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Resource-Expandable Railway Freight Transportation Routing Optimization

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ABSTRACT This paper improved the algorithm of swarm intelligence, and the adaptability of improved algorithm in the design of door-to-door full-loaded transportation of railway goods was analyzed. The optimization model of the door-to-door full-loaded transportation routing design was extended to the resource-expandable optimization model of the door-to-door full-loaded transportation routing design to explore the influence of the change of railway and highway transportation distance on the system optimization. The improved algorithm of swarm intelligence was applied to solve the selected benchmark cases, and the comparison and analysis were conducted from both quantitative and qualitative aspects to verify their performance in solving continuous optimization problems. Two improved methods of intelligent algorithm were applied to the calculation example based on the coding system of the problem of the door-to-door transportation routing design of the resource-expandable railway freight, and the performance of their application to the optimization model of the route design system was verified. Then, input the compromise solutions into Simio for simulation analysis. The results of this paper can provide decision support for the routing design and decision reference for the location of the new station, and support the layout optimization of the stations for the railway transportation enterprises.

INDEX TERMS Door-to-door full-loaded transportation, resource-expandable model, simulation analysis, swarm intelligence.

I. INTRODUCTION

With the implementation of the reform of railway freight organization and the unswerving promotion of the reform of railway corporation system, railway transportation enterprises expand cargo business from station-to-station transportation to door-to-door transportation, therefore, the design has become more complex. Facing the practical application of new complex environment, the swarm intelligence algorithm method has been widely applied in various practical fields, and the optimization results are presented in a reasonable amount of time. The results of this paper can provide decision support for the route design of railway transportation enterprises, so as to reduce the transportation cost and transportation time of the system.

In order to explore how the changes of railway and highway transportation distance affect the transportation cost and transportation time, this paper takes into account the extensibility of transport resources, assumes that the departure stations and terminal stations are unknown or to be determined, and constructs the resource-expandable optimization model of the full-loaded door-to-door transportation of railway. Railway transportation enterprises need to arrange the departure stations and terminal stations for the multiple shippers, and also need to determine the location of the departure stations and terminal stations. Swarm intelligence (SI), commonly known as bionic computing, was first created by Beni and Wang in 1989 under the background of the development of cellular robot system. Due to its flexibility and versatility, as well as its high efficiency in solving nonlinear design problems, it has won great popularity among people. Swarm intelligence is a new field of optimization, which is based on the behavior modeling of various group animals and insects [1]. Timmis et al. believe that swarm intelligence and artificial immune system are complementary tools that can be used together effectively to solve complex engineering

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problems [2]. The algorithm based on swarm intelligence has been proved to be a reliable and effective optimization tool by a large number of satisfactory results of practical engineering problems [1]. There are about 40 different optimization algorithms based on cluster intelligence in the current literature [3], including inspired by ant colony search for the shortest path between food source and nest, Alberto et al proposed Ant Colony Optimization [4]; Kennedy and Eberhart proposed particle swarm optimization (PSO) [11], inspired by the relevant work of heppner and grenander and the social behavior of birds and fish foraging;Karaboga proposed the Artificial Bee Colony Algorithm (ABC) by imitating the foraging behavior of bee colonies [6]. Krishnanand and Ghose proposed Glowworm Swarm Algorithm (GSA) based on the behavior pattern of fireflies that significantly changed the emission intensity of luciferin to generate different brightness [7]. Yang proposed firefly algorithm by imitating the behavior characteristics of fireflies through colorful luminous communication and mate search [8], [9]. Yang and Deb simulated cuckoo breeding strategy and proposed Cuckoo Search Algorithm [10]. Oftadeh et al. proposed Hunting Search Algorithm inspired by the group hunting behavior of wolves that surrounded prey and gradually tightened the siege circle until prey was caught [11].

Location selection problems such as multimodal transport terminal, railway freight station and logistics center station have been paid attention by researchers. Scholars have built site selection optimization model and adopted intelligent algorithm to solve the optimization model, which can provide the support for the decision of site selection problem. On the basis of the existing research, this paper improves the continuous multi-objective clustering intelligent algorithms—— IMOMPPSO (improved multi-objective multiphase particle swarm optimization) algorithm and IMOQPSO (improved multi-objective quantum behavioral particle swarm optimization) algorithm, and discusses their practical application in the routing design of resource-expandable railway freight door-to-door transportation.

Multiphase particle swarm optimization algorithm is suitable for solving combinatorial optimization problems, such as the scheduling problem of large ship berths in bulk ports [12], and the scheduling problem of flexible job shop [13]. In these areas, its performance is better than the standard PSO algorithm [13]. Therefore, the IMOMPPSO algorithm is proposed to solve the multi-objective optimization problem.

IMOMPPSO algorithm needs to set the parameters after initializing, and randomly initialize the velocity and position of particles, calculate their fitness, then obtain the nondominant solution set of the initial population. Then, repeating the same iterative steps to find the optimal solution set of the optimization problem, until the conditions for ending the cycle are met. In the iteration process, firstly, determining whether the velocity of all particles in the population needs to be re-initialized, and determining the phase of the current generation. Then, entering the evolution of individuals in the population. In the process of individual evolution of the current generation population, firstly, the grouping of individuals, the global optimal guide solution and the length of the subdimension of location updating need to be determined, and then, the evolution of the subdimension of individuals needs to be carried out until the updating of all dimensions is completed. In the evolution process of individual subdimensions, firstly, obtaining the updated subdimensions, and then updating the subdimensions needed updated to generate the temporary position of particles. After dealing with the constraints determined by practical problems, the fitness of the temporary position is calculated, and finally, whether the particle position should be updated or not is judged. After updating all the individuals in the current population, the non-dominant solution set is updated and pruned. Fig.1 shows the flow chart of the IMOMPPSO algorithm.

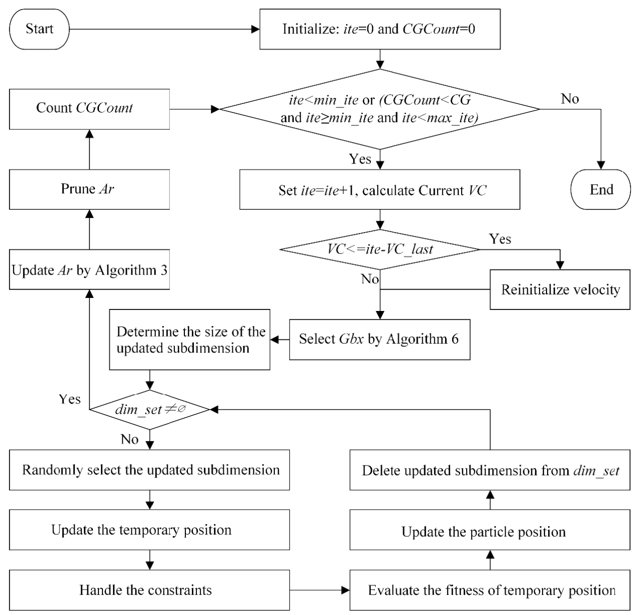

FIGURE 1. The flowchart of the IMOMPPSO. The figure reflects the specific process of IMOMPPSO algorithm, including the whole process of initializing the velocity and position of the particles, obtaining the non-dominant solution set and finally finding the optimal solution.

A. INITIALIZE

In the initialization stage of IMOMPPSO algorithm, the speed and position of each dimension of particles are randomly generated within the value range of the corresponding dimension. There is a nondominant solution set that used to store the nondominant solutions found in the whole search process, and the nondominant solution set is initialized through the initial population.

