for 50*50 orders, the average overall cost managed by GA-DF is 1.523, compared to 2.256 for the IOSA algorithm proposed in [20], resulting in a 31.16% improvement in efficiency with GA-DF. For 250*250 orders, the average overall cost managed by GA-DF is 1.208, while IOSA's is 2.614, leading to a 53.79% efficiency improvement with GA-DF. For 350*350 orders, the average overall cost managed by GA-DF is 1.662 compared to 1.786 for IOSA, resulting in a 6.94% improvement in efficiency with GA-DF. In summary, the improvement effect is more significant when goods occupy 50% of the total shelf space.

Based on the simulations and data, when comparing order quantities, the following conclusions can be drawn: GA-DF exhibits the best improvement at an order quantity of 250*250, with an improvement efficiency over 10% higher than the IOSA proposed in [20], and over 50% higher under



(a)50*50 Simulation (b)250*250 Simulation (c)350*350 Simulation

FIGURE 8. Comparison of algorithms at different scales with urgency as the dominant factor.



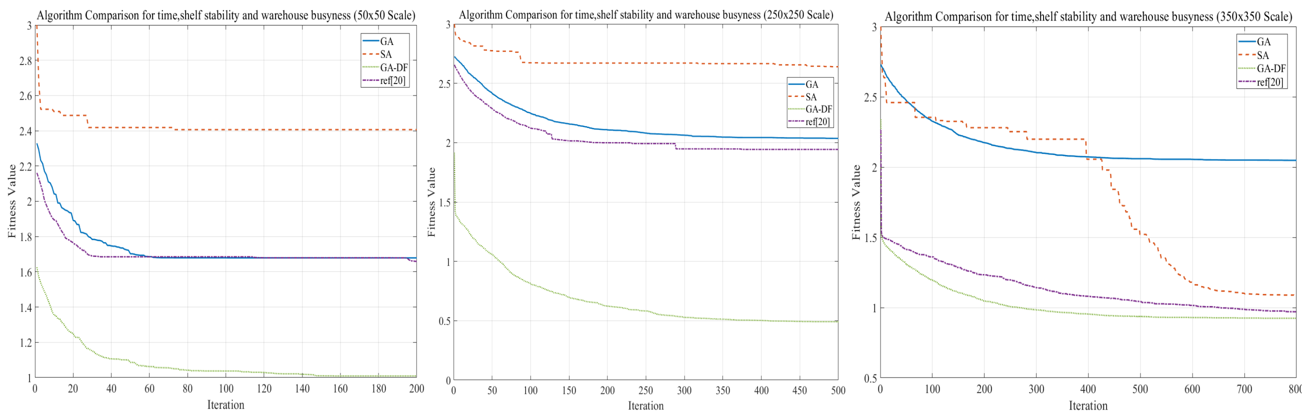
(a)50*50 Simulation (b)250*250 Simulation (c)350*350 Simulation

FIGURE 9. Comparison of algorithms at different scales dominated by stability.

TABLE 2. Performance metrics for each algorithm.

