Multi-objective Cluster Intelligent Algorithms for Railway Door-to-Door Transportation Routing Design

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ABSTRACT In this study, we aim to develop a system optimization model of Railway Freight Transportation Routing Design (RFTRD) and conduct solution analysis which is based on the improved multi-objective swarm intelligence algorithm. The proposed improved multi-objective swarm intelligence algorithm is applied to solve the combinatorial optimization problem of railway door-to-door freight transportation through design, and provide decision support for railway vehicle door-to-door freight transportation through design. The optimization results shows that, the random multi-neighborhood based multi-objective shuffled frog-leaping algorithm with path relinking (RMN-MOSFLA-PR) can be better applied to solve the combined multi-objective optimization problem, and this proposed improved algorithm can find Pareto frontier through the comparative analysis in the design example of railway door-to-door freight transportation. The frontier can provide support for railway transportation enterprises, arrange the decision-making of the starting and ending stations for multiple shippers, and optimize the use of existing transportation resources, so as to reduce the transportation cost and time of the system.

INDEX TERMS Intelligent Water Drops Algorithms; Multi-objective Cluster Intelligent Algorithms; Random Frog-leaping Algorithm; Random Multi-Neighborhood Structure; Routing Design

1. INTRODUCTION

Railway transportation is an important form of modern transportation. It has the characteristics of low cost, environmental protection, high reliability, accuracy and continuity. Railroad corporations provide two main products for industrial customers who want to transport goods by rail: large customers order 20 to 40 trains in batches, providing fixed group transportation of locomotives directly from the origin to the destination; on the other hand, small customers order 1 to 5 trains. In this case, it is too expensive to provide a single locomotive for each customer through the network, instead of the trains being pulled to the next marshalling station, and other customers' train formation, as a new train is pulled to the next marshalling station, that is, the train is decomposed and reorganized with other trains until all trains reach their final destination. The second kind of freight products of Railroad corporation has brought about natural network design problems, that is, the layout of marshalling yards and the path selection between them. Therefore, in the process of railway freight transportation, railway transport enterprises, based on the constraints of cost and resources, restrict the weight and length of trains, which makes their design problems more complex.

After railway transport enterprises expand the freight station-to-station transportation to door-to-door transportation, they should consider not only the railway itself, but also the optimization of resources in the whole process of transportation, such as highway at both ends, which poses new challenges to the design of railway freight transportation. The main manifestations are: (1) The existing railway freight transportation is usually chosen by the shipper according to the incomplete information he has. For the best cargo start-up and end-arrival stations, railway transport enterprises cannot comprehensively dispatch the existing transport resources; (2) Railway transport enterprises have limited transport resources. Facing more complex door-to-door transport environment, it is necessary to design reasonable cargo start-up and end-to-end stations for multiple shippers in a reasonable time from the perspective of system optimization; (3) The design of door-to-door transport by railway transport enterprises is influenced by various factors such as transmission, operation, transit, arrival and receiving and delivering at both ends.

Therefore, transportation design is a complex process with multi-agent modeling, multi-objective optimization and multi-factors[1]. For example, the selection of starting and ending stations determines the distance between highway and
railway transportation, and the location of each starting and ending station, unit operating cost, loading and unloading capacity, specific types of loading and unloading operations and station occupancy are different, which could conduce the significant impact for the cost and time of freight transportation. Railway transportation enterprises arrange and utilize the existing transportation resources for multiple shippers to reduce the transportation cost and time of the system. At the same time, classical optimization methods, especially in the face of highly complex application environment, have been difficult to meet the practical application requirements, even because of the continuity, solvability and differentiability are prerequisites but no longer applicable. The development of basic theories such as Cluster Intelligent Algorithms and the test of their practical application provide theoretical basis and important research tools for the design and research of door-to-door transport of railway goods. In this paper, based on the whole process of goods transportation from the origin to the destination door to door, combined with the existing transportation resources in the process of transportation, the optimal design of railway freight transportation is carried out systematically.

II. LITERATURE REVIEW

Through design, different methods have been developed to solve the design optimization problems for railway freight transportation, which can provide design decision support. Tong et al. considered that the special train transportation by fixed time, fixed line and fixed path is an advanced form of railway freight transportation, which has the advantages of large capacity, long distance, fast speed, simple organization and high profit[2]. It has become the main way of railway freight transportation, and established an optimization model to minimize the total operating cost to provide the best operation scheme (special purpose). According to Lin et al., the train connection services marshalling plan is the basis of the road network operation plan[3]. It is usually very complex to decide which yards provide direct train services while individual ODs merge into effective train services, and to establish a minimal accumulated service delay and related delay for freight train connection services in large-scale railway networks. The model is solved by simulated annealing algorithm to determine the optimal freight service, service frequency and classification workload distribution between yards. Borndrfer et al. argued that almost all European national railway systems consist of passenger transport, cargo transport and infrastructure (including services) [4]. According to railway infrastructure (such as network design), given passenger transport (route plan or even schedule) and forecast results of future freight transport demand, the freight train planning chain is determined, and studies the freight train routing problem (FTRP) in transportation network with fixed passenger train lines and a group of freight trains (requests) - destination and destination pairs.

