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RESEARCH ARTICLE

An Auxiliary Model of Intelligent Logistics Distribution Management for Manufacturing Industry Based on Refined Supply Chain

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ABSTRACT In the context of Industry 4.0 and based on the demand of digital logistics construction of industrial enterprises, this paper integrates the concept of digital twin into Refined Logistics Supply Chain construction. Considering the constraints of multi-distribution center, heterogeneous vehicle performance, distribution cost, quasi-shipment certificate and humanized management, Refined Logistics Supply Chain System (RLSCS) and cross-regional scheduling optimization model of logistics vehicles with multi-distribution center were established. The designed model can minimize the transportation cost, reduce the transportation time, and improve the vehicle load rate. An adaptive elite honey badger target algorithm based on cubic mapping mechanism (IHBA), is designed to solve the model. Further, performance evaluation by optimizing test functions, the convergence performance of IHBA algorithm was demonstrated. Finally, the simulation experiment is carried out according to the actual business data and it is compared to eight other optimistic algorithms. The experimental results show that the proposed algorithm is more effective and more robust, and the related models and algorithms can provide research basis for industrial products digital supply chain system.

INDEX TERMS Industry 4.0, refined supply chain, multi-objective constraint, logistics distribution, honey badger algorithm, cubic mapping mechanism.

I. INTRODUCTION

Considering the rapid development process of industrialized city construction, enabling intelligent and smart construction is the key in the context of Industry 4.0 [1]. Thus, smart cities and smart manufacturing planning are significant [2], [3], while industrial manufacturing has long tended to rely on automated operations [4]. With the motivation of Artificial Intelligence (AI), the Internet of Things (IoT), and other technologies, the industrial transformation has become the trend of industrial development. The logistics industry has been also developed going from traditional logistics to reach intelligent logistics [5], [6]. Therefore, making logistics systems fully autonomous and systematically controlling, optimizing, and managing the corresponding complex systems are essential points to research criteria in logistics and distribution in the context of Industry 4.0. In most of previous studies, some logistics distribution-related problems were solved. For example, in mathematical models, Li et al. [7] developed a bi-objective mixed-integer linear programming model considering cost and commodity quality. As for Yu [8], he thoroughly thought about the problem of energy and vehicle allocation. Furthermore, Mendes et al. proposed an online dimensionality reduction method to deal

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with the Vehicle Route Problem with Demand-Response Transportation (VRPDRT). Most of the algorithms in solving logistics distribution are exact and heuristic [10]. Heuristics are actually more commonly used than exact algorithms because of their superior parallelism and lower limitations on the properties of the objective function, whereas exact algorithms struggle to provide efficient solutions when the objective function and the constraints are complicated [11]. In the studies of Montes Dorantes [12], Onieva [13] and others, logistics distribution paths were optimized based on evolutionary strategies. In addition, algorithms, such as Ant Colony Algorithm [14] and HSA-HGBS Algorithm [15], have been applied in logistics distribution path optimization in a general way. These studies show that the innovation and application of mathematical models play a key role in logistics scheduling, and the selection and improvement of optimization algorithms are indispensable links in solving mathematical models. However, most scholars have studied logistics scheduling at the level of mathematical models and optimization algorithms, and it is undeniable that the research of these scholars has made valuable contributions to the solution of VRPDRT problems. With the deepening and advancement of Industry 4.0, logistics scheduling still needs to further integrate information and physics at the system level, such as full life cycle management and visual information display.

In the recently years, many scholars have explored and researched the intelligent logistics supply chain (LSC) system. For example, Issaoui et al. [16] presents an advanced logistics service, which warrants dynamic coordination among all the actors in the smart logistics environment, which consists of two main parts: the delivery prediction model to compute the expected arrival time, and a hybrid optimization model to tackle path issues. In addition, Wang et al. [17] and Distefano et al. [18] developed, respectively, an intelligent distribution system and a vehicle information system. To sum up, the different publications, listed above, made considerable contributions to intelligent distribution. It provides a lot of reference significance for the construction of LSC; however, they lacked refining data in the process of logistics distribution tasks such as the vehicle status, its current task situation, and its completed task order registration.

With the rapid development of microelectronics, automation, computers, communication, information, and artificial intelligence, the digital twin concept was born to crack the problem of physical experiments' high cost [19]. Influenced by the concept of digital twin technology, an increasing number of logistics and distribution companies are conducting research toward building a fine-grained digital supply chain system [20], [21]. In the field of intelligent distribution, Leung et al. [22] constructed a multi-level framework based on the digital twin to enhance the construction of digital logistics. Based on the above research, this paper will be focusing on drawing on the system concept of digital twins further study the digital logistics based on the refined supply chain and will explore the intelligent logistics scheduling model.

Based on the idea of parallel system, this paper uses RFID technology to apply product visualization management in the Industry 4.0 platform, and establishes RLSCS (Refined Logistics Supply Chain System), which includes five levels: physics, model, Internet of Things, data and service, making the logistics and distribution management and scheduling of vehicles more efficient, and realizing data visualization and full life cycle management in transportation. At the same time, vehicle scheduling and cargo planning are studied from the perspective of both vehicles and commercial customers, to integrate the actual needs and physical systems in RLSCS. This presents a valuable exploration for the application of the Refined Logistics Supply Chain, and the contribution of the paper is summarized below:

(1). The concept of Refined Logistics Supply Chain construction was introduced, and RLSCS were established by drawing on the theory of parallel systems, which were applied to the whole life cycle logistics management.

(2). The cross-regional scheduling optimization model of logistics vehicles in multiple distribution centers is established, and the actual constraints are established according to the real-time storage capacity of different warehouses for different goods and the time window requirements of commercial customers for orders. Further combine the state perception and actual order data in the physical level to complete the interaction and data simulation between the model and the actual in RLSCS.

(3). To improve Honey Badger Optimization Algorithm (HBA) and optimize vehicle scheduling, combining cubic chaotic mapping strategy, adaptive weights strategy and a multi-elite perturbation selection strategy based on population hierarchy. An adaptive elite honey badger target algorithm based on cubic mapping mechanism (IHBA) is designed

(4). Simulation experiments are carried out on the proposed model to evaluate and verify the reliability and integrity of the algorithm and the established system, and realize visual management.

To sum up, the rest of the paper is organized as follows: in Section II, the establishment of fine logistics distribution supply chain system module is introduced whereas, a cross-regional scheduling optimization model of logistics vehicles in multiple distribution centers is constructed in Section III. As for Section IV, it represents the design of an adaptive elite honey badger objective algorithm, based on cubic mapping mechanism and the experiments and simulations are conducted in Section V. Finally, the conclusion in presented in Section VI.

II. CONSTRUCTING REFINED LOGISTICS SUPPLY CHAIN SYSTEM MODULE

The business process of distribution task consists of the following sequence: order receiving - task assignment - route planning - distribution transportation - customer point delivery - unloading. The Refined Logistics Supply Chain System (RLSCS) is based on the digital twin concept, which virtually maps the distribution business process and the business activities on the computer and runs backward on the distribution business process to optimize the distribution process and to improve the performance. Therefore, in addition to the essential business information management, such as the order management, the management and the service functions of the distribution business process primary activities must be completed. Material distribution for manufacturing generally has a single type of goods and fixed customer locations in a single delivery, and the business activities involved do not require repeated planning. However, distribution for service and process has complex requirements due to the inventory of goods at the shipping point, the different loading capacity of heterogeneous vehicles, and the diversified customers.

The distribution routes are planned and optimized according to the distribution planning tasks, the real-time tasks, and the route distances. As for the distribution order and route optimization considering the boxing results, it consists of saving the distribution distance and time, improving the distribution effectiveness and resource utilization efficiency, and thus further improving the distribution volume. For simulation purposes, we have established a RLSCS module to solve the logistics scheduling allocation tasks.