B. REINITIALIZE THE SPEED

In the evolution process of IMOMPPSO algorithm, when the condition of reinitialization velocity is met, the particle flight velocity will be reinitialized to ensure that the particle can continue to evolve without falling into the local minimum value. Experiments show that the multiphase particle swarm optimization algorithm periodically re-randomly initializes the particle velocity [15], which reduces the convergence of the algorithm. Therefore, the re-initialization strategy of particle velocity is improved. The velocity updating of the particle changes from a fixed period to a linearly decreasing dynamic period.

$$VC = round(VC_{max} - (VC_{max} - VC_{min})ite/max([ite\ min\_ite])) \quad (1)$$

Here, VC_{max} and VC_{min} are the initial and final velocity variables respectively; ite is the current iteration algebra; min_ite is the minimum number of iterations; $round(\cdot)$ is the rounding function.

$$e = exp(-\alpha * ite/max([ite\ min\_ite])) \quad (2)$$

$$v = e(lu(2, j) - lu(1, j)) * randn \quad (3)$$

Here: α is the speed re-initialization parameter; $exp(\cdot)$ is a power operation function based on the natural number e; $randn$ is a function that generates normally distributed random numbers [14].

C. GLOBAL OPTIMUM

The nondominant solution set with maximum capacity constraint is used to store the nondominant solutions found in the optimization process, and the nondominant solution set needs to be updated in the optimization process. A global optimal position is selected for each particle from the nondominant solution set to guide the particle to search in the search space.

D. SUBDIMENSION

In the evolution process of multiphase PSO algorithm, the updating way of particle is different from the standard PSO algorithm, only the subdimension of the continuous part of the particle is updated. If better fitness is obtained, it will move to the new position, otherwise, it will not update. With this updating strategy, local search space can be better explored and developed. In order to further improve the local exploration and development capability of particles, firstly, the maximum length limit of updating subdimensions is changed from the original equal to the number of dimensions to less than or equal to half of the number of dimensions:

$$sl\_max = min(10, round(Nd/2)) \quad (4)$$

Secondly, in the process of updating the subdimensions of particles, the number of subdimensions to be updated should be randomly determined until the updating of all dimensions is completed. In order to further improve the flexibility of updating subdimensions, random selection of subdimensions should be made every time.

$$sub\_dim\_set = dim\_set(sub\_dim\_set\_indices) \quad (5)$$

$$sub\_dim\_set\_indices = randperm(dim\_set\_size, si\_size) \quad (6)$$

$$si\_size = \min([si\_size\ dim\_set\_size]) \quad (7)$$

$$dim\_set\_size = length(dim\_set) \quad (8)$$

Here, $length(\cdot)$ is a function to obtain the parameter. dim_set is the nonupdated subdimension; si_size is the number of subdimensions that can be selected at random each time before entering the individual subdimension update.

E. PROCESSING CONSTRAINT

In the cluster intelligent algorithm, the penalty function or the back-sweep mechanism can be changed from the optimization problem under the constraint to the unconstrained optimization problem and the problem of not allowing individuals to fly out of a viable area after processing the constraint conditions.

$$x_{i,j}(r) = \begin{cases} lu(1, j) + (lu(2, j) - lu(1, j)) .* rand, & r < 0.25 \\ Pbx_{i,j}, & 0.25 \le r < 0.5 \\ Gbx_{i,j}, & 0.5 \le r < 0.75 \\ bv_{i,j} & \text{otherwise} \end{cases} \quad (9)$$

$$r = U(0, 1) \quad (10)$$

$$bv_{i,j} = \begin{cases} lu(1, j) + iz, & x_{i,j} < lu(1, j) \\ lu(2, j) - iz, & x_{i,j} > lu(2, j) \end{cases} \quad (11)$$

$$iz = \begin{cases} 0, & \text{if the boundary value is available} \\ \to 0, & \text{otherwise} \end{cases} \quad (12)$$

F. PARTICLE POSITION UPDATE

In the IMOMPPSO algorithm, the particle only moves to the position where the fitness value is improved, so the current position of the particle is the optimal position in the history of the particle. Using the continuous cluster intelligent algorithm to solve the combinatorial optimization problem will produce more equivalent solutions, that is, the solution obtained after decoding two similar (or even distant) locations may be the same. However, this is a process of algorithm evolution, which means that it is possible to produce better solutions by continuing to fly in the current direction. Therefore, the current position needs to be used to update the particle position as long as the newly generated position is not dominated by the historical optimal position:

$$Pbx_i(t) = \begin{cases} Pbx_i(t-1), & \text{if } fb_i(t-1) \prec f_i \\ x_i(t), & \text{otherwise} \end{cases} \quad (13)$$

G. TRIM THE NONDOMINANT SOLUTION SET

In the IMOMPPSO algorithm, considering to improve the optimal guide solution and operating efficiency, it is necessary to use the nondominant solution set with the maximum capacity limit to save the nondominant solution obtained in the optimization process of the algorithm, and trim it until it reaches the maximum capacity limit [16]. After updating the nondominant solution set, it is sorted in descending order of the selected probability according to the selection strategy of the global optimal wizard solution, and the nondominant solution is obtained after the sorting is deleted. For example, in order to obtain a more uniform nondominant front, the solution with a smaller crowding distance should be deleted when CD-FPS selects the global optimal solution.

Quantum behavioral particle swarm optimization (QPSO) has better searched ability than traditional PSO and fewer control parameters, which improves the global search ability of the algorithm and avoids falling into local optimization [17]. Many improved PSO algorithms for quantum behavior have been proposed and successfully applied to single-objective and multi-objective optimization problems. Based on the improvement of QPSO algorithm [18], [19] its application in multi-objective optimization problem [20], and the introduction of fast nondominant sort [21], this paper proposes IMOWPDO algorithm.

IMOQPSO algorithm, initializing the population after initializing the parameters, through chaotic mapping the position of particles, calculating their fitness and the individual optimal position and fitness of initialized particles, then obtaining the nondominant solution set of the initial population. After initializing the chaotic parameters and variation parameters of the particle position update formula, the iteration is started to find the Pareto frontier of the optimization problem until the conditions of ending the cycle are met. In the iterative process, firstly, the mainstream idea of the current generation (the average optimal position) needs to be determined, as well as the contraction and expansion coefficient. Then, the evolution of individual particles begins. In the process of evolution of the current generation of particles, firstly, through the chaotic mapping to determine the random number of particle position update, the global optimal solution and the local point of interest. Then, the particle position updated, the mutation operation is performed randomly, the constraint conditions are processed, and the fitness of the new position is calculated [22]. Finally, the optimal position of the current particle is updated. The global nondominant solution set is updated and pruned after all the individual positions in the current population are updated. Fig.2 shows the flow chart of IMOQPSO algorithm.

H. INITIALIZATION

In the initialization phase of IMOQPSO algorithm, the initial position is generated by logistic mapping within the value range of the corresponding dimension. The optimal position and fitness of the particle are initialized into the initial position and fitness of the particle. After the population is initialized, the nondominant solution set is initialized. Finally, the logistic mapping is initialized to generate k, u, and θ.

I. GLOBAL OPTIMUM

In IMOQPSO algorithm, the nondominant solution set with maximum capacity limit is used to store the nondominant solution set, and the solution set is updated in the optimization process. A global optimal position is selected for each particle from the solution set based on CD-FPS to guide the particle search.