With the rise of various modes of transport to promote the improvement of the comprehensive freight transport system, single mode of transport has been difficult to meet the transport needs of customers. Multimodal transport, because of its comprehensive mode of transport, can make full use of and give full play to the advantages of various modes of transport to achieve complementary advantages and more economic and environmental protection, has been widely welcomed. Multimodal transport is a comprehensive system for transporting goods. It uses more than one effective combination of modes of transport between the origin and destination to realize freight transport. The European Commission defines multimodal transport as a feature of the transport system, which allows at least two different modes of transport to be used in an integrated manner in the door-to-door transport chain; in cargo transport, multimodal transport is generally considered to be an interpretation of multimodal transport services that link the initial shipper to the final consignee of the goods, in which the conversion between different modes is: The designated terminal/hub proceeds without handling the goods themselves[5]. In multimodal transport, environmentally friendly modes of transport, such as rail or inland waterway, are usually used in most transport routes, while road transport is usually used in short-distance transport, front-end transport at the origin and back-end transport at the destination, and towing. According to Pinto et al., when trying to reduce atmospheric emissions, experts usually recommend the strategy of replacing road transport with rail transport[6]. However, due to the lack of available railway infrastructure or the high cost of investment, it is not feasible for many countries and companies around the world to make a complete transition to freight rail transport, thus assessing the potential of road-rail multimodal transport, railway multimodal transport can reduce emissions up to 77.4% compared with road transport alone, fuel efficiency up to 43.48% and cheapness up to 80%. Therefore, road-rail multimodal transport is a feasible strategy to mitigate global climate change. Ye et al. compared with the existing Swedish truck regulatory framework, the comprehensive economic and emission costs of highway-railway multimodal transport, highway-railway multimodal transport with longer and heavier vehicles and direct highway transport, the profit-loss balance of highway-railway multimodal transport will be significantly reduced compared with direct highway transport[7]. Baykasoglu and Subulan considered import and export load flow to meet customers' transport needs and many other related issues, and propose a mixed integer programming model for multi-objective, multi-mode and multi-cycle sustainable load planning problems. The model is applied to large international logistics companies to configure multi-modal intermodal logistics network for load planning problems[8]. Mostert et al. constructed optimization models to analyze the impact of policies on multimodal transport and multimodal transport network design[9]. Liu et al. believed that railway transportation has the advantages of large quantity and low carbon emission[10]. Transferring some goods from highway to railway would help to reduce the negative environmental impact associated with transportation. Therefore, a flow distribution model was developed to quantitatively analyze the flow distribution of truck freight to railway transportation. Demir et al. argued that multimodal transport allows different combinations of modes to take advantage of their respective advantages[11]. Multimodal transport networks provide flexible, powerful and environmentally friendly alternatives to transport large quantities of goods over long distances. Aiming at the decision-making of combined off-line multimodal transport routes for a variety of goods, a green multimodal transport service network design problem with
uncertainty of travel time is introduced and sampled. The sample average approximation method generates robust transportation plans. Gohari et al. use ArcMap software to build transport network, use MATLAB software to design user interface and develop the shortest path algorithm for analysis of transport network, construct the path selection model of multimodal transport network, and determine the best transport route and mode from the origin to destination for different objective functions (such as distance, time, emission and cost)[12]. Sun et al. pointed out that in large urban centers (such as Chicago or Los Angeles), road transport at both ends of road-rail intermodal transport may involve hundreds of drivers and up to 500 containers moving to or out of several different rail ramps every day[13]. Cost and environmental factors drive drivers to maximize their efficiency and minimize their time and mileage, and heuristic calculations are generated based on practical application. The model is solved by the method and applied to the commercial transportation management system. Aiming at the transportation cost of railway freight transportation through design, Baykasoglu and Subulan consider the cost of road, sea and railway multimodal transport, simplify the railway transportation cost, i.e. according to the whole train or box, while the road transportation cost is linearly related to the box and transport distance[8]. Mostert et al. consider the cost of multimodal transport, which is divided into transport cost and transport emission cost[14]. The cost of railway-highway intermodal transport is divided into front-end road transport cost, start-end transshipment cost, railway transport cost, end-to-end transshipment cost and back-end road transport cost. The cost of transshipment is linearly related to the weight of goods, and both road and railway transport costs are related to the weight of goods. There is a linear relationship between the weight of the goods and the distance of transportation. Liu et al. took time cost into account when calculating road, transshipment and railway costs considering bulk cargo flow of railway evacuation highway, and used the same way as Mostert et al. to deal with its transport costs[10][14]. Lin et al. simplified railway transportation cost as a linear correlation with cargo weight and transportation distance, and introduced workload to calculate transportation carbon emissions[15]. Existing research divides the cost of railway-highway intermodal transport into different categories, and takes into account additional transport costs such as time cost and emission cost to simplify the handling of road, transshipment and railway transport costs.

In view of the transportation time problem in the design of railway goods transportation, Demir et al. considered the design problem of green multimodal transport service network, and divided the transportation time into loading, picking up road, sending and transferring, railway, arriving and transferring, sending road and unloading and other process time according to the process of combined transportation[11]. Liu et al. considered the time of highway transportation, transshipment and railway transportation, and also believed that the highway transportation time was affected by traffic flow, and the railway transportation time was also operated according to the figure, and did not consider the mutual influence between the operating vehicles at the same station during transit, and believed that the transportation time was proportional to the distance and inversely proportional to the running speed[10]. Baykasoglu and Subulan divided the transportation time of multimodal transport into road, sea and railway service time according to the mode of transport, including loading/unloading time, road, sea and railway transport time, combined operation time at the transfer point, customs clearance time and waiting time of the port and railway station[8]. Gohari et al. divided the transportation time of multimodal transport into transit time and change time, and transit time is directly proportional to distance and inversely proportional to running speed[12]. The existing studies consider the time of combined transport, which is mainly divided according to the mode and process of transport. The loading and unloading time from the beginning to the end is considered. The highway transport time is affected by the road traffic flow, while the railway transport runs on time according to the map.

As a multi-neighborhood structure in the optimization process of Cluster Intelligent Algorithms, path relinking operator, as one of the most important components of path reconnection method, aims to generate new promising solutions by creating paths connecting two high-quality parent solutions[16][17]. Neighborhood structure is the key of path reconnection. Neighborhood is usually defined as transforming a solution to produce an adjacent solution[17]. Neighborhood structure, which has been applied to scheduling problems, must play a role in preventing any infeasible solution[18]. In order to generate new solutions, ensure that the new solutions are feasible, and improve the quality of the new solutions, it is necessary to design the neighborhood structure. Gonzalez et al. used the path reconnection algorithm as a local search to solve flexible job shop scheduling problems, and divided it into two kinds of neighborhood structures: sequencing sub-problem and allocation sub-problem, respectively, to solve the job order and machine allocation of flexible job shop scheduling problems[19]. There are many classical neighborhood structures, which can be classified as sorting structure. Block insertion is used as the path of neighborhood structure generation, which can easily generate a series of mobile. Yang et al. used two complementary neighborhood structures, insertion and exchange, which can be combined to improve search efficiency[17]. The variable neighborhood search algorithm was developed to solve the flexible job shop scheduling problem under uncertainty, so we can know the effect of resources on revenue and cost[18][20-22]. Jia and Hu also use neighborhood structures, directly randomly assigned to Machinable machines, and randomly select a process from the machine in the wizard solution, as well as the front and back processes on the machine, inserting the corresponding process in the initial solution into the corresponding position of the corresponding machine, but the neighborhood structure may lead to loops[23]. Gonzalez et al. believed that the machine that changed the non-critical process would not improve the completion time immediately, so they chose a key process to allocate to the new Machinable machine and insert the process into the new machine according to its original start-up time, that is, the original process on the new machine and the key process, according to the original processing time sequence[19]. Li and Gao adopt hybrid genetic algorithm and taboo search to solve the flexible job shop scheduling problem[24]. When they
mutate the machine allocation string, they randomly select half of the processes to redistribute the workable machines to generate new offspring.