The presentation of various data, based on a RLSC, is critical to the business, including monitoring and (visual) reflection of the real-time status of cargo transportation (distribution status such as transport stability). Data visualization in actual transportation is the key to improve the quality and the level of distribution service. Finally, the whole life cycle management of supply chain logistics scheduling system is realized. Thus, the different layers responsible of this supply chain will be defined here after:

A. MODEL LAYER

It provides a library for RLSCS, and the covered models include two types: the logistics distribution process model and the management service model. The first model consists of the logistics vehicle cross-territory dispatch optimization model that is established to digitally describe and abstract the physical distribution and management by considering the order time window of commercial customers, the driver fatigue driving rest, the empty vehicle rate, etc. Based on these inputs, a RLSCS model of physical distribution is formed relying on the data layer, which is used to describe the geometric and the dynamic information structure of entity objects in the management system, *i.e.,* the optimization model of cross-territory dispatching of logistics vehicles in multiple distribution centers and the management service model is a decision support model for management operation and maintenance services, such as the path planning algorithm, for vehicle distribution.

B. PHYSICAL LAYER

The physical distribution, in charge of completing the loading and the transportation delivery of actual goods, accepts feedback control information from the distribution and the transport virtual scenario and the distribution management system. Comprehensive consideration of the actual scenario is based on the optimization results for real-time distribution. There are three main scenarios:

- loading and delivery of goods;
- real-time monitoring and feedback on the status of goods and trucks as required;
- accepting real-time orders and seeking real-time interactive services from the Digital twin distribution management system.

C. IOT LAYER

All vehicles, responsible for delivery, transmit data relative to:

- their real-time location using their GPS;
- order completion based on RFID feedback;
- their status information.

D. DATA LAYER

It is mainly responsible for the storage, the initial processing, and the fusion of the LSC data collected by the IoT layer and generated by the operation and maintenance service layer with the system management data (such as customer data) to provide support for the operation of the physical scenario, the virtual scenario and RLSCS.

E. SERVICE LAYER

It performs visual data representation, provide decision support, maps virtual and reality, etc.

III. MULTI-DISTRIBUTION CENTER LOGISTICS VEHICLE CROSS-TERRITORY SCHEDULING OPTIMIZATION MODEL

A. PROBLEM DESCRIPTION

The presented logistics vehicle cross-territory dispatching problem is realized under several conditions that are listed here below: the knowledge of the spatial location and the demand of customer points, the location of distribution centers, and the maximum vehicle load capacity. This is established by collecting real-time distribution data of A vehicles delivering homogeneous goods to j customers in a certain region. The optimal distribution solution obtained, through the use of iterative optimization, is fed back to the physical model in order to minimize the comprehensive cost of the vehicle utilization and the transportation time. To sum up, the following hypotheses were made for the problem understudy:

(1) Each vehicle is equipped with two drivers, and each driver cannot drive for more than four consecutive hours and cannot exceed eight hours of vehicle travel time in a day, according to the traffic law;

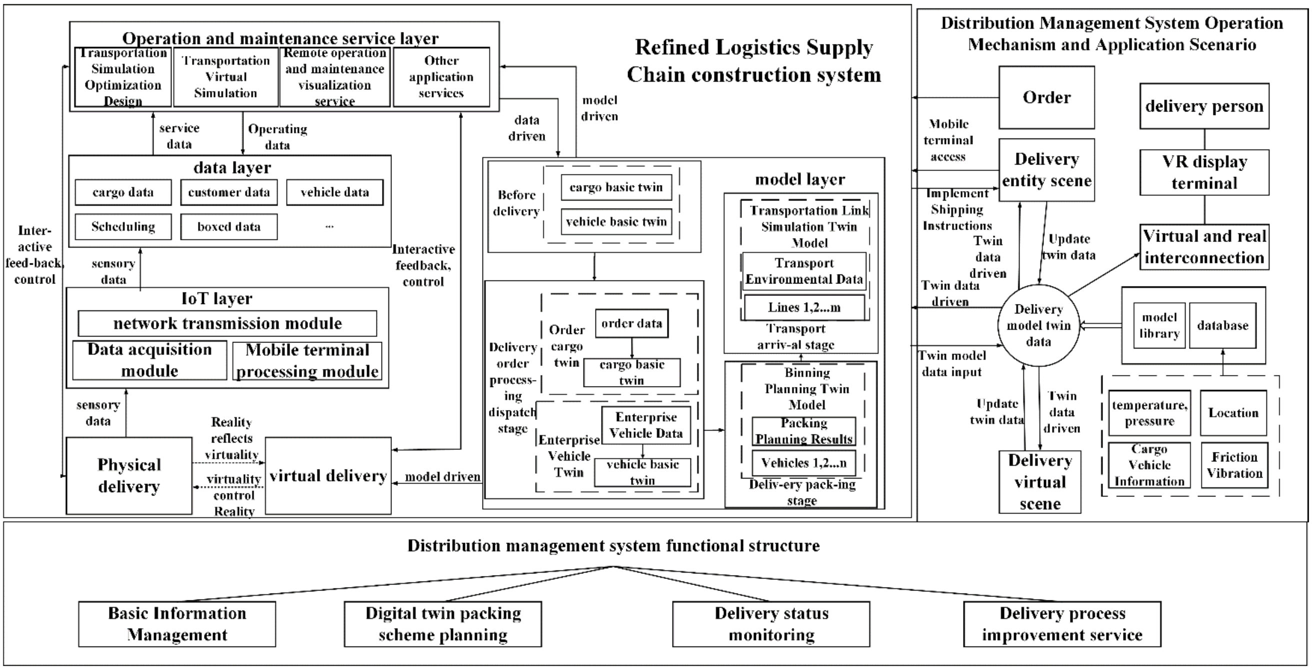

FIGURE 1. Refined grained supply chain based on logistics scheduling.

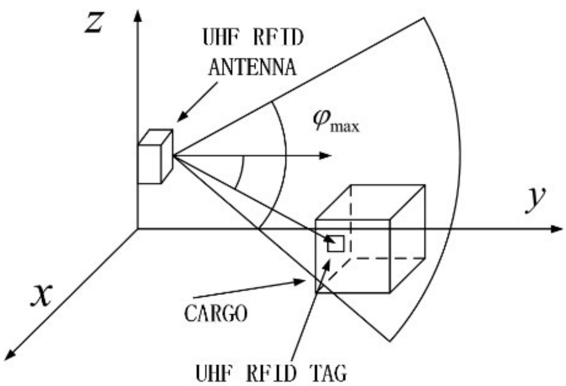

FIGURE 2. RFID reader working principle.

(2) Fuel filling of the vehicle and driver's eating and rest are included in the daily eight hourly rest period;

(3) The goods are packaged with the same specifications at each shipping point; thus, there are no differences;

(4) Each vehicle is circulating in only one path, and they all start from the distribution center and return finally to the distribution center.

(5) All incoming or outgoing goods will be identified by the RFID reader at the entrance of the warehouse; thus, an automatic recording of the information of incoming and outgoing goods is performed. At the same time, the carriage will be also equipped with an RFID reader, and the incoming and outgoing goods will be automatically registered.

The sets, indices, parameters and variables of the proposed problem are defined in Table 1.