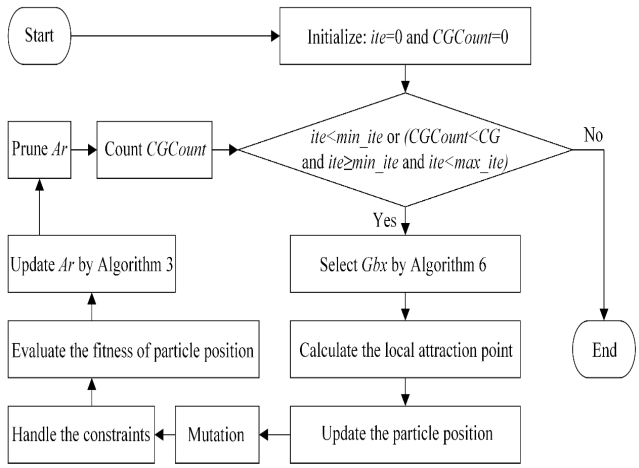

FIGURE 2. The flowchart of the IMOQPSO. The figure reflects the detailed process of IMOQPSO algorithm, including the whole process of initializing the velocity and position of particles, pruning the global non-dominant solution set and finally finding the optimal solution.

J. MAINSTREAM IDEOLOGY

Xi et al. hold that the mainstream ideology determines the search scope and creativity of particles, and it is reasonable to define the mainstream ideology as the average optimal position, but it is contrary to the more important role of elites in the social and cultural evolution in the real world [23]. Therefore, in IMOQPSO algorithm, it is necessary to calculate the average optimal position based on the fast nondominant sorting method. That is, after sorting the current population by fast nondominant sorting method, the individuals in the population are distributed on different nondominant frontiers, and the average optimal position on each frontier is the same. In order to ensure better convergence of the algorithm, the average best position of k at the current nondominant frontier is the mean of the best positions of individuals before k (including k), namely:

$$Mbests_i = Mbests(fns \cdot frontIndex(i)) \tag{14}$$

$$Mbests_k = mean(Pbx_k) \tag{15}$$

$$Pbx_k = Pbx\ (fns.frontIndex <= k, :)\ k \in [1, fns \cdot Nf] \tag{16}$$

$$[fns] = fastNondominatedSort(x, f) \tag{17}$$

Here, *fastNondominatedSort* is a fast nondominant sorting function of the structure that returns the output result after sorting, including the number of frontier *Nf* and the nondominant frontier *frontIndex* on which the individual is located. k is the kth nondominant front; $mean(\cdot)$ is a function of the mean value of the calculated parameter.

K. PARTICLE POSITION UPDATE

In the IMOQPSO algorithm, the position is updated by the quantum behavior of particles. Firstly, logistic mapping was used to generate the updating parameters of k, u and θ [18]. After selecting the global optimal position and calculating the average optimal position, the local attractive point is calculated to update the particle position. In the process of particle updating, each dimension has a 25% probability of using the individual optimal or 25% probability of using the global optimal position to correspond to the value of the dimension. Therefore, particle position update formula:

$$x(i,j) = \begin{cases} Pi(i,j) - \beta(Mbests_i(j) \\ \qquad -x(i,j))\ln(1/u), & k \leq 0.25 \\ Pi(i,j) + \beta(Mbests_i(j) \\ \qquad -x(i,j))\ln(1/u), & 0.25 < k \leq 0.5 \\ Pbx(i,j), & 0.5 < k \leq 0.75 \\ Gbx(j), & k > 0.75 \end{cases} \tag{18}$$

After the position is updated, the optimal position of the particle needs to be updated. As long as the current position of the particle is not dominated by its historical optimal position, the optimal position of the particle will be updated.

L. MUTATION OPERATION

In order to improve the performance of the algorithm and consider its convergence, the IMOQPSO algorithm introduces mutation operation [16]. In the IMOQPSO algorithm, the mutation parameter is introduced to control the speed at which the mutation probability decreases. As the number of iterations increases, the mutation probability decreases.

M. PROCESSING CONSTRAINT

In the IMOQPSO algorithm, the method of not allowing individuals to fly out of the feasible region is used to deal with the constraints of the optimization problem. After the particle flew out of the feasible region, four processing methods, i.e. random generation, individual optimization, global optimization and corresponding dimension boundary value, were adopted by random equal probability to replace the value of the particle flew out of the feasible region dimension.

N. TRIM THE NONDOMINANT SOLUTION SET

In IMOQPSO algorithm, when the nondominant solution set found in the storage algorithm optimization reaches the maximum capacity limit, the nondominant solution beyond the capacity limit needs to be deleted. There are different strategies for selecting the optimal wizard solution from the nondominant solution set, but all of them remove the solution with the lowest probability of being selected until the capacity limit is satisfied.

In order to better discuss the influence of the change of railway and highway distance on the optimization of full-loaded transportation, this paper considers the extensibility of resources on the basis of existing transportation resource constraints.

It is assumed that the location of the departure station and terminal station is unknown or to be determined, but the number and the unit operating cost, cargo handling capacity and specific cargo handling type of each departure station. The terminal station haa been given, decision makers can choose a site within a given range [24]. That is, railway transportation enterprise C, after receiving transportation entrustment from A to B with a quantity of N_C shippers, there are respectively N_O departure stations and N_D terminal stations available for use in A and B. The operating capacity of each departure station and terminal station is known, the location is unknown, but it can be randomly distributed in a given range. Railway transport enterprises need to optimize the layout of departure station and the terminal station based on the existing information of the shipper, and through the optimization to improve transport efficiency and benefits, reduce the transportation cost and shipping time.

II. MATHEMATICAL MODELING

This paper builds the resource-expandable railway freight transportation routing design (RERFTRD), need to determine which departure station j is converted to railway transportation and which terminal station k is converted to highway transportation for each shipper's i cargo transportation to reach the designated location of the consignee, as well as the location of departure station j and the terminal station k respectively y'_j and y''_k.

$$\min_{x,y} f(x,y) = \begin{cases} TC(x,y) \\ T(x,y) \end{cases} \tag{19}$$

$$\begin{aligned} TC(x,y) &= \sum_{i=1}^{N_C}\sum_{j=1}^{N_O} x'_{ij}\left(TC'_{ij} + TCO_{ij}\right) \\ &\quad + \sum_{i=1}^{N_C}\sum_{j=1}^{N_O}\sum_{k=1}^{N_D} x'_{ij}x''_{ik}TC_{ijk} \\ &\quad + \sum_{i=1}^{N_C} TC_i + \sum_{i=1}^{N_C}\sum_{k=1}^{N_D} x''_{ik}\left(TCD_{ik} + TC''_{ik}\right) \\ &= \sum_{i=1}^{N_C}\sum_{j=1}^{N_O} x'_{ij}\Big(C_{51}W_iL'_{ij} + (C_{11}\varpi_i \\ &\quad + C_{12}\frac{TO_{ij}\varpi_i(1+\varepsilon)}{24}\Big)\Big) \\ &\quad + \sum_{i=1}^{N_C}\sum_{j=1}^{N_O}\sum_{k=1}^{N_D} x'_{ij}x''_{ik}\Big(C_{21}\frac{L_{jk}\,(W_i + \varpi_i\omega_1)}{\sigma} \\ &\quad (1+\zeta_1+\zeta_2+\zeta_3)\times(1+\zeta_4) + C_{22}L_{jk}\,(W_i + \varpi_i\omega_1) \\ &\quad + C_{23}\left(\frac{W_i\omega_2L_{jk}}{\sigma_i} + L_{jk}\,(W_i + \varpi_i\omega_1)\right) \\ &\quad + C_{24}\frac{L_{jk}\,(W_i + \varpi_i\omega_1)}{\sigma} + C_{25}\varpi_iL_{jk}(1+\varepsilon) \\ &\quad + C_{26}\frac{\varpi_iL_{jk}(1+\varepsilon)}{24\ v}\Big) \\ &\quad + \sum_{i=1}^{N_C}\left(C_{31}\pi_i\varpi_i + C_{32}\frac{\pi_i\tau_2\varpi_i(1+\varepsilon)}{24}\right) \\ &\quad + \sum_{i=1}^{N_C}\sum_{k=1}^{N_D} x''_{ik}\Big(\Big(C_{41}\varpi_i + C_{42}\frac{TD_{ik}\varpi_i(1+\varepsilon)}{24}\Big) \\ &\quad + C_{52}W_iL''_{ik}\Big) \end{aligned} \tag{20}$$