In the research of swarm intelligence algorithm, taking random frog leaping algorithm and intelligent water droplet algorithm as examples, Zhang et al. first used the path reconnection algorithm as a local search for random frog leaping algorithm, and proposed a random frog leaping algorithm based on random multi-neighbourhood path reconnection for solving combinatorial optimization problems[25]. Chaves et al. applied a variety of neighborhood structures in a pre-determined order, while Zhang et al. used random neighborhood structure size and random application order[25][26]. In multi-objective optimization problems, frog location cannot be directly compared[27]. Therefore, RMN-MOSFLA-PR algorithm introduces a fast non-dominated sorting method[28]. Choosing a frog as the best frog position from the first frog on the non-dominant frontier has different bases and strategies. For example, according to the crowding distance[28] and sigma[29], the strategy has the proportion selection of fitness (i.e. roulette selection)[30], the minimum value based on chaotic selection and sigma method[29]. In order to improve the performance of intelligent water drop algorithm, the researchers improved the algorithm by randomly initializing the initial soil amount and the speed of water drop, setting the update boundary of soil amount, adjusting the global soil amount update formula, and taking into account multiple elite solutions[31-35][37-39]. The non-dominant solution set in the population is used in the multi-objective problem. In the RMN-MOIWD-PR algorithm, when updating the global soil quantity, multiple elite solutions are considered simultaneously, the non-dominant solution set obtained by the current iteration is considered. In order to organically combine path reconnection with local search, all solutions constructed by water droplets are considered and the non-dominant solution set obtained by local search with RMN-PR algorithm is obtained. For more Cluster Intelligence Algorithms see [40].Existing dispatching plans make routing choices and parking modes to maximize efficiency and utilization of existing transport resources, usually involving as much relaxation as possible and minimization through the network, and usually choose to control failure time to reduce costs and maximize profits. However, it assumes that all operations will be carried out according to the plan, without considering unexpected service interruptions and service peaks. With the reliability of transport system becoming the key decision-making element of transport users and providers, such assumptions are no longer applicable to most real networks. The existing railway freight transportation design is generally based on the station-to-station mode, and the route selection in railway transportation network has strategic significance. It can be used as input guidance to optimize the specific freight train operation schedule. After railway transportation enterprises expand the freight station-to-station transport to door transport, its design will become more complex change.

III. DESIGN ANALYSIS AND MODELING OF RAILWAY GOODS DOOR-TO-DOOR TRANSPORTATION

In this section, we give a detail analysis of the railway goods door-to-door transportation and establish a corresponding model.

3.1 Design Influencing Factors

Firstly, we introduce the design of influencing factors.

(1) Transportation cost

According to the basic requirements of activity-based costing, the production process of railway door-to-door freight transportation is divided into different operation links. According to the characteristics of railway logistics operation, its service process is divided into 11 operation links, such as receiving at the delivery end, loading at the delivery terminal, trunk transportation, unloading at the arrival end and delivery at the arrival end. The operation links of railway transportation production process are not only diversified in specialty, but also closely related with each other. On the premise of conforming to the reality of railway transportation production, the operation links can be simplified and merged. According to the process of freight transportation, railway freight door-to-door transportation cost can be divided into five operation links: sending, running, transit, arrival and service at both ends. According to the actual situation, each link is subdivided into operation volume indicators, as shown in Table 1.

**TABLE 1. The indices of workload.**

<table>
<thead>
<tr>
<th>Operation link</th>
<th>Index number</th>
<th>Index name</th>
<th>Index symbol</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sending</td>
<td>11</td>
<td>Number of vehicles sent</td>
<td>$H_{11}$</td>
<td>Vehicles</td>
</tr>
<tr>
<td></td>
<td>12</td>
<td>Occupancy time of delivery trucks and vehicles</td>
<td>$H_{12}$</td>
<td>Vehicle.Day</td>
</tr>
<tr>
<td></td>
<td>21</td>
<td>Locomotive total running kilometers</td>
<td>$H_{21}$</td>
<td>km</td>
</tr>
<tr>
<td></td>
<td>22</td>
<td>Total traction weight tonnage kilometers</td>
<td>$H_{22}$</td>
<td>t·km</td>
</tr>
<tr>
<td></td>
<td>23</td>
<td>Pass through total weight tonnage kilometer</td>
<td>$H_{23}$</td>
<td>t·km</td>
</tr>
<tr>
<td>Running</td>
<td>24</td>
<td>Train kilometer</td>
<td>$H_{24}$</td>
<td>km</td>
</tr>
<tr>
<td></td>
<td>25</td>
<td>Vehicle kilometers with freight cars</td>
<td>$H_{25}$</td>
<td>Vehicle-km</td>
</tr>
<tr>
<td></td>
<td>26</td>
<td>Occupancy time of trucks and vehicles</td>
<td>$H_{26}$</td>
<td>Vehicle.Day</td>
</tr>
<tr>
<td>Transit</td>
<td>31</td>
<td>Number of Transfer Trains Handled</td>
<td>$H_{31}$</td>
<td>Vehicle</td>
</tr>
<tr>
<td></td>
<td>32</td>
<td>Transit truck occupancy time</td>
<td>$H_{32}$</td>
<td>Vehicle.Day</td>
</tr>
<tr>
<td>Arrival</td>
<td>41</td>
<td>Number of vehicles reached</td>
<td>$H_{41}$</td>
<td>Vehicle</td>
</tr>
</tbody>
</table>
Operating capacity indicators are divided into five working links: sending, operation, transit, arrival and service at both ends. They correspond to the operation of stations, locomotives, power supply, engineering, telecommunications, vehicles and highway transportation at both ends. The details are as follows:

1. One is the sending link that corresponds to the operation of the sending station and the vehicle department. The amount of work of the sending station is the number of sending vehicles, and the amount of work of the vehicle department is the occupied time of sending freight cars.

1) Delivery volume: number of vehicles sent.

$$\alpha = \left\lfloor \frac{W}{\gamma (1 + \lambda)} \right\rfloor$$ (1)

$$H_{21} = \alpha$$ (2)

Where: $L$ is transportation distance; $\alpha$ is average traction weight of locomotive; $\omega_4$ is self-weight of vehicle; $\zeta_1$ is single probability; $\zeta_2$ is reconnection rate; $\zeta_3$ is supplementary probability; $\zeta_4$ is converted running rate.

2) Locomotive traction operation volume of internal combustion or electric power (power supply department): total traction weight ton kilometers

$$H_{22} = L(W + \alpha_1 \omega_4)$$ (5)

3) Work volume: through the total weight of tonnage kilometers

$$H_{23} = \frac{W \omega_4 L}{\sigma} + L(W + \alpha_1 \omega_4)$$ (6)

Where: $\omega_2$ is locomotive deadweight.