TABLE 1. Symbol description.

symbol	meaning
Am	A vehicle with the code name A and the model number m
i	The i-th point of delivery
j	The j-th point of receiving
w_j	The tonnage of cargo required at the j-th receiving point
α^i_{Am}	The 0-1 variable, which indicates whether the car Am departs at the point of origin i
α^j_{Am}	0-1 variable, indicating whether the car Am is delivered to the receiving point j
wAm_j	Tonnage of cargo delivered by the car Am to the j-th receiving point
wAm_i	The tonnage of cargo loaded by the car Am from the i-th point of origin
tAm_i	The shipping time of the car Am at the i-th point of shipment
tAm_j	The arrival time of the car Am at the j-th receiving point
TAm_{ij}	The journey time of the car Am from the i-th point of origin to the j-th point of delivery
$TAm_{jj'}$	The journey time of the car Am from the j-th receiving point to the j'-th receiving point
T^{ij}_{Am}	The total working time of the car Am
Tr^{ij}_{Am}	Total rest time for car Am
V_i	Indicates the shipping speed of the i-th point of shipment
L_{ij}	Indicates the path from the i-th point of delivery to the j-th point of receiving
$L_{jj'}$	Indicates the path from the j-th point of receiving to the j'-th point of receiving
M	Indicates the total shipping cost
M^{ij}_{Am}	Indicates the total cost of car Am during transportation
v	Indicates the average speed of the vehicle
u	Unit price per kilometer of transport

B. OBJECTIVE FUNCTION

Based on the orders of commercial companies, enterprises are scheduled, *i.e.,*the scheduling of enterprises is constrained by subsequent order scheduling, and the key to optimize the logistics vehicle scheduling problem across geographical areas is how to solve the optimal solution of the constructed model so that the total transportation time is the shortest. The total transportation cost will decrease due to the optimization of the transportation routes and the vehicle allocation. This paper still takes the shortest transportation time and lowest cost, and the highest vehicle utilization rate as the objective function. According to the survey, transportation cost is related to weight and mileage, while transportation time is only related to the transportation mileage, referring to the transport freight calculation rules. Thus, one can write the following equation: Actual freight cost (CNY) = unit price of transportation (CNY/ (ton. km)) $^{\times}$mileage (km).

Below, Eqs. (1) to (13) represent goods logistics scheduling model.

$$M_{Am}^{ij} = u\left(wAm_i \times L_{ij} + \sum (wAm_i - \sum wAm_j) \times L_{jj'}\right) \tag{1}$$

$$wAm_i = \sum_{j=1} w_j \times \alpha_{Am}^j \tag{2}$$

$$M = \sum_{A=1}\sum_{i=1}\sum_{j=1} M_{Am}^{ij}, \quad m = \{1, 2, 3\} \tag{3}$$

$$\alpha_{Am}^i = \begin{cases} 1, & \text{the vehicle } Am \text{ } departsfrom\ i-th \\ & \quad\quad \text{shipping point} \\ 0, & \text{Otherwise} \end{cases} \tag{4}$$

$$\alpha_{Am}^j = \begin{cases} 1, & \text{the vehicle } Am \text{ is sent to the } j-th \\ & \quad\quad \text{receiving point} \\ 0, & \text{Otherwise} \end{cases} \tag{5}$$

$$W_{Am} = 1 - \frac{\sum_{j=1} w_j \times \alpha_{Am}^j}{wAm_{\max}} \tag{6}$$

$$\beta_{Am} = \begin{cases} 1, & \frac{wAm_i}{wAm_{\max}} < 95\% \\ 0, & \text{Otherwise} \end{cases} \tag{7}$$

$$C_{Am} = \sum_{A=1} \beta_{Am} \times cc \tag{8}$$

$$T_{Am}^{ij} = tAm_i + TAm_{ij} + \sum TAm_{jj'} + \sum tAm_j + TAm_{ij'} \tag{9}$$

$$Tr_{Am}^{ij} = \left[\frac{TAm_{ij} + \sum TAm_{jj'}}{16}\right] \times 8 \tag{10}$$

$$\begin{cases} TAm_{ij} = \frac{L_{ij}}{v} \\ TAm_{jj'} = \frac{L_{jj'}}{v} \\ tAm_i = \frac{wA_i}{V_i} \end{cases} \tag{11}$$

$$T = \sum_{A=1}\sum_{i=1}\sum_{j=1} (T_{Am}^{ij} + Tr_{Am}^{ij}) \tag{12}$$

$$\min f = \sum_{A=1}\sum_{i=1}\sum_{j=1} \left\{M_{Am}^{ij} \times (T_{Am}^{ij} + Tr_{Am}^{ij}) \times C_{Am} \times W_{Am}\right\} \tag{13}$$

Eq. (1) represents the transportation cost of vehicle A_m whereas Eq. (1) indicates that the number of pickups by vehicle A_m at the shipping point is equal to the total weight of goods delivered by vehicle A_m to all receiving points. As for Eq. (3), it represents the total transportation cost of all vehicles and Eq. (4) α_{Am}^i shows whether vehicle A_m starts at the i^{-th} shipping point. In Eq. (5), α_{Am}^j indicates whether vehicle A_m is sent to the j^{-th} receiving point and Eq. (6) calculates the empty rate of vehicle. In Eq. (7), β_{Am} indicates whether the empty rate of vehicle A_m exceeds 5% and Eq. (8) represents the penalty cost, where cc is the low empty rate penalty cost of a single vehicle. Eq. (9) calculates the total working time of transportation of vehicle A_m and Eq. (10) is the total rest time of the vehicle knowing that the total driving time of two drivers in 24 hours is 16 hours, *i.e.* 8 hours of rest for every full 16 hours. Eq. (11) indicates the specific transportation time calculation equation and Eq. (12) shows the total transportation time of all vehicles. Finally, Eq. (13) is the objective function of the model, which indicates the shortest total transportation time, the lowest cost, and the lowest vehicle empty rate.

C. CONSTRAINTS

Eqs. (14) to (26) represent goods logistics scheduling model constraints

$$\sum_{A=1} \alpha_{Am}^i = 1 \tag{14}$$

$$\sum_{A=1} \alpha_{Am}^j \leq 3 \tag{15}$$

$$\xi_{Am}^i = \begin{cases} 1, & \text{The goods of vehicle } Am \\ & \text{have been} \\ & \text{identified by the RFID reader of} \\ & \text{the warehouse} \\ & \text{of the } \ i-th \text{ shipping point out} \\ & \text{ of the warehouse} \\ 0, & \text{Otherwise} \end{cases} \tag{16}$$

$$\delta_{Am}^i = \begin{cases} 1, & \text{Vehicle } Am\text{ 's cargo has been} \\ & \text{ identified} \\ & \text{by the car RFID reader into the} \\ & \text{ carriage} \\ 0, & \text{Otherwise} \end{cases} \tag{17}$$

$$\xi_{Am}^{j} = \begin{cases} 1, & \text{The goods of the vehicle Am} \\ & \text{have been recognized} \\ & \text{into the warehouse by the RFID} \\ & \text{reader of the} j-th \\ & \text{receiving point warehouse} \\ 0, & \text{Otherwise} \end{cases} \tag{18}$$

$$\delta_{Am}^{j} = \begin{cases} 1, & \text{Vehicle } Am \text{ sent to the } j-th \\ & \text{receiving point of} \\ & \text{the goods have been identified by} \\ & \text{the car RFID} \\ & \text{reader to leave the carriage} \\ 0, & \text{Otherwise} \end{cases} \tag{19}$$