$$\begin{aligned} T(x,y) &= \sum_{i=1}^{N_C}\sum_{j=1}^{N_O} x'_{ij}\left(T'_{ij} + TO_{ij}\right) \end{aligned}$$

$$
\begin{aligned}
&+\sum_{i=1}^{N_C}\sum_{j=1}^{N_O}\sum_{k=1}^{N_D} x'_{ij}x''_{ik}T_{ijk}\\
&+\sum_{i=1}^{N_C} T_i+\sum_{i=1}^{N_C}\sum_{k=1}^{N_D} x''_{ik}\left(TD_{ik}+T''_{ik}\right)\\
=&\sum_{i=1}^{N_C}\sum_{j=1}^{N_O} x'_{ij}\left(\frac{L'_{ij}}{v_s}+\frac{w_i}{v'_j}\left(1+\alpha\left(\frac{\sum_{i=1}^{N_c} x'_{ij}}{\psi'_j}\right)^{\beta}\right)\right)\\
&+\sum_{i=1}^{N_C}\sum_{j=1}^{N_0}\sum_{k=1}^{N_D} x'_{ij}x''_{ik}\frac{L_{jk}}{v}+\sum_{i=1}^{N_C}(\pi_i\tau_2)\\
&+\sum_{i=1}^{N_C}\sum_{k=1}^{N_D} x''_{ik}\left(\frac{w_i}{v''_j}\left(1+\alpha\left(\frac{\sum_{i=1}^{N_c} x''_{ik}}{\psi''_j}\right)^{\beta}\right)+\frac{L''_{ik}}{v_s}\right)
\end{aligned}
\tag{21}
$$

$$\varpi=\left\lceil\frac{W_i}{\gamma(1+\lambda)}\right\rceil \tag{22}$$

$$L'_{ij}=L'_{ij}\left(y'_j\right)=\sqrt{(Po_{i1}-y'_{j1})^2+(Po_{i2}-y'_{j2})^2} \tag{23}$$

$$L_{jk}=L_{jk}\left(y'_j,y''_k\right)=\sqrt{y'^2_{j1}+y'^2_{j2}}+L_{AB}+\sqrt{y''^2_{k1}+y''^2_{k2}} \tag{24}$$

$$L''_{ik}=L''_{ik}\left(y''_k\right)=\sqrt{(Pd_{i1}-y''_{k1})^2+(Pd_{i2}-y''_{k2})^2} \tag{25}$$

The constraint condition is:

$$x'_{ij}=\begin{cases}1, & \text{if consignor} i \text{is assigned to the departure station } j\\ 0, & \text{otherwise}\end{cases} \tag{26}$$

$$x'_{ik}=\begin{cases}1, & \text{if consignee} i \text{is assigned to the terminal station } k\\ 0, & \text{otherwise}\end{cases} \tag{27}$$

$$x'_{ij}=0,\quad j\in OE_i \tag{28}$$

$$x''_{ik}=0,\quad k\in DE_i \tag{29}$$

$$\sum_{j=1}^{N_O} x'_{ij}=1 \tag{30}$$

$$\sum_{k=1}^{N_D} x'_{ik}=1 \tag{31}$$

$$y'_{j1}\_min\le y'_{j1}\le y'_{j1}\_max \tag{32}$$

$$y'_{j2}\_min\le y'_{j2}\le y'_{j2}\_max \tag{33}$$

$$y'_{k1}\_min\le y''_{k1}\le y''_{k1}\_max \tag{34}$$

$$y''_{k2}\_min\le y''_{k2}\le y''_{k2}\_max \tag{35}$$

In the formula: respectively Po_i and Pd_i are the pick-up place $Po_i=(Po_{i1},Po_{i2})$ and the delivery place $Pd_i=(Pd_{i1},Pd_{i2})$ designated by the shipper; L_{AB} is the distance between marshalling yards (logistics centers) of A and B. TC'_{ij} and T'_{ij} are respectively the road transportation cost and time between the pick-up place and the departure station j designated by shipper i; TCO_{ij} and TO_{ij} are respectively the transshipment cost and time of goods of shipper i at the departure station j; TC_i and T_i are respectively the shipper i goods transfer in the process of railway transportation cost and time; TCD_{ik} and TD_{ik} are respectively transportation cost and time of cargo at terminal k; TC''_{ik} and T''_{ik} are respectively cost and time of road transportation of cargo from terminal k to the place designated by the consignee; OE_i and DE_i respectively represent the collection of departure station j and terminal station k that cannot handle the consignment business ($OE_i=\emptyset$ and $DE_i=\emptyset$ respectively mean that the cargo can be shipped at all the departure and arrival stations).

The location of the departure station and the terminal station can be changed, and the change of the location of the departure station or the terminal station will lead to the change of the transportation distance of railway and highway. In the case of door-to-door full-loaded transportation, and the transportation distance of railway and highway can be increased or decreased respectively [25]. Therefore, there are four combinations for a shipper to choose from. When the position of departure station or terminal station changes, as shown in Fig.3. Therefore, this paper discusses how the distance of railway and highway affects the transportation cost and time of the system from the system.

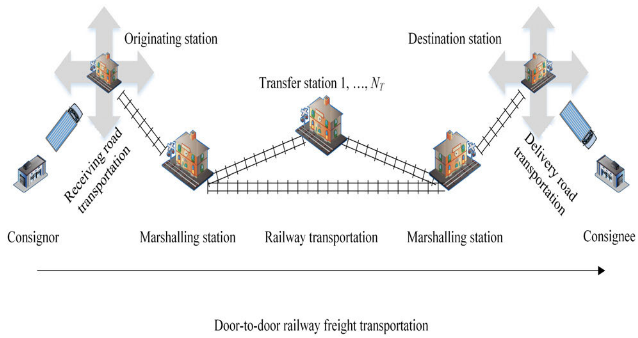

FIGURE 3. The impact of station location changes in transportation distance of railway and highway in door-to-door railway freight transportation. The figure reflects the specific relationship between railway transportation and road transportation in door-to-door cargo transportation.

The model in this paper is an extension of the optimization model. It is necessary to determine the location of the departure station and the terminal station at the same time of arranging the departure station and the destination station of each shipper, and the locations (coordinates) of the departure station and the destination station are randomly selected within a given range, so there are infinite possibilities for the locations of the departure station and the terminal station. The solution space complexity (SSC) is:

$$SSC\left(N_C,N_O,N_D\right)=N_O^{N_C}\cdot N_D^{N_C}\cdot\infty\cdot\infty=\infty \tag{36}$$

Therefore, the solution space complexity of the optimization model for the resource-expandable door-to-door full-loaded transportation is infinite. However, the heuristic method based on cluster intelligence can be used to give the suboptimal solution of the problem in a reasonable time.

III. ALGORITHM VALIDATION

This paper uses the improved continuous multi-objective clustering intelligent algorithm to solve the benchmark function of the selected continuous optimization problem, and

TABLE 1. The information of ZDT benchmark instances.