4) Train operation volume: train kilometers

$$H_{24} = \frac{L(W + \alpha_1 \omega_4)}{\sigma}$$ (7)

5) Vehicle workload: kilometers of freight vehicles

$$H_{25} = \sigma L (1 + \epsilon)$$ (8)

6) Car Occupancy Time: Car Occupancy Time

$$H_{26} = \frac{\sigma L (1 + \epsilon)}{24 v}$$ (9)

Where: $v$ is travel speed.

Three is the transit link that corresponds to the operation of the transit station and the vehicle department. The amount of the transit station is the number of transit vehicles handled and the operation amount of the vehicle department is the occupied time of the transit freight vehicles.

1) Locomotive running capacity: total locomotive running kilometers

$$H_{21} = \frac{L(W + \alpha_1 \omega_4)}{\sigma} (1 + \zeta_1 + \zeta_2 + \zeta_3)(1 + \zeta_4)$$ (4)

Where: $W$ is cargo weight; $\gamma$ is static load; $\lambda$ is allowable loading rate; $[.]$ is upward rectification.

2) Send vehicle occupancy time: Truck occupancy time

$$H_{22} = \frac{\tau_1 m (1 + \epsilon)}{24}$$ (3)

Where: $\tau_1$ is sending job dwell time; $\epsilon$ is empty rate.

Two is operating links that correspond to the operation of locomotive, power supply, engineering, electrical and vehicle departments respectively. The working capacity of locomotive department is locomotive running capacity, locomotive traction capacity of internal combustion or electric power (power supply department); the working capacity of Engineering Department is through the total weight ton kilometers; the working capacity of electrical department is train kilometers; and the working capacity of vehicle department is vehicle running capacity and time occupied by running freight cars.

1) Acceptance of tonnage kilometers

$$H_{51} = W t - km$$ (10)

2) Delivery of tonnage kilometers

$$H_{52} = W t - km$$ (11)

Where: $W$ is cargo weight; $t$ is allowable loading rate; $[.]$ is upward rectification.

Four is the arrival link that corresponds to the arrival at the station and the operation of the vehicle department. The arrival amount at the station corresponds to the arrival number of vehicles and the operation amount of the vehicle Department corresponds to the occupied time of arriving at the freight vehicle. The number of jobs arrived is equal to the number of jobs sent.

1) Arrival workload: number of arrival vehicles

$$H_{41} = \alpha$$ (12)

2) Occupancy time of arrival trucks: occupancy time of trucks

$$H_{42} = \frac{\tau_2 m (1 + \epsilon)}{24}$$ (13)

Where: $\tau_2$ is residence time for arrival operation.

Five is the service links at both ends that correspond to the operation of road transportation at both ends. Only the
operation of road transportation at both ends is considered. The corresponding operation volume is tonnage kilometers for receiving and delivering.

1) Operational capacity of service pick-up at both ends: pick-up tonnage kilometers

\[ H_{42} = \frac{t_3 \sigma(1+\varepsilon)}{24} \]  

(14)

Where: \( L_1 \) is transport distance from door to station.

2) Service delivery at both ends: tonnage kilometers

\[ \begin{align*}
VC(W, E, L) &= (C_{21}H_{21} + C_{22}H_{22} + C_{23}H_{23} + C_{24}H_{24} + C_{25}H_{25} \\
&\quad + C_{26}H_{26}) + (C_{31}H_{31} + C_{32}H_{32}) \\
FC(W, E) &= (C_{11}H_{11} + C_{12}H_{12}) + (C_{31}H_{31} + C_{32}H_{32}) \\
&\quad + (C_{41}H_{41} + C_{42}H_{42}) \\
TC &= VC(W, E, L) + FC(W, E)
\end{align*} \]  

(16) (17) (18)

Where: \( E \) is operational efficiency parameters; \( H_{ij} \) is the first link of the operation volume index; \( C_{ij} \) is the corresponding operation volume index \( H_{ij} \); \( \sigma \) is the fixed operation costs; \( VC(W, E, L) \) is variable costs; \( FC(W, E) \) is fixed costs; \( TC \) is railway freight door-to-door transport costs.

(2) Transport time

On the basis of existing research, according to the basic requirements of activity-based costing, transportation time is considered in the production process of railway door-to-door freight transportation, while the loading and unloading time of starting and ending points is not affected by selection, so it is not considered [11-13,15]. Therefore, we also have five working links: sending, operation, transit, arrival and service at both ends. The details are as follows:

One is the sending link that corresponds to the loading operation at the sending station, taking into account the loading operation time and the interaction between different shippers’ cargo operations at the same station. Loading operation time is the residence time of sending operation. Reference to the average delay time of each truck in hub [17], transmission link time:

\[ t_1 = \frac{w}{v_1}(1 + a(\frac{\kappa_1}{\psi_1})^\beta) \]  

(19)

Where: \( v_1 \) is the loading speed of the starting station; \( \kappa_1 \) is the number of shippers that can be processed in parallel for the starting station; \( \psi_1 \) is the total number of shippers that are currently operating at the starting station; \( a \) and \( \beta \) are the undetermined parameters.

Two is operating links that correspond to railway transport operations, taking transport time into account, without considering the impact of other trains running on the same line.

\[ t_2 = \frac{L}{v} \]  

(20)

Three is the transit link that corresponds to the transit operation at the transit station. Considering the transit operation time, and without considering the influence of other transit vehicles, the transit average residence time is used, because the transit operation needs to reorganize the trucks according to the direction of the goods, which means waiting.

\[ t_3 = \pi r_2 \]  

(21)

Four is the arrival link that corresponds to the unloading operation at the arrival station, considering the unloading operation time, and also considering the interaction between different shippers’ cargo operations at the same station. Unloading operation time is the residence time of arrival operation. Reference to the average delay time of each truck in hub [17], arrival time:

\[ t_4 = \frac{w}{v_2}(1 + a(\frac{\kappa_2}{\psi_2})^\beta) \]  

(22)

Where: \( v_2 \) is the terminal unloading operation speed; \( \kappa_2 \) is the terminal to be able to handle the number of shippers in parallel; \( \psi_2 \) is the total number of shippers for the current terminal operation.

Five is the service links at both ends that correspond to road transport operations at both ends. Only the transport time of road transport at both ends, i.e. pick-up time and service time, is considered.

1) Access time:

\[ t_5 = \frac{L_{41}}{v_3} \]  

(23)

Where: \( v_3 \) is highway transport speed.