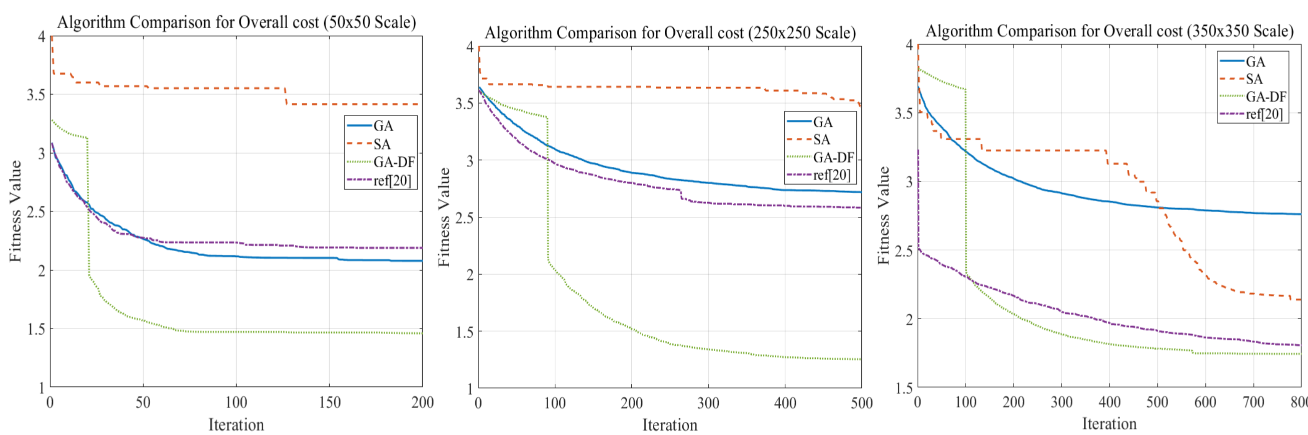
Order Number	algorithms	O Average	Improving efficiency/%	M Average	Improving efficiency/%	T、M、R Average	Improving efficiency/%	F Average	Improving efficiency/%
50*50	GA	0.693	-	0.205	-	1.631	-	2.204	-
	SA	0.766	-	0.651	-	2.521	-	3.301	-
	Ref[20]	0.682	-	0.181	-	1.553	-	2.256	-
	GA-DF	**0.678**	**0.59**	**0.168**	**7.18**	**1.212**	**21.96**	**1.523**	**32.49**
250*250	GA	0.735	-	0.367	-	1.939	-	2.765	-
	SA	0.881	-	0.774	-	2.509	-	3.442	-
	Ref[20]	0.692	-	0.304	-	1.883	-	2.614	-
	GA-DF	**0.571**	**17.49**	**0.261**	**14.14**	**0.501**	**73.39**	**1.208**	**53.79**
350*350	GA	0.723	-	0.313	-	2.036	-	2.749	-
	SA	0.908	-	0.804	-	1.484	-	1.751	-
	Ref[20]	0.719	-	0.297	-	1.003	-	1.786	-
	GA-DF	**0.687**	**4.45**	**0.207**	**30.30**	**0.876**	**12.66**	**1.662**	**6.94**

various cost functions. In the case of 350*350 orders with multiple cost functions, GA-DF also demonstrates significant improvement, with an efficiency increase of more than 4% compared to IOSA. For an order quantity of 50*50, where urgency is the dominant cost factor, GA-DF's improvement is less pronounced, but it still shows an efficiency increase of more than 20% compared to IOSA under multiple cost functions. In summary, GA-DF shows significant improvements over traditional GA, SA, and IOSA, especially when the order quantity is large.



(a)50*50 Simulation (b)250*250 Simulation (c)350*350 Simulation

FIGURE 10. Comparison of algorithms at various scales emphasizing time, stability, and urgency.



(a)50*50 Simulation (b)250*250 Simulation (c)350*350 Simulation

FIGURE 11. Comparison of algorithms at different scales dominated by the overall cost.

VI. CONCLUSION

This paper addresses the limitations of traditional warehouse operations by focusing on SBS/RS. It establishes an optimization model based on goods urgency, shelf stability, time cost, and warehouse busyness for inbound and outbound storage space. GA-DF optimizes the selection operator to avoid local optimal solutions, adopts a preferred selection method to expedite finding the optimal solution, and utilizes a decay factor to facilitate escaping local optima. To assess the effectiveness of GA-DF, this study compares it with traditional genetic algorithms, simulated annealing algorithms, and IOSA algorithms. The results indicate that when goods occupy 50% of the shelf space and various cost environments are considered, the GA-DF algorithm improves efficiency by more than 50% compared to the IOSA algorithm. In other scenarios, the GA-DF algorithm outperforms the simulated annealing algorithm, genetic algorithm, and IOSA algorithm in optimizing storage and retrieval locations.

The paper indicates that the improvement efficiency of shelf stability is lower when there are fewer incoming goods involved in the study. Therefore, future research on GA-DF should focus on further enhancements to enable it to find optimal solutions effectively across diverse environments, regardless of the quantity of incoming goods.

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