Serial number	Category	Function	Range
1	ZDT1	$f_1(x_1) = x_1$ $g(x_2,..,x_n) = 1 + 9\sum_{i=2}^{n} x_i/(n-1)$ $h(f_1,g) = 1 - \sqrt{f_1/g}$	$0 \le x_i \le 1$ $0 \le i \le 30$
2	ZDT2	$f_1(x_1) = x_1$ $g(x_2,..,x_n) = 1 + 9\sum_{i=2}^{n} x_i/(n-1)$ $h(f_1,g) = 1 - (f_1/g)^2$	$0 \le x_i \le 1$ $0 \le i \le 30$
3	ZDT3	$f_1(x_1) = x_1$ $g(x_2,..,x_n) = 1 + 9\sum_{i=2}^{n} x_i/(n-1)$ $h(f_1,g) = 1 - \sqrt{f_1/g} - (f_1/g)\sin(10\pi f_1)$	$0 \le x_i \le 1$ $0 \le i \le 30$
4	ZDT4	$f_1(x_1) = x_1$ $g(x_2,..,x_n) = 1 + 10(n-1) + \sum_{i=2}^{n}\left(x_i{}^2 - 10\cos(4\pi x_i)\right)$ $h(f_1,g) = 1 - \sqrt{f_1/g}$	$0 \le x_1 \le 1$ $-5 \le x_i \le 5$ $2 \le i \le 10$
5	ZDT6	$f_1(x_1) = 1 - \exp(-4x_1)\sin^6(6\pi x_1)$ $g(x_2,..,x_n) = 1 + 9(\sum_{i=2}^{n} x_i/(n-1))^{0.25}$ $h(f_1,g) = 1 - (f_1/g)^2$	$0 \le x_i \le 1$ $0 \le i \le 10$

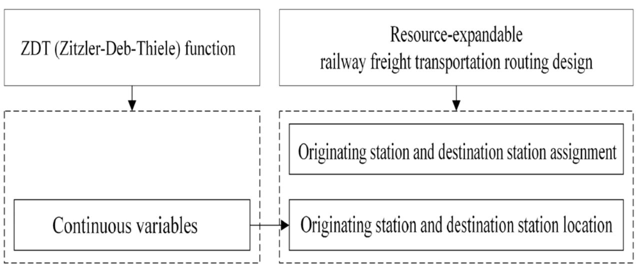

FIGURE 4. The relationship between ZDT and railway freight transportation routing design. The figure reflects how the parameters in the zDT function can achieve the door-to-door freight transport results by affecting the allocation and location of the originating station and the terminal station.

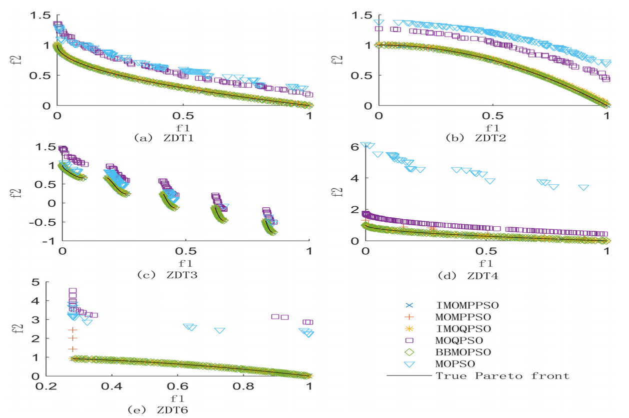

FIGURE 5. The Pareto front convergences of the continuous SI for the ZDT benchmark instances. The figure reflects the Pareto front convergence, the mean of population diversity, the statistical analysis results of the relevant running time and the number of iterations of the continuous cluster intelligence algorithm.

make comparative analysis from the quantitative and qualitative perspectives to verify its performance in solving the continuous optimization problem [26].

In order to verify the performance of IMOMPPSO algorithm and IMOQPSO algorithm proposed above in solving continuous multi-objective optimization problems, ZDT function (ZDT), a famous continuous benchmark function was selected [27]. Fig.4 shows the relationship between the ZDT function and the design problem of resource-extended rail door to door freight transport.

The ZDT functions are all made up in the same way, and are made up of three work functions:

$$\min f(x) = \begin{cases} f_1(x_1) \\ f_2(x) \end{cases} \tag{37}$$

$$f_2(x) = g(x_2, \ldots, x_n)\, h(f_1(x_1), g(x_2, \ldots, x_n)) \tag{38}$$

Here, $f_1(x_1)$ is the function of only the first decision variable; $g(x_2, \ldots, x_n)$ is the function of the remaining n-1 decision variables; $h(f_1(x_1), g(x_2, \ldots, x_n))$ is the function of $f_1(x_1)$ and $g(x_2, \ldots, x_n)$.

Five ZDT functions are selected as benchmark examples [27]. When g(x) = 1, Pareto optimal frontier of five ZDT benchmark instances can be obtained. Table.1 shows the information of selected five ZDT benchmark instances.

In the ZDT benchmark instances, the parameter Settings of all algorithms are the same as those of IMOMPPSO algorithm and IMOQPSO algorithm. The Pareto frontier convergence and the mean of population diversity of the selected

TABLE 2. The computational statistics of the continuous SI on GD and IGD for The ZDT benchmark instances.

Master serial number	Subpart number	Algorithm	GD				IGD			
			Min	Max	Mean	Std	Min	Max	Mean	Std
1	1	IMOMPPSO	0.00016	0.0003	0.00023	3.7E-05	0.00016	0.0002	0.00018	7.9E-06
	2	MOMPPSO	0.00061	0.00095	0.00079	9.2E-05	0.00024	0.00033	0.00028	2.6E-05
	3	IMOQPSO	0.00096	0.00192	0.00155	0.00019	0.00034	0.00061	0.00051	5.5E-05
	4	MOQPSO	0.01826	0.03372	0.02301	0.00325	0.00511	0.00717	0.00601	0.00056
	5	BBMOPSO	**9.8E-05**	**0.00039**	**0.00016**	**5.1E-05**	**0.00015**	**0.00017**	**0.00016**	**4.9E-06**
	6	MOPSO	0.02046	0.14429	0.05399	0.02764	0.00495	0.04267	0.01542	0.01046
2	1	IMOMPPSO	0.00013	0.00023	0.00018	2.7E-05	0.00016	0.00019	0.00018	6.9E-06
	2	MOMPPSO	0.00084	0.0012	0.00098	0.00011	0.00031	0.00045	0.00035	4.2E-05
	3	IMOQPSO	0.00155	0.00227	0.00192	0.00021	0.00051	0.00075	0.00062	6E-05
	4	MOQPSO	0.0293	0.05314	0.03838	0.00559	0.00696	0.01153	0.00863	0.00086
	5	BBMOPSO	**4.4E-05**	**0.00014**	**6.8E-05**	**2.2E-05**	**0.00016**	**0.00019**	**0.00017**	**7.4E-06**
	6	MOPSO	0.03551	0.23097	0.12778	0.04853	0.01245	0.05569	0.03441	0.01119
3	1	IMOMPPSO	0.00016	0.00027	0.00019	2.3E-05	0.00018	0.00022	0.0002	9.8E-06
	2	MOMPPSO	0.00038	0.00079	0.0005	9.8E-05	0.00024	0.00032	0.00027	2E-05
	3	IMOQPSO	0.00056	0.00162	0.00116	0.00019	0.00031	0.00068	0.00057	6.9E-05
	4	MOQPSO	0.01705	0.02549	0.02086	0.0023	0.00522	0.00635	0.00568	0.0003
	5	BBMOPSO	**0.00014**	**0.00021**	**0.00016**	**1.8E-05**	**0.00017**	**0.0002**	**0.00019**	**6.6E-06**
	6	MOPSO	0.00767	0.08621	0.03212	0.01859	0.00293	0.03542	0.00875	0.00791
4	1	IMOMPPSO	8.3E-05	0.00019	0.00012	2.3E-05	0.00017	0.0002	0.00019	8E-06
	2	MOMPPSO	0.0455	2.54406	1.41291	0.67916	0.00382	0.14973	0.07285	0.03817
	3	IMOQPSO	4.9E-05	0.01257	0.00049	0.00228	0.00016	0.00398	0.00031	0.00069
	4	MOQPSO	0.04062	5.89268	0.5911	1.46657	0.01236	0.27372	0.05344	0.06445
	5	BBMOPSO	**5.4E-05**	**9.4E-05**	**7.2E-05**	**1E-05**	**0.00016**	**0.0002**	**0.00018**	**7.8E-06**
	6	MOPSO	0.72271	10.5817	4.26012	2.13121	0.09927	0.78356	0.43827	0.18619
5	1	IMOMPPSO	3.8E-05	0.00586	0.00224	0.00133	0.00017	0.00048	0.00028	7.9E-05
	2	MOMPPSO	0.13868	0.51018	0.31105	0.07951	0.00222	0.02508	0.01424	0.00501
	3	IMOQPSO	3.4E-05	0.01038	0.00219	0.00239	**0.00012**	**0.00014**	**0.00013**	**4.9E-06**
	4	MOQPSO	0.63375	1.27554	0.87581	0.1311	0.06092	0.08553	0.07623	0.00611
	5	BBMOPSO	**3.1E-05**	**3.8E-05**	**3.5E-05**	**1.8E-06**	0.00013	0.00024	0.00017	3.2E-05
	6	MOPSO	0.46047	1.32609	0.68756	0.20833	0.04344	0.14873	0.07634	0.02846