$$\xi_{Am}^{i} = \delta_{Am}^{i} \tag{20}$$

$$\xi_{Am}^{j} = \delta_{Am}^{j} \tag{21}$$

$$\sum_{j=1} \alpha_{Am}^{j} = \sum_{j=1} \xi_{Am}^{j} \tag{22}$$

$$wAm_{\min} < wAm_i < wAm_{\max} \tag{23}$$

$$\sum_{A=1} wAm_i \times \alpha_{Am}^{i} \leq w_i \tag{24}$$

$$T_j \geq T_{Am}^{ij} + Tr_{Am}^{ij} \tag{25}$$

$$\sum_{A=1} \delta Am \leq \delta m_{\max}, \quad m = \{1, 2, 3\} \tag{26}$$

Eq. (14) indicates that the supply chain vehicle can only start from one shipping point whereas Eq. (15) shows that a vehicle can only serve at most three customers. Eq. (16) presents whether the goods of vehicle A_m are detected by the RFID reader of the warehouse of the i^{-th} shipping point before leaving whereas Eq. (17) indicates whether the goods, loaded by vehicle A_m from the warehouse of the i^{-th} shipping point, are recognized by the RFID reader inside the vehicle to enter the carriage and Eq. (18) indicates whether the goods of vehicle A_m are detected by the RFID reader of the warehouse of the j^{-th} receiving point to enter the warehouse. In addition, Eq. (19) indicates whether the goods sent by vehicle A_m to the warehouse of receiving point j are recognized by the RFID reader in the vehicle to leave the carriage type and Eq. (20) restricts all the goods out of the warehouse of the shipping point to enter the carriage. As for Eq. (21), it restricts all the goods leaving the vehicle to enter the warehouse of the receiving point and Eq. (22) restricts the integrity of goods from the shipping point to the receiving point. Moreover, Eq. (23) is the vehicle A_m loading limit, determined by the vehicle's own performance, where $wAm_{\min}$ and $wAm_{\max}$ are the maximum and minimum loading values and Eq. (24) is the upper limit of daily shipments from the shipping point of industrial enterprises, determined by the warehouse structure, staff, and working hours. Added to that, Eq. (25) is the transportation time limit, determined by the receiving point commercial company, where T_j is the maximum time for vehicle A_m to travel from production shipment point i to commercial customer company j. Finally, Eq. (26) is the constraint on the number of each model.

IV. ADAPTIVE ELITE HONEY BADGER OBJECTIVE ALGORITHM BASED ON CUBIC MAPPING MECHANISM

A. BASIC HONEY BADGER OPTIMIZATION ALGORITHM

The Honey Badger Algorithm (HBA) is a biological heuristic-based intelligent optimization algorithm proposed by Hashima et al. It mainly simulates the foraging behavior of honey badgers in digging and searching for honey and then defines the global dynamic search behavior of the algorithm. Compared to the traditional intelligent optimization algorithm, the digital twin logistics scheduling system needs an efficient core algorithm to help enterprises complete the tasks of (1) planning cargo order matching, (1) vehicle sorting, and (3) vehicle path planning more easily and quickly. The Honey Badger Optimization Algorithm (HBA) has the advantages of fewer parameters, simple structure but strong optimization capability, and fast convergence speed. Therefore, the HBA has a broader application prospect in dealing with such multi-objective optimization problems with complex conditions and large-scale constraints.

In the standard HBA, location of each individual honey badger populations equivalent to a potential solution to the problem. The merit of the potential solution is associated with its location from the honey, which represents the optimal solution to the problem. The location of the honey badger closest to the honey is the optimal solution for the current population. While being updated, the algorithm is iteratively going through two main phases: the mining (or excavation) phase and the honey harvesting phase. Both phases will be presented below.

1) EXCAVATION STAGE

In the mining optimization phase, the honey badger performs a search motion like a novel line, and in the mining phase, the algorithm performs a global search. The mathematical model of this motion can be simulated by equation (27).

$$x_{\text{new}} = x_{\text{prey}} + F\beta I x_{\text{prey}} + F r_1 \alpha d_i \times |\cos(2\pi r_2) \times [1 - \cos(2\pi r_3)]| \tag{27}$$

where x_{new} is the new location of the individual honey badger, and x_{prey} is the current global most location. Added to that, $\beta \geq 1$ represents the ability of the individual honey badger to obtain food, r_1, r_2, r_3 and r_4 are different random numbers ranging between [0,1], and $F$is the change of the honey badger search direction parameter sign as shown in Eq. (29). I_i is the prey scent intensity; the higher the scent intensity is, the faster the honey badger search speed will be, and vice versa. α represents the density factor, which ensures the algorithm smooth transition between global search and local search, and the mathematical model of the following relations is shown as follows:

$$\alpha = C \times \exp(\frac{-t}{t_{\max}}) \tag{28}$$

$$F = \begin{cases} 1, & \text{if rand} \le 0.5 \\ -1, & \text{else} \end{cases} \tag{29}$$

$$I_i = r_4 \frac{S}{4\pi d_i^2} \tag{30}$$

In Eq. (28), C is a constant, $t$is the number of current iterations, and t_{max} is the total number of iterations. It is worth noting in Eq. (30) that the scent intensity I_i of each honey badger in the population is different and is related to the source intensity S and the distance between the current global optimal position and the current position of the individual d_i honey badger. The mathematical equation of the source intensity S and the relative distance d_i are represented as follows:

$$S = (x_i - x_{i+1})^2 \tag{31}$$

$$d_i = x_{prey} - x_i \tag{32}$$

2) HONEY HARVESTING STAGE

In this stage, the honey badger follows the bee guide straight to the hive case, in which the algorithm focuses more on the local search capability. This latter is represented by Eq. (33).

$$x_{\text{new}} = x_{\text{prey}} + F \times rand \times \alpha \times d_i \tag{33}$$

where *rand* is the random number varying between 0 and 1, and F,α,and d_i are derived by solving Eqs. (28), (29) and (32).

B. IMPROVEMENT HONEY BADGER ALGORITHM(IHBA)

1) CUBIC CHAOTIC MAPPING

In the current swarm intelligence optimization algorithm for solving logistics scheduling, initial order assignment populations are, in general, randomly generated in the search space. However, the quality of such populations is essential for the subsequent search of the optimization algorithm, especially in logistics scheduling. The uniformly distributed populations are more conducive to expanding the search range of the algorithm and, thus, improving the convergence speed and the accuracy of the algorithm.

When HBA solves complex optimization problems, even with the presence of cases multiplicity, there is also a reduction in the diversity of population individuals at the late iterative stage. Thus, the algorithm may fall into local optimum in the process of iterative optimization. Therefore, to increase the population's diversity, the concept of chaos is introduced to map the initial population in view of the traversal diversity of the chaotic factors. Since cubic mapping works better than traditional logistic mapping [23], the first approach will be used to generate the initial order population.

The equation for the cubic mapping is shown below:

$$c(o+1) = 4c(o)^3 - 3y(o) \tag{34}$$

$$-1 < c(0) < 1, \quad c(o) \neq 0 \; \text{o} = 0, 1, 2, \ldots \tag{35}$$

The initial honey badger population is assumed to be composed of *Nop* individuals of *D* dimension. The mapping process is as follows: first, a random *rand* number, whose value is in the interval [0,1], is generated as the position of the first dimension in each population individual, then the subsequent *D-1* individuals of each dimension in the population individual are generated by an iterative method according to Eq. (36), and finally the values of the variables generated by the cubic mapping are mapped to the honey badger population individuals according to Eq. (37).

$$X_c = X_{\text{initial}} \cdot (c+1)/2 \tag{36}$$

where X_c is the mapped order population and X_{initial} is the initial order population.

2) ADAPTIVE WEIGHTS

For the swarm intelligence optimization algorithm, inertia weights can regulate and control the algorithm during the exploration and the local mining capacity for global search. For the insufficient stability, robustness, and later exploration capacity problems of the HBA, global regulation is carried out by adaptive inertia weights to effectively balance the algorithm's global search and local search capacities. Thus, the introduced adaptive weight factor [24] equation is as follows:

$$w = \sin(\frac{\pi t}{2T_{\max}} + \pi) + 1 \tag{37}$$

where t is the current number of iterations and T_{max} is the maximum number of iterations.