2) Arrival time:

\[ t_6 = \frac{L_{42}}{v_3} \]  

(24)

Railway cargo door-to-door transport time is the sum of all transport links, that is, the collection of highway access, transmission, railway, transit, arrival and highway service time.
\[ T = \sum_{i}^{N} t_i \]
\[ = \frac{W}{v_1} \left( 1 + \alpha \left( \frac{\pi_1}{\psi_1} \right)^{\delta_1} \right) + \frac{L}{v_1} + \pi \frac{\pi_2}{v_2} \left( 1 + \alpha \left( \frac{\pi_2}{\psi_2} \right)^{\delta_2} \right) + \frac{L}{v_3} + \frac{L}{v_3} \]

(25)

Where: \( t_i \) is the operation time of the first link; \( N \) is the railway cargo door-to-door transport to consider the number of links of operation time, that is, \( N = 6 \) is the railway cargo door-to-door transport time.

### 3.2 Design Modeling of Railway Freight Door-to-Door Transportation

Railway transport enterprise C, which receives the entrustment of a shipper, needs to transport goods from place A to place B through its domestic door-to-door vehicle freight transport service. Each shipper provides specific information about the location of the door-to-door pick-up and the designated delivery place of the corresponding consignee. In place A, there is \( N_O \) departure station for use, and information about the location and operation capability of each departure station is known; in place B, there is \( N_D \) departure station for use, and information about the location and operation capability of each terminal station is known. Railway transportation enterprises, based on the above information, design the system of the shipper's cargo transportation, determine the starting and ending stations of each shipper's cargo, make rational and balanced use of existing transportation resources, improve transportation efficiency and efficiency, and reduce system transportation costs and transportation time. Figure 1 shows the design system model of door-to-door transport of railway goods.

FIGURE 1. The routing system model of door-to-door transportation of railway freight.

Railway cargo door-to-door transportation is a highly complex nonlinear system, so its optimization through design is also a highly complex nonlinear optimization problem. In order to simplify the analysis problem and seize the main influencing factors of the problem, the optimization model of railway cargo door-to-door transportation through design system is constructed based on the following assumptions:

1) After accepting the one-time charge for door-to-door freight transportation entrusted by the shipper, the transportation revenue has been determined, and reducing the transportation cost can improve the profit of the highway transportation enterprises[41].

2) Under the existing available transport resources, unit cost does not change with time, that is, it does not consider the change of transport conditions, for example, does not consider investment in infrastructure construction to enhance transport capacity.

3) The effect of door-to-door loading and unloading operations on the design is not considered, that is, the operation cost and operation time are not considered.

4) Highway transportation time is directly proportional to distance and inversely proportional to speed, and the average speed is known, that is, the capacity of trucks is unlimited or there are enough trucks to transport goods almost simultaneously.

5) Each shipper's cargo transportation can and can only choose one starting and ending station, that is, the same shipper's cargo is not considered to operate at different starting or ending stations, for example, the whole vehicle is unloaded separately.
6) The operational efficiency of the starting and ending stations is relatively stable, i.e. the known average operational efficiency, but the cargo operations of different shippers at the same station interact with each other.

7) Railway transportation time is directly proportional to transportation distance, but inversely proportional to travel speed, and the average travel speed is known, that is, the capacity of a train is unlimited or there are enough trains to transport goods almost simultaneously, that is, the same shipper's cargo is not considered separately.

8) For each shipper's cargo, the number of transit times and operation residence time have been given in the course of railway transportation according to experience. The railway freight transport routing design (RFTRD) model is constructed to determine which departure station each shipper's freight transport passes for rail transport, which end-stop for road transport, and finally to the destination designated by the consignee, i.e. the railway freight transport door-to-door transport. The decision variable is to determine which departure station each shipper's freight transport passes through for rail transport, which end-to-end station for road transport, and finally to the destination designated by the consignee. For the specific research object, from the perspective of railway transport enterprises, the starting and ending stations of each shipper's cargo are determined systematically. Based on the analysis of the whole process of railway door-to-door freight transportation and the optimization objective of the optimized model, the transportation cost and time of the system are minimized. Therefore, the mathematical model is as follows:

$$\min f(x) = \left( T'(x) + \frac{T(x)}{\sigma} \right)$$

$$T'(x) = \sum_{i=1}^{N_{C}} \sum_{j=1}^{N_{O}} x_{ij}' \left( T_{ij}' + T_{i}O_{j} \right) + \sum_{i=1}^{N_{C}} \sum_{j=1}^{N_{O}} \sum_{k=1}^{N_{D}} x_{ijk}' T_{ijk} + \sum_{i=1}^{N_{C}} T_{i} + \sum_{i=1}^{N_{C}} x_{ik}' (T_{Dik} + T_{ik})$$

$$= \sum_{i=1}^{N_{C}} \sum_{j=1}^{N_{O}} x_{ij}' \left( L_{ij}' + W_{i,j}' \left( 1 + \alpha \left( \frac{\sum_{k=1}^{N_{D}} x_{ijk}' \psi_{j}}{\psi_{j}} \right)^{\beta} \right) \right) + \sum_{i=1}^{N_{C}} \sum_{j=1}^{N_{O}} \sum_{k=1}^{N_{D}} x_{ijk}' \frac{L_{ik}}{\psi_{j}} + \sum_{i=1}^{N_{C}} x_{ik}' \left( 1 + \alpha \left( \frac{\sum_{k=1}^{N_{D}} x_{ijk}' \psi_{j}}{\psi_{j}} \right)^{\beta} \right) + \frac{W_{i}}{\psi_{j}}$$

$$\sigma = \left[ \frac{W_{i}}{\gamma(1+\varepsilon)} \right]$$

The constraints are:

$$x_{ij}' = \begin{cases} 1, & \text{if consignor } i \text{ is assigned to the originating station } j \\ 0, & \text{otherwise} \end{cases}$$

(30)

$$x_{ik}' = \begin{cases} 1, & \text{if consignee } i \text{ is assigned to the destination station } k \\ 0, & \text{otherwise} \end{cases}$$

(31)

$$x_{ij}' = 0, \quad j \in OE_{i}$$

(32)

$$x_{ik}' = 0, \quad k \in DE_{i}$$

(33)

$$\sum_{j=1}^{N_{O}} x_{ij}' = 1$$

(34)
Where: $TC_{ij}, T_{ij}$ is the cost and time of road transportation between the designated pick-up place and the departure station $j$ of the shipper iare respectively; $TC_{ik}, T_{ik}$ is the cost and time of transportation of the shipper’s goods at the departure station $j$; $TC_{ik}, T_{ik}$ is the cost and time of railway transportation of the shipper’s goods between the departure station $j$ and the end-arrival station $k$; $TC_{ik}, T_{ik}$ is the cost and time of transshipment of the shipper’s goods at the end of arrival $k$; $T_{ik}$ is the cost and time of road transportation between the shipper’s goods from the end of arrival $k$ to the place designated by the consignee; $OE_i, DE_i$ is the collection of the starting station $j$ and the end-to-end station $k$ where the shipper's goods can be transacted at all the starting and ending stations).