continuous cluster intelligent algorithm in five ZDT benchmark instances are shown in Fig.5 and Fig.6 respectively.

It can be seen from the Pareto frontier convergence diagram (Fig.5) of the selected ZDT benchmark cases that, except for MOQPSO algorithm, MOPSO algorithm and MOMPPSO algorithm in ZDT4 and ZDT6, other algorithms have achieved good Pareto frontier convergence. Both IMOMPPSO algorithm and IMOQPSO algorithm have achieved better frontier convergence than the original algorithm. The IMOQPSO algorithm improves the convergence of Pareto's leading edge and achieves obvious effect in all ZDT benchmark cases, whereas the IMOMPPSO algorithm improves the convergence of Pareto's leading edge and achieves obvious effect in the selected low-dimensional ZDT benchmark cases.

It can be seen from Fig.6, with the increase of iteration times, IMOMPPSO algorithm and IMOQPSO algorithm achieved better population diversity decline than their original algorithm. In the iterative process, the convergence performance of the improved algorithm is better than that of the original algorithm. BBMOPSO algorithm shows a good decrease of population diversity in most selected five ZDT reference cases.

As shown in the statistical analysis results of Table.2, it can be seen that BBMOPSO algorithm shows strong convergence and robustness in all five ZDT benchmark cases. In the low dimensional ZDT reference example, IMOMPPSO algorithm has obvious improvement effect compared with the original algorithm. IMOQPSO algorithm, compared with the original algorithm, also achieved obvious results.

TABLE 3. The computational statistics of the continuous SI on running time and iteration number for The ZDT benchmark instances.

Master serial number	Subpart number	Algorithm	Running time (s)				Iteration number			
			Min	Max	Mean	Std	Min	Max	Mean	Std
1	1	IMOMPPSO	47.33	48.48	47.77	0.31	300	303	300.1	0.55
	2	MOMPPSO	44.49	48.02	45.36	0.66	300	319	301.1	4.24
	3	IMOQPSO	**94.98**	**185.94**	**107.01**	**16.15**	1000	1016	1001.4	3.51
	4	MOQPSO	88.55	191.84	103.57	17.84	1005	1141	1056.03	31.46
	5	BBMOPSO	22.78	23.27	22.89	0.11	600	611	600.37	2.01
	6	MOPSO	19.55	82.44	37.28	17.61	600	2433	1109.83	516.41
2	1	IMOMPPSO	47.42	50.5	48.11	0.58	300	315	300.83	2.97
	2	MOMPPSO	44.88	45.78	45.4	0.21	300	300	300	0
	3	IMOQPSO	96.84	115.09	105.5	3.99	1000	1017	1002.5	4.53
	4	MOQPSO	**93.23**	**132.36**	**115.42**	**8.57**	1016	1214	1108.4	39.95
	5	BBMOPSO	22.89	25.08	23.24	0.49	600	655	606.47	12.67
	6	MOPSO	18.91	24.89	19.47	1.15	600	763	609.8	32.17
3	1	IMOMPPSO	47.81	49.5	48.23	0.38	300	310	300.6	2.04
	2	MOMPPSO	45.36	48.59	46.06	0.79	300	318	301.17	4.44
	3	IMOQPSO	**94.72**	**296.22**	**121.83**	**41.32**	1000	1009	1000.3	1.64
	4	MOQPSO	86.2	114.31	96.13	5.85	1000	1105	1053.73	28.65
	5	BBMOPSO	22.8	23.28	22.9	0.09	600	609	600.3	1.64
	6	MOPSO	22.02	110.17	61.09	23.31	649	3161	1764.17	669.03
4	1	IMOMPPSO	27.55	63.47	35.42	8.5	302	550	370.03	68.54
	2	MOMPPSO	19.33	21.76	19.73	0.51	300	315	303.73	5.18
	3	IMOQPSO	47.42	50.41	48.05	0.55	1000	1019	1004.07	5.59
	4	MOQPSO	**33.05**	**104.72**	**65.15**	**34.68**	1000	3000	1893.47	985.33
	5	BBMOPSO	22.06	23.09	22.69	0.19	600	609	601.5	2.4
	6	MOPSO	18.27	19.2	18.57	0.22	600	608	600.27	1.46
5	1	IMOMPPSO	27.64	29.05	27.95	0.34	300	312	301.2	3.17
	2	MOMPPSO	19.47	23.47	20.3	0.93	300	361	310.27	13.98
	3	IMOQPSO	**60.14**	**65.81**	**61.63**	**1.54**	1000	1066	1012.73	20.57
	4	MOQPSO	43.31	68.5	53.44	9.14	1000	1061	1007.8	12.59
	5	BBMOPSO	22.87	24.77	23.18	0.39	600	648	606.73	10.16
	6	MOPSO	18.48	18.98	18.69	0.09	600	600	600	0

It can be seen from the statistical analysis results of 30 independent experiments of running time and iteration times (Table.3), there is no significant difference in the optimal time of continuous cluster intelligent algorithm. The optimal time of the selected multiphase particle swarm optimization algorithm and quantum behavior particle swarm optimization algorithm is obviously correlated with the complexity of the problem. As the problem dimension increases, the optimal time increases obviously.

IV. ANALYSIS OF EXAMPLES

The location of both the departure station and the terminal station is unknown, but the value range is given. It is possible to design the examples of optimization model of the door-to-door transportation, and then to analyze the practical application of IMOMPPSO algorithm and IMOQPSO algorithm in the design of the door-to-door transportation.

In the design problem of resource-expandable railway freight door-to-door transportation, it is necessary to determine the departure station and terminal station of each shipper's freight transportation, and at the same time, the location of all the starting station and destination station should be determined. Therefore, on the basis of the traditional continuous coding method of railway freight door-to-door routing design problem, the design of resource-extended railway freight door-to-door transportation routing design problem coding method is proposed.

Fig.7 shows an example of resource-extended railway freight door-to-door transportation. Two subcodes are added

TABLE 4. The computational statistics of the continuous SI on SC and ISC for the RERFTRD example.