With the addition of the adaptive inertia weighting factor, the optimization process of HBA is expressed as follow:

$$x_{new} = w \times (x_{\text{prey}} + F\beta I x_{\text{prey}} + F r_1 \alpha d_i \times |\cos(2\pi r_2) \times [1 - \cos(2\pi r_3)]|) \tag{38}$$

$$x_{\text{new}} = w \times (x_{\text{prey}} + F \times rand \times \alpha \times d_i) \tag{39}$$

3) A MULTI-ELITE PERTURBATION SELECTION STRATEGY BASED ON POPULATION HIERARCHY

When the algorithm is prone to fall into local optimal solutions in the late iterations of the algorithm update, it is first determined that, if the fitness value of the dominant population average does not change in five consecutive generations, it can be determined that the algorithm is stagnant. At this time, the population hierarchy is used to divide the elite individual position of the current population with the individual inferior position. Individuals are set as elite when their fitness is less than the average population fitness function and as inferior when they are greater than the average population fitness function. Elite populations implement elite strategies for location updates. A more "aggressive" perturbation strategy is used for the inferior population to expand the population-wide search ability by fine-tuning its position with that of other individuals. Finally, the greedy strategy is used to select the dominant population from the parent population and the newly generated individuals to ensure an efficient convergence of the algorithm. The specific mathematical equation is as follows:

$$X_i^{t+1} = \begin{cases} X_{\text{best}}^t + \varepsilon \times (X_{best}^t - X_i^t) + rand \times X_{\text{best}}^t - rand \\ \quad \times X_i^t, & f_i < f_{\text{average}} \\ X_i^t + rand(0,1) \times (X_{\text{rand}}^t - X_i^t), & f_i \geq f_{\text{average}} \end{cases} \tag{40}$$

where X_i^{t+1} is the location of the next generation of honey badgers, X_{best}^t is the current optimal honey badger individual location, ε is a normal distribution within the interval [0 - 1], X_i^t is the contemporary population individual location, X_{rand}^t is the current population any honey badger individual location, f_{average} is the current average fitness function value, and fi is the contemporary individual fitness function value.

C. STEPS FOR SOLVING THE MODEL WITH IMPROVED HONEY BADGER ALGORITHM

In this paper, the HBA is improved by using a cubic chaos mapping, an adaptive inertia weights combined with a multi-elite perturbation selection strategy of population hierarchy. Then, the IHBA is proposed, and the main process steps of the change algorithm are shown below:

Step1: Initialize D, the feasible scheduling order population X_{initial} with the number of populations *Nop*and its dimensionality, and construct the mapped initial order population X_c with high ergodicity by cubic chaos mapping;

Step2: Define the parameters upper *up*limit, lower *down* limit of search space, update density factor α, adaptive inertia factor w, current iteration number t, maximum iteration number T, etc.

Step3: Calculate the fitness value $fitness_i^t$ for each order scheme scheduling and treat the order scheduling scheme with the smallest fitness function value as the current global optimal solution $Xbest_i^t$. Furthermore, calculate the odor intensity I_i of each individual in the population based on the global optimal solution.

Step4: Generate a random *rand*number; if *rand <0.5*, then the new order scheduling scheme is updated according to Eq. (38); otherwise, it will be updated according to Eq. (39).

Step 5: Determine whether the algorithm iteration enters the stagnation phase; if so, proceed to the step6, otherwise skip it and go to the step7.

Step 6: If the algorithm falls into the stagnation phase, the population order is first sorted by fitness value and it is divided into dominant and inferior populations, respectively, according to the current average fitness function value. Added to that, the dominant order population is updated by local range perturbation according to the elite strategy, and the inferior order population is updated by random perturbation as shown in Eq. (40).

Step7: The parent order scheduling population and the newly generated scheduling order population are selected according to the greedy strategy to select the dominant scheduling scheme in order to form a new order population.

TABLE 2. Composite benchmark functions.

Functions	Dimension	Range	Theoretical minimum value
F_1	2	[-65,65]	1
F_2	2	[-5,5]	-1
F_3	2	[-5,5]	0.3
F_4	3	[1,3]	-4
F_5	4	[0,10]	-10
F_6	30	[-32,32]	0

Step8: Check if the iteration condition is satisfied; if not, go back to step2; otherwise, deliver the optimal order scheduling solution.

D. PERFORMANCE EVALUATION BY OPTIMIZING TEST FUNCTIONS

To test the performance of the IHBA algorithm, we selected four cutting-edge optimization algorithms for performance testing [25], [26], [27], [28], namely Golden Jackal Optimization (GJO), Hunter-prey optimization (HPO), Pelican Optimization Algorithm (POA), and Reptile Search Algorithm (RSA). The objective functions for conducting the tests are shown in Eq. 41-46:

$$F_1(x) = \left(\frac{1}{500} + \sum_{j=1}^{25} \frac{1}{j + \sum_{i=1}^{2} \left(x_i - a_{ij}\right)^6} \right)^{-1} \tag{41}$$

$$F_3(x) = 4x_1^2 - 2 \cdot 1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^4 \tag{42}$$

$$F_4(x) = \left(x_2 - \frac{5.1}{4\pi^2}x_1^2 + \frac{5}{\pi}x_1 - 6\right)^2 + 10\left(1 - \frac{1}{8\pi}\right)\cos x_1 + 10 \tag{43}$$

$$F_6(x) = -\sum_{i=1}^{4} c_i \exp\left(-\sum_{j=1}^{3} a_{ij}\left(x_j - p_j\right)^2\right) \tag{44}$$

$$F_7(x) = -\sum_{i=1}^{5} \left[\left(X - a_i\right)\left(X - a_i\right)^T + c_i\right]^{-1} \tag{45}$$

$$F_8(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos\left(2\pi x_i\right)\right) + 20 + e \tag{46}$$

The dimensions, ranges and theoretical minima of the 6 composite test functions (note the use of standard benchmarks) are shown in Table 2. To ensure objectivity between algorithm comparisons, we standardize the population size to 30 and the number of iterations to 1000. And we ensure that the boundary conditions of each algorithm are the same as the experimental conditions.

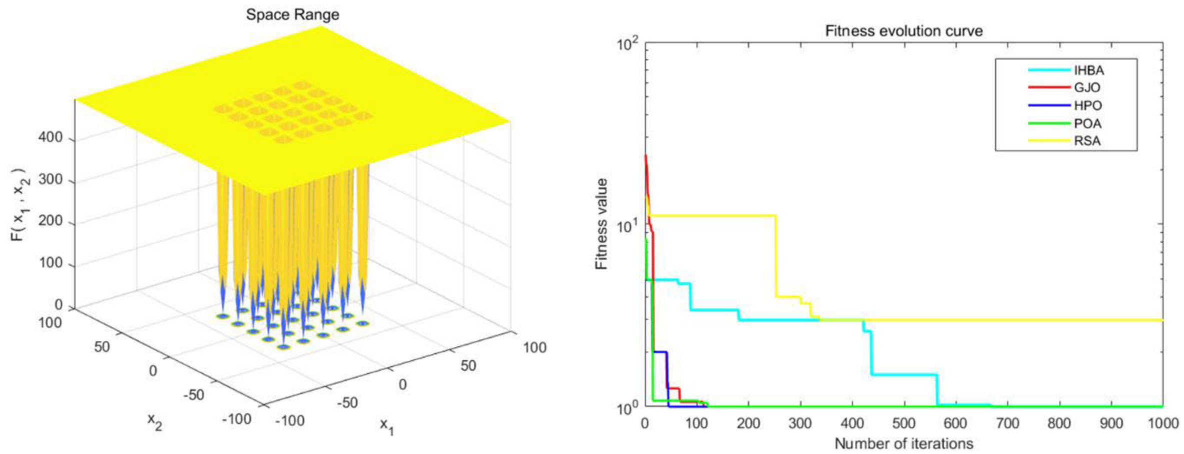

FIGURE 3. Function.1 performance testing.