The optimization model of railway door-to-door freight transportation through design system takes domestic door-to-door freight transportation as a specific objective of study. Based on the perspective of railway transportation enterprises, the starting and final arrival stations of goods for multiple shippers are arranged systematically to minimize the transportation cost and time of the system. The transportation cost and time of the system are the sum of each shipper's transportation cost and time. Based on the analysis of the whole process of railway freight door-to-door transportation, the transportation cost and time of each shipper can be divided into the operation links of highway receiving, sending, running, transit, arrival and service at both ends. Figure 2 shows the optimization model structure of railway freight door-to-door transportation through the design system.

![Diagram](image.png)

FIGURE2. The structure of railway freight transportation routing design.

In the optimization model of railway door-to-door freight transport, railway transport enterprises need to arrange the starting and ending stations for $N_C$ shippers. The number of starting and ending stations available in A and B are respectively $N_A, N_B$. Without considering the special requirements of the type of cargo operation at the starting and ending stations, each shipper has $N_D$ starting stations selections and $N_D$ end station selections, therefore, the solution space complexity (SSC):

$$SSC(N_C, N_A, N_B) = N_C \cdot N_A \cdot N_B$$

Therefore, the solution space complexity of door-to-door railway freight transportation optimization model is exponentially related to the number of shippers, and the base number is the number of starting and ending stations respectively. That is to say, with the increase of the number of shippers, the solution space complexity increases exponentially. Therefore, on the premise that the number of starting and ending stations (more than 1) is determined, with the increase of the number of shippers, it becomes more impossible to obtain the mathematical optimal solution in a reasonable time by using the classical method or computer power violence, while using the heuristic method based on cluster intelligence algorithms, used to solve multi-objective optimization problems, needs to expand the algorithm, so that the algorithm can deal with multi-objective optimization problems.
problems. In order to improve the performance of the algorithm, a local search algorithm is introduced to enhance the local search ability of the algorithm. As an advanced hybrid and path reconnection method with more refined meta-heuristic schemes, it can be used as an advanced crossover or combination operator in group-based random local search algorithm [18]. In order to discuss the application of discrete swarm intelligence algorithm in the design of multi-objective railway door-to-door freight transportation, the random frog-leaping algorithm is improved, so that it can be better applied to solve the combined multi-objective optimization problem.

4.1 The complexity of the algorithm

As a multi-neighborhood structure in the optimization process of Cluster Intelligent Algorithms, path relinking operator is one of the most important components of path reconnection method; and neighborhood structure is the key of path reconnection which plays an important role in preventing any infeasible solution. There are many classical neighborhood structures that can be classified as sorting structures, such as insertion, insertion of two adjacent elements, exchange and exchange of two adjacent elements (see Figure 3 a-d) [23]. In order to transform one solution to another in search space, two different neighborhood structures, random block-insertion and random block-swap, are introduced. The number of random adjacent elements, i.e. the size of blocks, is set to [20, 23, 24]:

\[ B_{\text{size}} = \text{randi}(\min([j - i, N_d - j + 1, B_{\text{max}}])) \]  

neighborhood structure is denoted as \( NS_2 \), the random exchange of \( B \) size adjacent connection elements at two locations (see Figure 3 g). 2-opt neighborhood structure, denoted as \( NS_3 \), the operator of the most classical heuristic algorithm for solving traveling salesman problem, generates new ideas by reversing the elements between two locations in advance (see Figure 3), and is also introduced as the basic neighborhood structure.

![Figure 3. The examples of the neighborhood structures for the sequencing](image)

Random substitution, random generation and random key substitution or neighborhood structure are introduced to generate new solutions, where the randomly selected location index is set to [21, 22, 25, 26]:

\[ SI = \text{ismember}(\text{rand}(1, \text{size}(SI), SI_{\text{num}})) \]  
\[ SI_{\text{num}} = \text{rand}([\min([IC_{\text{size}}, SI_{\text{max}}])]) \]  
\[ IC_{\text{size}} = \text{size}(IC_{\text{and}}) \]  
\[ IC_{\text{and}} = \begin{cases} \text{different}(SI, SG), & NSA \in \{NSA_1, NSA_2\} \\ \text{critical}(SI, CE), & NSA = NSA_3 \end{cases} \]  
\[ IC_{\text{size}} = \text{size}(IC_{\text{E}}) \]  
\[ IC_{\text{E}} = \text{find}(\text{ismember}(SI, CE)) \]

Where: \( SI \) and \( SG \) respectively is the initial solution and guide solution; \( \text{different}(SI, SG) \) is the return \( SI \) and \( SG \) element of different location index; \( CE \) is the size-medium-key elements (e.g., flexible job shop scheduling machinery with the largest completion time or workload); \( \text{critical}(SI, CE) \) is the return of random (not more than half of the number of optional elements or the largest number of selected elements); \( \text{ismember}(SI, CE) \) is the determination of whether each element is the partial element of \( \text{ismember}(SI, CE) \); \( \text{find}(\cdot) \) is position index of non-zero elements in return parameters; \( \text{size}(\cdot) \) is size of return parameters; \( \text{floor}(\cdot) \) is downward
integer; randperm\( (n, k) \) is \( k \) non-repetitive pseudo-random integers from \([1, n]\).

Random replacement is denoted as \( NSA_1 \), that is, \( S1num \) element at the corresponding position in the initial solution is replaced by the element at the position different from the element in the initial solution by random selection from the guide solution (see Figure 3 a). Randomly generated neighborhood structure (the random generation), to remember \( NSA_2 \), that is, from initial solution in a random selection of \( S1num \) initial solutions and guide the elements in a different position, and in the corresponding position element values randomly generated in addition to the elements within the scope of possible values for replace the elements (see Figure 3 b), in order to increase the diversity of the neighborhood structure and has certain intelligence, use three generation strategy, namely:

\[
\begin{align*}
\begin{cases}
\text{random} \left( l_u_{\text{new}_j} \right), & r_i = 1 \\
\text{probability} \left( l_u_{\text{new}_j} \right), & r_i = 2 \\
\text{logistic} \left( l_u_{\text{new}_j} \right), & r_i = 3
\end{cases}
\end{align*}
\]

\[
\text{random} \left( l_u_{\text{new}_j} \right) = l_u_{\text{new}_j} \left( \text{randi}(\text{LNsize}_j) \right)
\]

\[
\text{LNsize}_j = \text{size} \left( l_u_{\text{new}_j} \right)
\]