Subject	Object	SC				ISC			
		Min	Max	Mean	Std	Min	Max	Mean	Std
1	2	25	100	70.28	17.7	**-5**	**100**	**54.76**	**28.13**
	3	0	11.54	0.67	2.34	-100	-46.67	-75.06	14.87
	4	0	42.86	13.17	13.32	-93.33	1.68	-45.65	27.48
	5	66.67	100	84.4	8.42	**66.03**	**100**	**83.53**	**9.45**
	6	8.7	76.47	37.37	16.47	**-29.76**	**76.47**	**35.55**	**20.06**
2	1	0	47.83	15.52	13.46	-100	5	-54.76	28.13
	3	0	5.26	0.41	1.28	-100	-41.18	-74.98	13.01
	4	0	42.86	8.37	12.14	-85.71	-3.81	-54.2	23.01
	5	46.15	93.94	75.88	9.73	**31.15**	**93.94**	**71.25**	**14.12**
	6	4.35	64.71	32.34	14.31	**-28.98**	**64.71**	**29.33**	**18.76**
3	1	46.67	100	75.73	14.81	**46.67**	**100**	**75.06**	**14.87**
	2	41.18	100	75.39	12.96	**41.18**	**100**	**74.98**	**13.01**
	4	60	100	95.24	8.06	**60**	**100**	**94.3**	**9.26**
	5	70	100	83.32	7.95	**70**	**100**	**83.32**	**7.95**
	6	89.19	100	99.47	2.15	**89.19**	**100**	**99.47**	**2.15**
4	1	26.67	93.33	58.82	17.27	**-1.68**	**93.33**	**45.65**	**27.48**
	2	40	85.71	62.57	13.51	**3.81**	**85.71**	**54.2**	**23.01**
	3	0	17.65	0.93	3.44	-100	-60	-94.3	9.26
	5	57.69	92.11	80.47	8.16	**50.79**	**92.11**	**79.76**	**9.7**
	6	13.04	100	56.11	19.51	**-25.06**	**100**	**52.16**	**25.38**
5	1	0	11.11	0.87	2.72	-100	-66.03	-83.53	9.45
	2	0	29.41	4.63	8.05	-93.94	-31.15	-71.25	14.12
	3	0	0	0	0	-100	-70	-83.32	7.95
	4	0	21.43	0.71	3.91	-92.11	-50.79	-79.76	9.7
	6	0	88.24	25.25	19.95	-80	88.24	-3.67	35.88
6	1	0	38.46	1.82	7.12	-76.47	29.76	-35.55	20.06
	2	0	33.33	3.01	7.04	-64.71	28.98	-29.33	18.76
	3	0	0	0	0	-100	-89.19	-99.47	2.15
	4	0	38.46	3.95	10.12	-100	25.06	-52.16	25.38
	5	0	80	28.92	18.1	**-88.24**	**80**	**3.67**	**35.88**

to determine the location of departure station and terminal station respectively.

RERFTRD calculation example is given as the optimization model of the routing design system for the full-loaded door-to-door transportation. According to the actual situation, the value range of the departure station and the terminal station is set as respectively, departure station $y'_{j1}\_min = y'_{j2}\_min = 18$ and $y'_{j1}\_max = y'_{j2}\_max = 36$, terminal station $y''_{k1}\_min = y''_{k2}\_min = 18$ and $y''_{k1}\_max = y''_{k2}\_max = 36$. The statistical analysis of the Pareto frontier convergence of the selected continuous cluster intelligent algorithm in RERFTRD example and the population diversity mean, running time and iteration times are shown in Fig.8 and Fig.9 respectively. The statistical analysis of its SC and ISC in 30 independent experiments is shown in Table.4.

The "subject" and "object" columns in Table.4 are similarly numbered as the "numbered" column in Table.2 and Table.3.

It can be seen from the Pareto front convergence diagram of the continuous cluster intelligent algorithm in the RERFTRD example (Fig.8), quantum behavior particle swarm optimization algorithm achieves the best Pareto front convergence. The effect of multiphase particle swarm optimization algorithm is second. The BBMOPSO algorithm was the worst performer. As shown in Fig.8, due to the strong convergence in the test problem, it is easy to fall into the local optimal value. It can be seen from the statistical analysis of the running time and the number of iterations (Fig.9) that the optimization time of the multiphase particle swarm optimization algorithm is the longest, whereas the quantum behavior particle swarm optimization algorithm can obtain

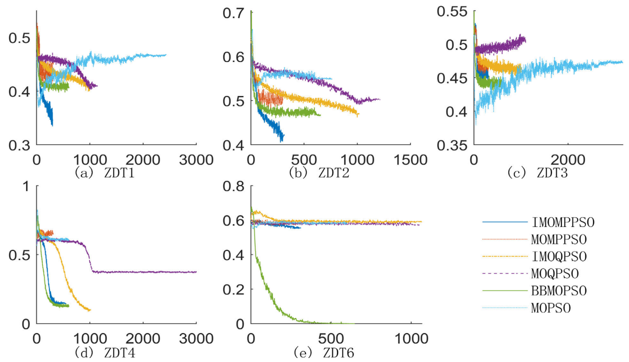

FIGURE 6. **The population entropy of the continuous SI for the ZDT benchmark instances. The images reflect the different effects of various continuous swarm intelligence algorithms, which are embodied in the different mean values of population diversity in the ZDT benchmark instance.**

Table 1: Originating station operation time

Consignor	Station 1	Station 2	Station 3
1	2.4	3.0	2.0
2	1.6	2.0	1.3
3	2.2	2.8	1.8
4		1.5	
5	2.0	2.5	1.7
6	1.0	1.3	0.8

Table 2: Destination station operation time

Consignor	Station 1	Station 2	Station 3
1	2.1	1.5	1.9
2	1.4	1.0	1.3
3	2.0	1.4	1.7
4	1.1		1.0
5	1.8	1.3	1.6
6	0.9	0.6	0.8

Table 3: Originating station priority order

Consignor	Priority 1	Priority 2	Priority 3
1	S3	S1	S2
2	S3	S1	S2
3	S3	S1	S2
4	S2		
5	S3	S1	S2
6	S3	S1	S2

Table 4: Destination station priority order

Consignor	Priority 1	Priority 2	Priority 3
1	S2	S3	S1
2	S2	S3	S1
3	S2	S3	S1
4	S3	S1	
5	S2	S3	S1
6	S2	S3	S1

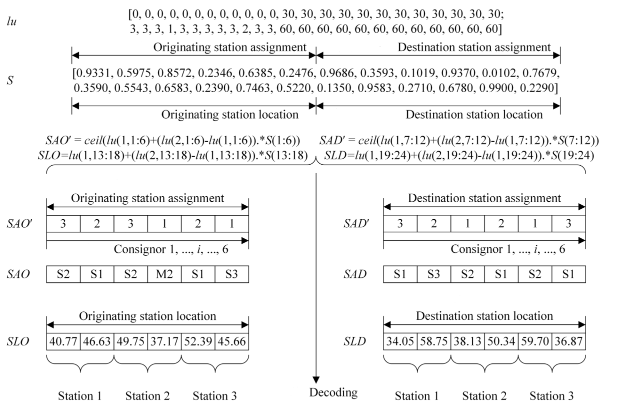

FIGURE 7. **The example of coding for resource-expandable railway freight transportation routing design. The figure shows the specific process of encoding and decoding the positions of the departure station and the terminal station.**

better optimization results with relatively short optimization time.