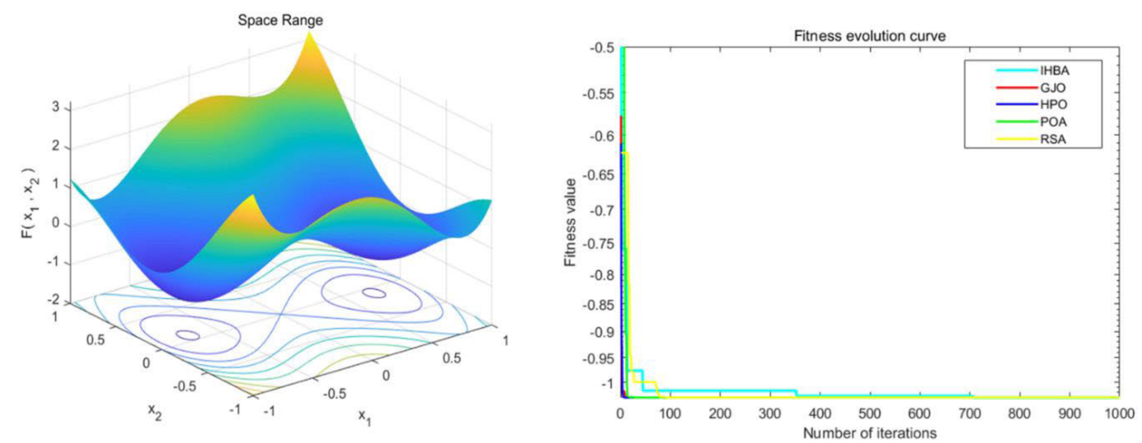

FIGURE 4. Function.2 performance testing.

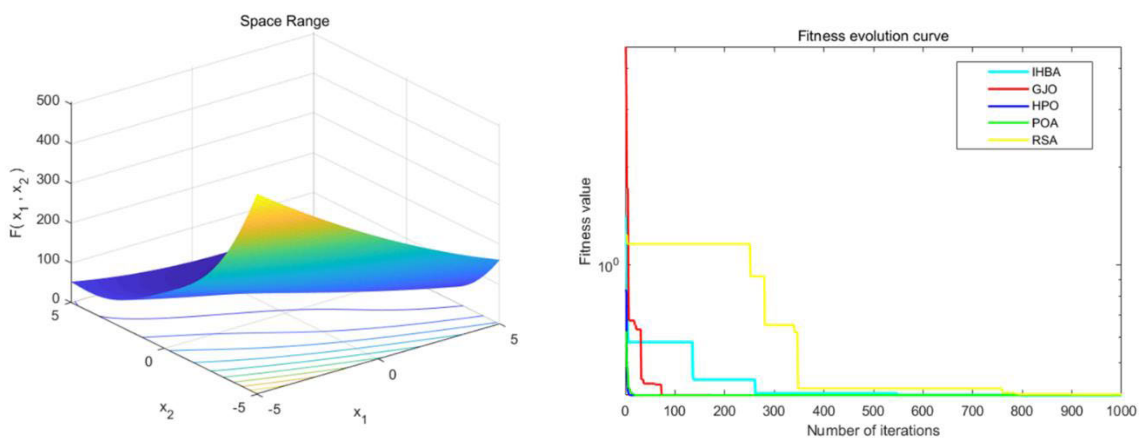

FIGURE 5. Function.3 performance testing.

Fig. 3 to Fig. 8 represent the search space range of the six composite benchmark test functions, and the Fitness evolution curve of the IHBA algorithm and the other four latest algorithms published in 2022. the 3D search space range visually reflects the solution value region within the range of values, and the curve plots clearly compare the

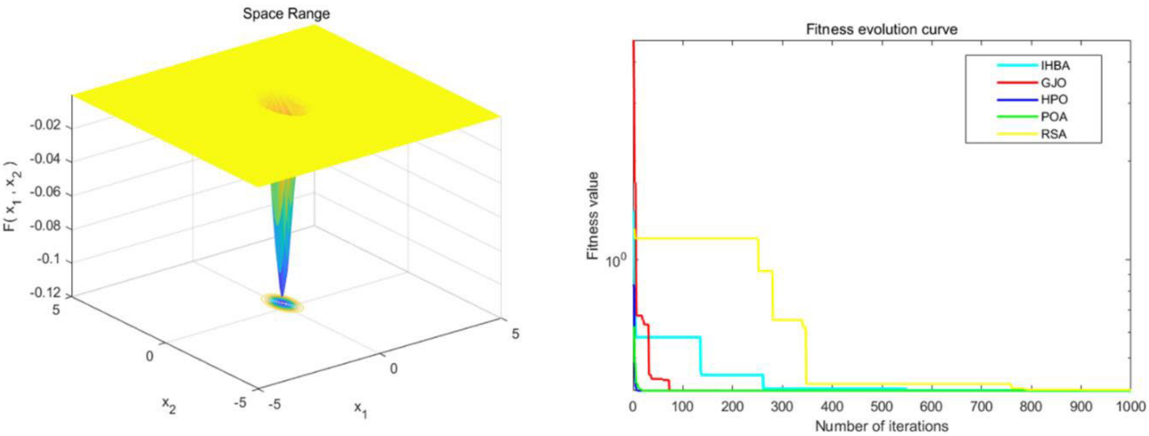

FIGURE 6. Function.4 performance testing.

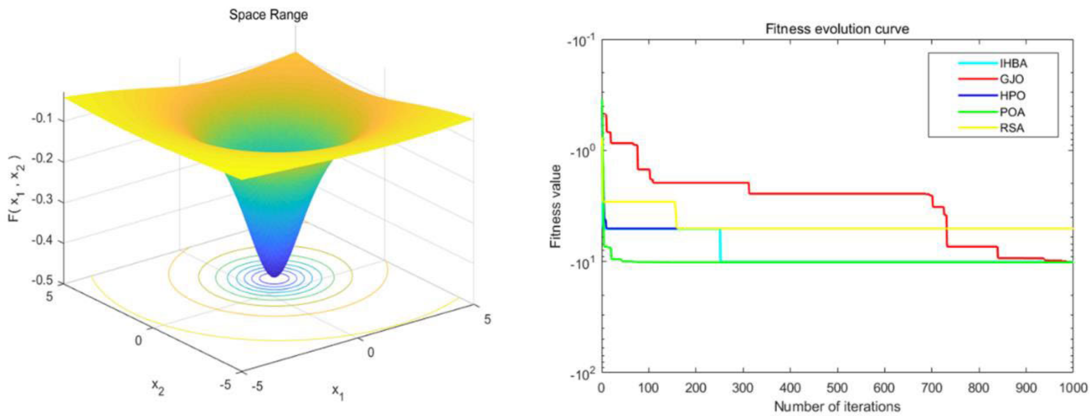

FIGURE 7. Function.5 performance testing.