\[
l_u_{\text{new}_j} = \left\{ \begin{array}{ll}
l_u_{\text{newtemp}_j} & \text{if } l_u_{\text{newtemp}_j} \neq \emptyset \\ l_u_{j} & \text{otherwise}
\end{array} \right.
\]

\[
l_u_{\text{newtemp}_j} = \{ e \mid e \in l_u_{j} \land e \neq Si_j \}
\]

\[
\text{probability} \left( l_u_{\text{new}_j} \right) = \text{fitnessProportionateSelection} \left( p_{LNj} \right)
\]

\[
p_{LNj} = \frac{1}{\text{costLN}_{jk}} \sum_{i=1}^{\text{LNsize}_{j}} \frac{1}{1/\text{costLN}_{ji}}
\]

\[
\text{costLN}_{j} = \text{cost} \left( j, l_u_{\text{new}_j} \right) + \text{cost}_{Si} \left( l_u_{\text{new}_j} \right)
\]

\[
\text{logistic} \left( l_u_{\text{new}_j} \right) = l_u_{\text{new}_j} \left( \text{I} \left( \text{ceil} \left( a_{z_i} \text{LNsize}_j \right) \right) \right)
\]

\[
\left[ \text{CLNsort}_j \right] = \text{sort} \left( \text{costLN}_{j} \right)
\]

Where: \( ri = \text{randi}(3) \), random selection of one of the three generation strategies; \( j \) is the selected position; \( l_u_{j} \) is the range of values of the elements in the \( j \) position; \( \text{random} \left( l_u_{\text{new}_j} \right) \) is the function of randomly selecting an element from \( l_u_{\text{new}_j} \); \( \text{probability} \left( l_u_{\text{new}_j} \right) \) is the function of selecting an element from \( l_u_{\text{new}_j} \) according to roulette; \( \text{logistic} \left( l_u_{\text{new}_j} \right) \) is the function of selecting an element from \( l_u_{\text{new}_j} \) according to chaotic sequence; \( \text{fitnessProportionateSelection} \left( p_{LNj} \right) \) is the function of selecting an element based on \( p_{LNj} \) fitness ratio (roulette selection); \( \text{cost}() \) is the function of cost in parameter position (i.e. processing time in flexible job shop scheduling problem); \( \text{cost}_{Si} \left( l_u_{\text{new}_j} \right) \) returns the cost of elements \( l_u_{\text{new}_j} \) in the initial solution \( Si \) (i.e. the completion time and workload of the corresponding machine in the initial solution of flexible job shop scheduling problem); \( \text{sort}() \) is defaults to ascending order sorting function, which \( I \) is the index of each element in the original position \( \text{costLN}_{j} \) after sorting \( \text{CLNsort}_j \); and \( \text{ceil}(\cdot) \) integrates upward; \( a_{z_i} \) is the chaotic map determined logistically (12).

Random key replacement or generated (the random critical replacement or generation), to remember \( NSA_3 \), that is, from the initial solution randomly selected \( S1num \) candidate key element of random selection a key element in the location, if the corresponding location on the wizard solution element is different, the probability of 50% using the wizard solution corresponding to the location element to replace the initial solution on the corresponding position elements, otherwise, the element values in the corresponding position randomly generated in addition to the elements within the scope of possible values for replace the elements (see Figure 3 c), namely:

\[
S_{ij} = \begin{cases} 
S_{g_j}, & \text{if } \text{rand} < 0.5 \text{ and } S_{ij} \neq S_{g_j} \text{ and } S_{g_j} \notin CE_{Sg} \\
\left[ r_i \right], & \text{otherwise}
\end{cases}
\]

Where: \( CE_{Sg} \) is key elements for the wizard's solution \( Sg \).
4.2 An improved multi-objective stochastic leaping frog algorithm

In this paper, a random multi-neighbourhood based multi-objective shuffled frog-leaping algorithm with path relinking (RMN-MOSFLA-PR) is proposed to solve multi-objective combinatorial optimization problems. Figure 5 shows the flow chart of RMN-MOSFLA-PR algorithm (see Algorithm 1 for pseudocode).

(1) Initialization

In the initialization stage of RMN-MOSFLA-PR algorithm, each virtual frog is initialized randomly in the problem search space, and the fitness of the initial population is calculated. Unlike single-objective optimization problems, there are usually no feasible solutions to optimize all objective functions simultaneously in multi-objective optimization problems. Therefore, the main objective of evolutionary algorithms for solving multi-objective optimization problems is to find their non-dominant or Pareto frontiers [28]. Moreover, in the multi-objective optimization problem, the fitness of the solution cannot be directly compared with that of single objective. Therefore, it is necessary to introduce dominant relationship and compare the solutions generated by the algorithm in order to select a better guide solution to guide the algorithm for the next optimization. Therefore, a set of non-dominated solutions with maximum capacity constraints is introduced into RMN-MOSFLA-PR algorithm to store the non-dominated solutions it finds in the optimization process and update the archive during each iteration of the algorithm. After the initialization of RMN-MOSFLA-PR algorithm, the non-dominant solution set of population is initialized based on the non-dominant relationship (see Formula 28, Pseudo-code Algorithm 4). The pseudo-code is found in Algorithm 3, from which the guided solution is selected to guide the evolution of frogs.
FIGURE 5. The flowchart of the RMN-MOSFLA-PR.

(2) Arrange frogs
After population initialization, it enters the iterative evolution process of frog population. Before the evolution of memes in meme complex, virtual frogs need to be divided into meme complexes which are determined in advance according to the actual problems. That is to say, they are divided into meme complexes. Each meme complex has a virtual frog. Before dividing virtual frogs into meme complexes, it is necessary to descend the order of frog populations according to their fitness. In multi-objective optimization problems, frog fitness cannot be directly compared. Therefore, RMN-MOSFLA-PR algorithm introduces a fast and non-dominant sorting method (pseudo-code see Algorithm 5) [29]. According to the dominant relationship between Frog individuals, frog groups are sorted so that frogs can be divided into different meme complexes according to their fitness. At the same time, it should be noted that the effect of rapid non-dominant sequencing, especially in the late evolution of frog populations, on the individual position of frogs on the same frontier will be reduced. In order to mix the frogs more fully, the virtual frogs were randomly disrupted, and then a fast and non-dominant sorting method was introduced to sort the frogs, and then the frogs were divided into different meme complexes.

\[ PW = Arl(s_i, \cdot) \quad PWf = Arl(s_i, \cdot) \quad Wi = Arli(s_i) \]  

(57)
Experiments show that the selection based on congestion distance fitness ratio performs best, followed by chaotic selection strategy, and the minimum selection based on Sigma method performs worst. Therefore, in RMN-MOSFLA-PR algorithm, the optimal location selection strategy is crowding-distance-based fitness proportionate selection (CD-FPS, pseudocode see Algorithm 6).