It can be seen from the statistical analysis of SC and ISC in RERFTRD examples of the continuous cluster intelligence algorithm (Table.4), quantum behavior particle swarm optimization algorithm achieves better optimization effect than other algorithms, and IMOQPSO algorithm achieves the best optimization result;The second is the multiphase particle swarm optimization algorithm;IMOMPPSO algorithm also achieves better optimization results than the original

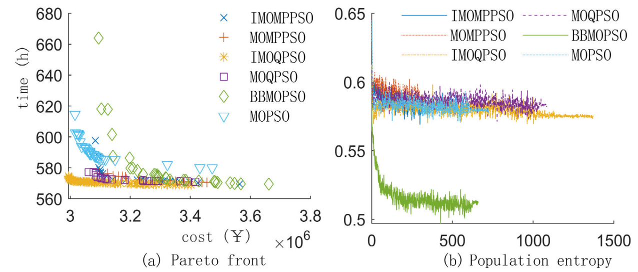

FIGURE 8. **The Pareto front convergences and population entropy of the continuous SI for the RERFTRD example. The figures respectively reflect the convergence of Pareto front edge and the mean value of population diversity of six intelligent algorithms in RERFTRD examples.**

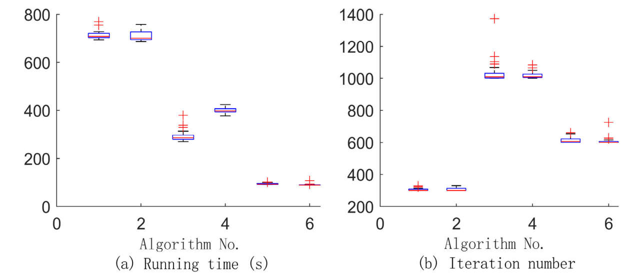

FIGURE 9. **The statistical analysis of the continuous SI on running time and iteration number for the RERFTRD example. Running time and number of iterations are important indexes to analyze the efficiency of an algorithm.**

algorithm;However, the optimization effect of BBMOPSO algorithm is the worst.

V. SIMULATION ANALYSIS

According to the above analysis, it can be known that IMOQPSO algorithm achieves the best optimization results. After decoding the compromise solution obtained by IMOQPSO algorithm, the routing design is shown in Table.5. Gong et al. found that the reasonable and optimized simulation results are beneficial to practical applications through the simulation analysis of charging piles of electric vehicles [28]. Gao et al. proposed the optimization decision and supervision strategy for the informal recovery channel of electric vehicle batteries through simulation analysis [29]. Liu et al. verified the optimal recycling strategy through simulation analysis of the recycling model of electric vehicle batteries [30]. Gong et al. artificially studied the impact of resource sharing on supply chain efficiency, conducted modeling and simulation, and analyzed the influence degree of each parameter [31].

In this paper, the simulation model was built in Simio, the transport time of the compromise solution selected by simulation and the simulation results were compared, besides, analyzed with the results obtained by the algorithm. The Simio simulation model of RERFTRD calculation example is shown in Fig.10, and the simulation results are shown in Table.5.

As we can see, from the simulation analysis (Table.5), there is a certain error rate between the optimized transportation

TABLE 5. The simio simulation analysis of the RERFTRD example.

Shipper number	Departure station number	Terminal station number	Optimization time (h)	simulation time (h)	error
1	1	3	20.14	19.78	1.82
2	6	5	34.56	34.20	1.05
3	1	4	35.69	35.24	1.28
4	5	3	32.69	32.17	1.62
5	4	6	25.26	24.88	1.53
6	2	6	39.40	39.19	0.54
7	5	2	20.50	20.05	2.24
8	6	4	32.30	31.73	1.80
9	5	3	35.26	34.70	1.61
10	2	3	34.67	34.26	1.20
11	2	2	28.02	27.64	1.37
12	4	5	20.14	19.56	2.97
13	3	1	31.50	31.18	1.03
14	1	4	38.05	37.67	1.01
15	6	1	34.38	34.05	0.97
16	5	2	24.31	23.98	1.38
17	4	5	44.38	44.03	0.79
18	1	3	39.94	39.49	1.14
total			571.19	563.80	1.31

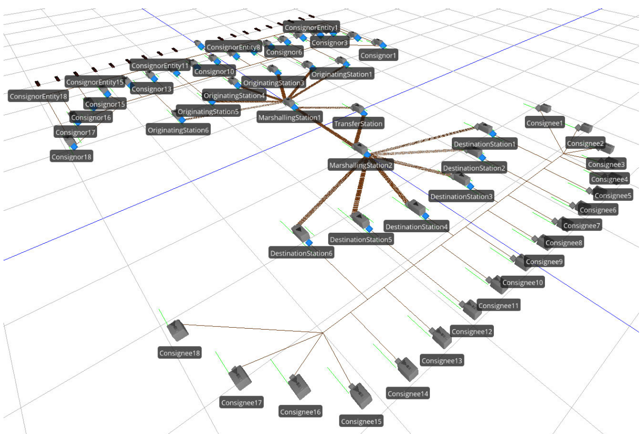

FIGURE 10. The Simio simulation model of the RERFTRD example. The figure reflects the specific relationship between the originating station, the terminal station and the cargo in the Simio simulation model.

time of the algorithm and the simulated transportation time, but the error rate is not large in most cases, and the maximum error rate is less than 3%. In terms of the total transportation time, the error rate between the optimized algorithm and the simulation is only 1.31%, that is, the transportation time obtained by the optimization algorithm is close to that obtained by the simulation.

VI. CONCLUSION

In this paper, the improved continuous multi-objective clustering intelligent algorithm is applied to solve the optimization model of resource-expandable railway door-to-door freight transportation routing design. By comparing the optimization results of the RERFTRD algorithm obtained by solving the RERFTRD algorithm with the RFTRD algorithm obtained by the improved multi-objective clustering intelligent algorithm, we can get:

(1)The improved continuous multi-objective cluster intelligent algorithm can be applied to solve the resource-expandable door-to-door transportation routing design problem, and can provide the design decision support for the whole railway cargo-door transportation, and provide reference for the selection of new stations and the optimization of station layout. The improved optimization results based on continuous multi-objective swarm intelligence algorithm, especially the Pareto front in RERFTRD example based IMOQPSO algorithm, can provide support for railway transportation enterprises to arrange departure station and terminal station for multiple shippers, and provide reference for site selection and layout optimization decision of new stations, and systematically optimize the use of existing transportation resources, so as to reduce the transportation cost and time of the system and improve the quality of service.

(2)Different continuous cluster intelligent algorithms have different effects in solving the resource-expandable railway freight door-to-door transportation routing design problem. In the RERFTRD example, the IMOQPSO algorithm obtains the true Pareto frontier that is closest to the RERFTRD example, whereas the original MOQPSO algorithm achieved the second result, IMOMPPSO algorithm ranked the third.

(3)When the intelligent continuous cluster algorithm achieves better optimization results in solving the benchmark instance, it may not achieve better results in solving complex practical problems. For example, BBMOPSO algorithm shows absolute advantage in the selected five benchmark instances, but performs the worst in RERFTRD algorithm.

(4)Changing the transportation distance of railway and highway in full-loaded door-to-door transportation will affect the transportation cost and time of the system, specifically, it can reduce the transportation cost and time of the system, and it has obviously influence the transportation time of the system, but relatively small influence on the transportation cost of the system.

(5)The system transport time of the RERFTRD example obtained by the improved continuous multi-objective clustering intelligent algorithm is not much different from the overall error rate obtained by Simio simulation, and the system transport time obtained by the improved continuous multi-objective clustering intelligent algorithm is close to that obtained by simulation.

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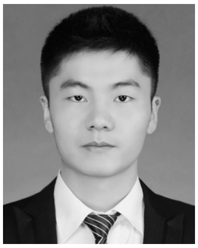

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