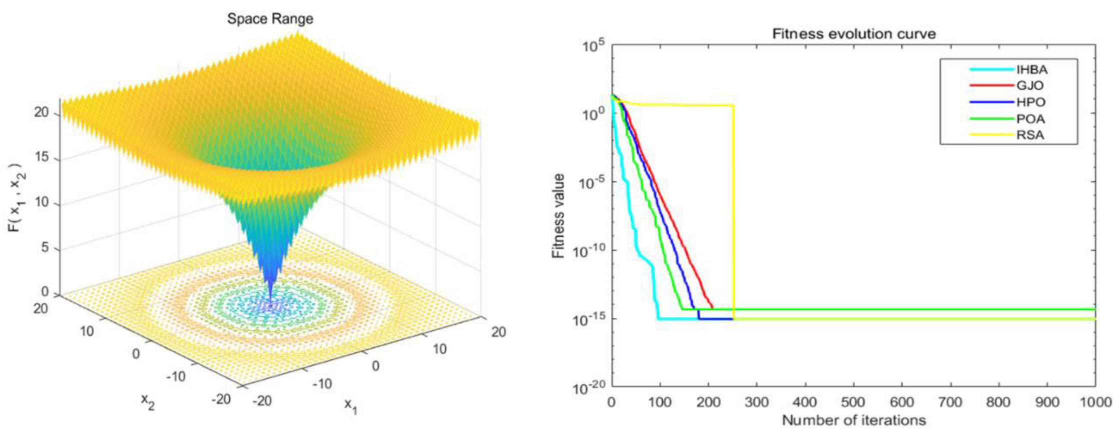

FIGURE 8. Function.6 performance testing.

performance of the algorithms. It can be seen from Table 3 that the IHBA algorithm proposed in this paper achieves the optimal solution value in the test results of different composite benchmark test functions. The results show the optimization performance of the IHBA algorithm in the composite function and prove that the IHBA algorithm can be used in other optimization problems

V. OPTIMAL MODEL SOLVING OF ADAPTIVE ELITE HONEY BADGER OBJECTIVE ALGORITHM BASED ON CUBIC MAPPING MECHANISM

In this paper, trucks with length, width and height of 5.2m, 2.1m and 2.1m respectively, with a load limit of 5 tons and a volume of $25m^3$ are used, and the experimental data is derived from the order demand of a distribution center of Hongyun

TABLE 3. Comparison table of test results.

Functions	Theoretical minimum value	Optimization result value				
		IHBA	GJO	HPO	POA	RSA
F_1	1	0.998	0.998	0.998	0.998	2.982
F_2	-1	-1.032	-1.032	-1.032	-1.032	-1.032
F_3	0.3	0.3981	0.3979	0.3979	0.3979	0.4
F_4	-4	-3.855	-3.855	-3.863	-3.863	-3.754
F_5	-10	-10.11	-10.15	-5.055	-10.15	-5.055
F_6	0	$8.882*10^{-16}$	$4.441*10^{-15}$	$8.882*10^{-16}$	$4.441*10^{-15}$	$8.882*10^{-16}$

TABLE 4. Order information sheet.

City	Order weight (ton)	City	Order weight (ton)	City	Order weight (ton)	City	Order weight (ton)
1	10	26	6	51	6	76	4
2	8	27	6	52	5	77	5
3	10	28	5	53	5	78	6
4	5	29	3	54	3	79	6
5	6	30	5	55	6	80	4
6	7	31	3	56	3	81	8
7	6	32	4	57	5	82	7
8	6	33	3	58	5	83	7
9	6	34	6	59	6	84	9
10	5	35	4	60	5	85	8
11	6	36	4	61	6	86	8
12	7	37	4	62	4	87	7
13	8	38	6	63	6	88	7
14	7	39	3	64	4	89	7
15	7	40	5	65	3	90	7
16	7	41	5	66	5	91	7
17	7	42	5	67	3	92	7
18	6	43	4	68	6	93	7
19	5	44	5	69	5	94	7
20	6	45	6	70	3	95	7
21	4	46	3	71	6	96	7
22	5	47	3	72	5	97	7
23	5	48	3	73	6	98	8
24	4	49	4	74	3	99	8
25	6	50	6	75	3	100	9

TABLE 5. Comparison of the values of the fitness functions of the four algorithms.

Algorithm	Worst fitness function	Average fitness function	Optimal fitness function
DE	3.4610×10^{13}	3.199×10^{13}	2.8321×10^{13}
WOA	3.0587×10^{13}	2.517×10^{13}	1.9208×10^{13}
HBA	3.5547×10^{13}	2.208×10^{13}	1.3620×10^{13}
IHBA	2.7432×10^{13}	1.994×10^{13}	6.8392×10^{13}

Honghe Group in Yunnan Province, China on August 12, 2022, and 100 city orders are randomly selected, and the number of goods that need to be loaded in each city is shown in Table 4.

To ensure the fairness of the designed algorithm, the same initial order population is to be taken for optimization, and the algorithm, proposed in this paper, will be compared to eight other algorithms that often used in logistics distribution, including Differential Evolution Algorithm (DE), Particle Swarm optimization (PSO), Multi-Verse Optimizer (MVO), Crow Search Algorithm (CSA), Whale Optimization Algorithm (WOA), Aquila Optimizer (AO), HBA, and Genetic Algorithm (GA). As for the parameters' values, they are defined as follow:

- Learning factor of PSO algorithm is $c_1 = c_2 = 1.5$;
- Maximum particle velocity is $v_{max} = 3$;
- Minimum particle velocity is $v_{max} = 3$;
- In the MVO, the number of universes is $pop_{max} = 807;$
- Maximum population size is $T_{max} = 60;$
- Initial variation operator is $F_0 = 0.4;$
- Crossover operator is $CR = 0.1.$

We performed a total of 100 simulation experiments and compared them. The average objective function convergence curves for each of the eight test algorithms for any one run and

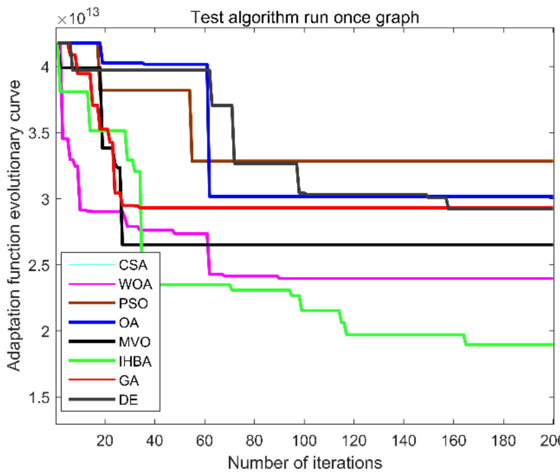

FIGURE 9. Evolutionary curve of the fitness function for each algorithm running randomly once.

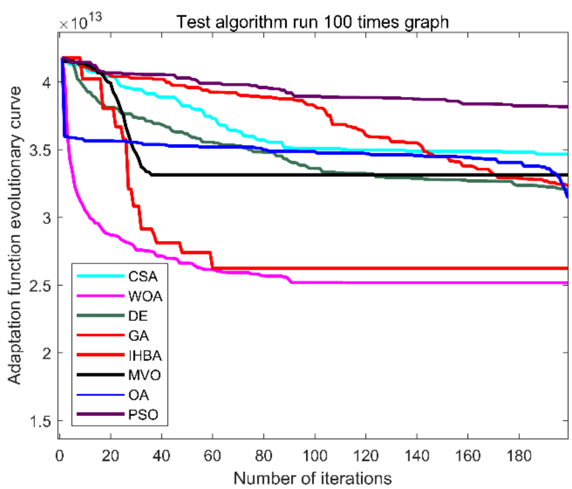

FIGURE 10. Comparison results of the average number of 100 runs for each tested algorithm.

for the 100 runs are shown in Fig. 9 and Fig. 10. Further select the best three algorithms from the eight algorithms compared for further comparison, as shown in Fig. 11 and Fig. 12. Among them, the parameter pairs of the fitness function of the three best algorithms and the IHBA algorithm are shown in Table 5., and the parameters such as freight and time mentioned in the model are shown in Table 6.

A. RESULTS OF SIMULATION EXPERIMENTS

Fig.13 shows the interface display of applying the multi-distribution center logistics vehicle cross-territory scheduling optimization model and IHBA algorithm to the RLSCS system, where the left side displays vehicle information, such as vehicle number, empty load rate, destination, delivery time, etc. The map in the middle shows the real-time route of the vehicle, the scheduled route, etc., and the right side shows the information of the cargo demand of specific provinces and cities, and the existing quantity of goods and the shipment speed at different shipping points.

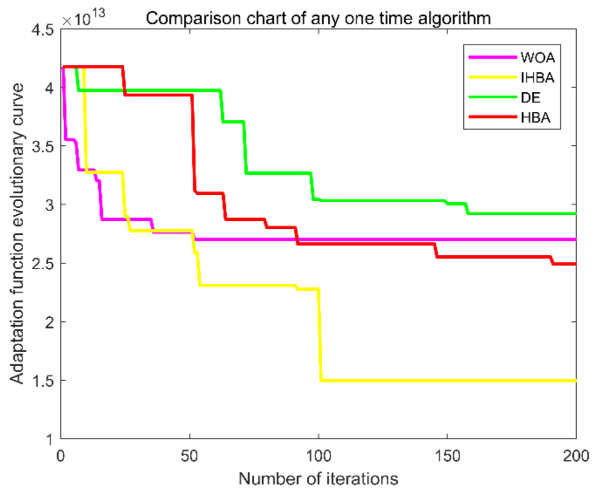

FIGURE 11. Comparison of arbitrary one-time algorithms.

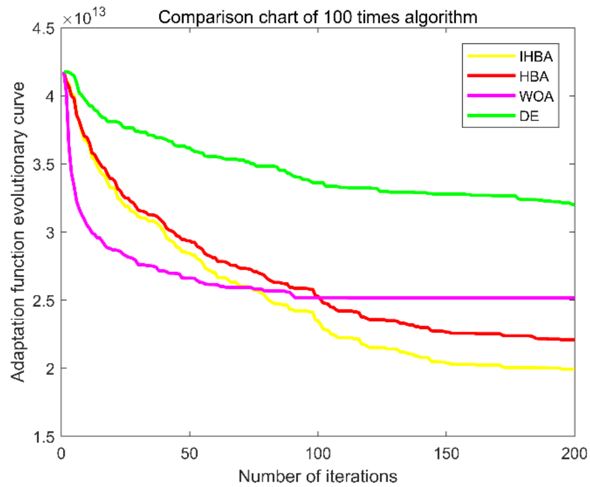

FIGURE 12. Comparison of algorithms with an average of 100 run times.

TABLE 6. Average comparison of the four algorithms for each indicator.

Algorithm / Indicators	DE	WOA	HBA	IHBA
Average total shipping cost (CNY)	327520	298930	275150	251350
Average number of vehicles required	22.33	30.10	22.66	21.33
Average transportation time (h)	5072.6	4914.3	5302.3	5069.4
Average loading rate	84%	75%	87%	90%
Average algorithm running speed (s)	47.3543	50.7366	50.4028	51.776

B. MODEL EVALUATION

Based on the comparison results of the four algorithms in Table 5, it can be seen that the proposed algorithm performs the best in terms of the average value, the worst fitness function value, and the optimal fitness function value. The excellent results of the designed algorithm are mainly due to the elite perturbation mechanism, based on the population

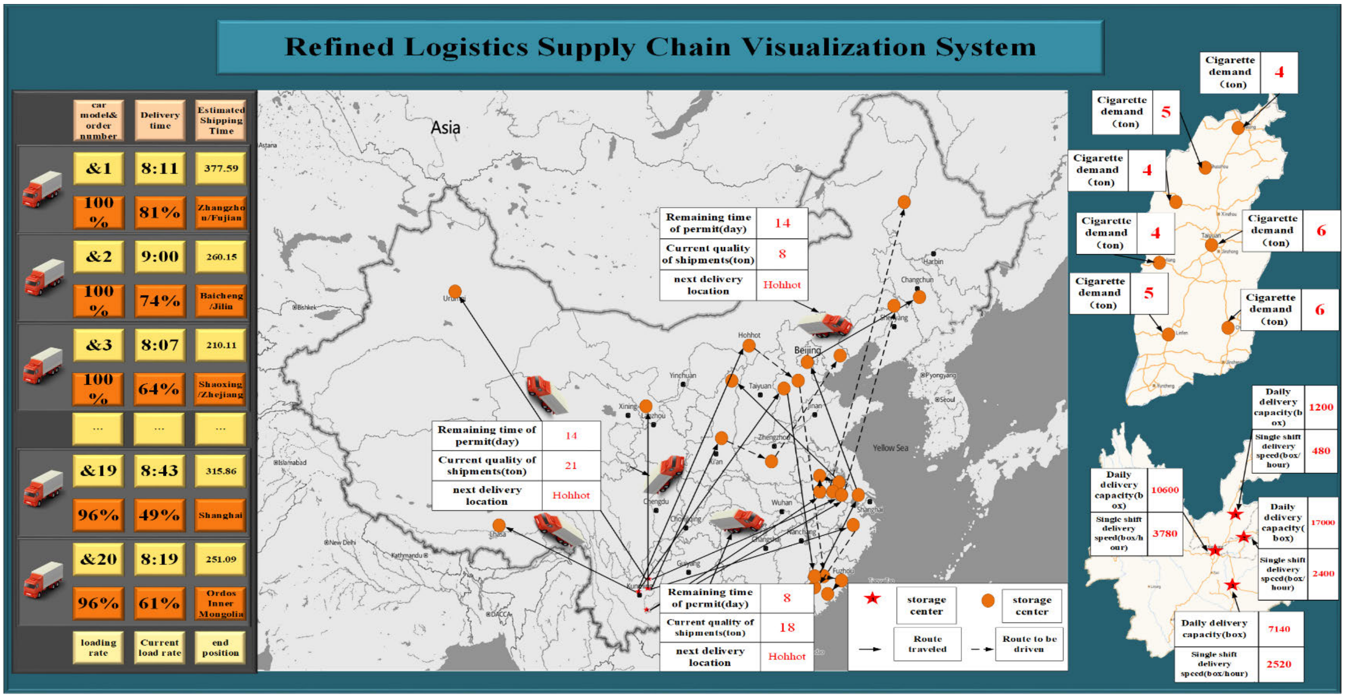

FIGURE 13. Visual display of scheduling results of refined Logistics Supply Chain System.

hierarchy, that allows the algorithm to actively break the current search space and thus obtain the optimal solution.

By combining Table 5 and Table 6, the proposed algorithm has improved by 60%, 26.23%, and 11%, respectively, in the adaptation function compared to the current frontier DE, WOA, and HBA. In the actual dispatch cost, the proposed algorithm in this paper has respectively reduced by 30%, 19%, and 10% the average total freight cost, decreased by 5%, 41%, and 6% the average number of vehicles required, and improved by 7%, 17%, and 3% the loading rate. Although the proposed algorithm does not perform as well as WOA in terms of average transportation time, this new algorithm has a better behavior to handle all the indicators.

Therefore, to sum up, for the logistics scheduling problem, this paper uses eight algorithms to be compared with the proposed algorithm, and the experimental results prove that the proposed algorithm has better performance in terms of convergence accuracy, convergence speed, global search capability, operation time and the obtained indexes, which can provide more reliable core algorithm support for the logistics scheduling digital twin aid model. Added to that, this algorithm can provide more reliable model support for the supply chain system module and support real-time big data scheduling in the future.

VI. CONCLUSION

Based on Industry 4.0, this paper researches the refined supply chain system module of intelligent logistics distribution and designs an industrial products distribution model for the refined logistics supply chain. Interactive simulation experiments are conducted by the constructed cross-regional scheduling optimization model of logistics vehicles in multiple distribution centers and the developed IHBA algorithm. Finally, the proposed algorithm is compared to several cutting-edge algorithms in order to evaluate the aid model's performance and the optimization performance. The results show that the proposed method outperforms other algorithms in reducing transportation cost and simulation time and improving humanized management. In the subsequent work, more attention will be paid to optimizing the information transmission module as well as the sensors of the digital twin to improve its functionality.

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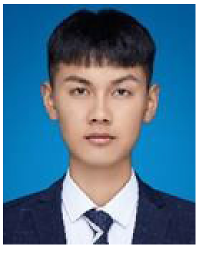

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