(4) Individual renewal

After selecting the best and worst frog positions in the sub-meme complex, the position of the worst frog was improved. In the RMN-MOSFLA-PR Algorithm, the random multi-neighborhood based path relinking to improve the worst frog’s position (pseudo code see Algorithm 2) is adopted. The path reconnection algorithm is introduced, and a variety of random neighborhood structures are used according to practical problems. To produce a better position. In the process of path reconnection, the initial solution and the guide solution of path reconnection are initialized according to the best and worst frog positions. The backward path reconnection algorithm tends to perform best [32], so the initial solution and the wizard solution of the path reconnection are set as $S_i = PB$ and $S_g = PW$, respectively. After initializing the allocation and sorting neighborhood structures according to the initial solution and the wizard, the path reconnection operation is started to randomly combine the allocation and sorting neighborhood structures to generate new solutions. After the creation of a new solution $S$, if different from the wizard solution is calculating the fitness, if the fitness of the new command worst frog’s position, or the dominant relationship between them and they are not identical, the fitness of the data processing is not governed by the location of the worst frog the fitness of the weak, replace the worst frog position, namely:

$$s_i = \text{randi}([\text{length}(Arli)])$$

(58)

To avoid premature convergence and falling into local optimum, in the process of path reconnection, as long as a new solution can replace the worst frog position, the path reconnection algorithm will exit and enter the next meme evolution.

In the meme evolution process of RMN-MOSFLA-PR algorithm, if the best and worst frog positions are selected in the sub-meme complex, the solution that can replace the worst frog position is not generated by IWFP-RMN-PR algorithm. From the current non-dominant solution set of meme complex, the optimal solution is selected based on CD-FPS, and the best frog position in the sub-meme complex is replaced by IWFP-RMN-PR. The algorithm improves the location of the worst frog in the selection. If the worst frog position cannot be replaced, the optimal solution is selected from the global non-dominant solution set based on CD-FPS to replace the best frog position in the meme complex, and then the worst frog position is improved by IWFP-RMN-PR algorithm. If none of the above operations can produce solutions that can replace the worst frog position, then randomly generate new positions to replace the worst frog position. In the iterative process of RMN-MOSFLA-PR algorithm, the global non-dominant solution set is updated after each meme evolution (see Algorithm 3 for pseudocode).

(5) Pruning non-dominant solution set

In RMN-MOSFLA-PR algorithm, after updating the global non-dominated solution set, if the non-dominated solution set reaches its maximum capacity limit, it needs to delete the redundant non-dominated solution. The optimal guided solution strategy is selected according to different non-dominated solution sets, and the individuals with the lowest probability are deleted according to the selection probability until the capacity limit of non-dominated solution sets is satisfied. Thus, it can reduce the space occupation of the algorithm and the time of selecting wizards and updating the non-dominated solution set, improve the efficiency of the algorithm, and ensure that there are better global optimal guide solutions in the evolution process of the algorithm.

4.3 Improved Multi-objective Intelligent Water Droplet Algorithms

In order to improve the performance of intelligent water droplet algorithm, a random multi-neighborhood based multi-objective intelligent water drops algorithm with path relinking (RMN-MOIWD-PR) is proposed to solve multi-objective combinatorial optimization problems by combining path reconnection algorithm with local search ability. Figure 6 shows the flow chart of RMN-MOIWD-PR algorithm (see Algorithms 7 for pseudocode).
In RMN-MOIWD-PR algorithm, the amount of soil and the speed of each water drop in the path between all nodes are randomly initialized [33,34], that is, the amount and speed of soil are randomly generated within a given range, and then the water droplets are randomly initialized at the selected nodes, and then the process of constructing solution begins to cycle.

**Step 0 path reconnection**

In RMN-MOIWD-PR algorithm, random multi-neighborhood based path relinking (RMN-PR, pseudo-code see Algorithm 8) is combined to enhance its local search ability. After all the solutions are constructed, all solutions are obtained and their fitness is evaluated. A fast and non-dominated sorting method [29] is introduced to rank all solutions currently obtained. Thus, all solutions on the first and last non-dominated frontier surface are obtained, and their positions, fitness and location indexes are recorded as $Arsx$, $Ars$, $Arsx$ and $Arsl$ by Algorithm 5, initialize path relinking: $i=1, S = size(Arsl)$.

**Step 1 Renewal of Global Soil Quantity**

Global soil quantity renewal formula:

$$soil(i,j) = (1 - \rho_{iwd})soil(i,j) - \rho_{iwd} \frac{\Sigma_{iwds(iwd)}soil\,wds(iwd), Nd - 1}{Nd - 1}$$

Where: $soil(i,j) = (1 - \rho_{iwd})soil(i,j) - \rho_{iwd} \Sigma_{iwds(iwd)}soil\,wds(iwd), Nd - 1$, $\forall (i,j) \in iwds(iwd)$, $iwd \in Arsi$, $\rho_{iwd}$is global soil quantity renewal parameters, $Nd$ is number of nodes in solution.

In RMN-MOIWD-PR algorithm, a set of non-dominated solutions with maximum capacity constraints is used to store the non-dominated solutions found in its search process. After updating the global soil amount, the global non-dominated solution set is updated according to the solution constructed by all water droplets and the non-dominated solution set obtained.
by path reconnection. When the non-dominant solution set reaches its maximum capacity limit, the non-dominant solution beyond the capacity limit is deleted. According to the strategy of selecting the guide solution from the non-dominated solution set in the path reconnection operation, the non-dominated solution is sorted in descending order according to the selection probability, and the non-dominated solution after capacity restriction is deleted from the sorted non-dominated solution set. It guarantees that RMN-PR algorithm can provide better global optimal guide solution, and reduces the time to select the guide solution from it, so as to improve the efficiency of the algorithm.

V. Example experiment

An example is designed to verify the practical application effect of the improved discrete multi-objective swarm intelligence algorithm in solving the design problem of door-to-door transportation of railway goods.

5.1 Encoding and decoding

In the design of door-to-door transport of railway goods, it is necessary to allocate the starting and ending stations of each shipper's goods systematically in order to make full use of the existing transport resources of railway transport enterprises. Compared with the flexible job shop scheduling problem, it is necessary to rank the processes on the same machine to determine the processing sequence and then determine the starting processing time of each process. According to document [42], the average delay time of each shipper's goods at the start and end of the station is determined, so as to consider the interaction between different shippers’ freight operations at the same station. In the design of door-to-door transportation, only the starting and ending stations of each shipper's cargo need to be allocated, regardless of the order of cargo operations of different shippers at the same station. Figure 7 shows an example of discrete coding for railway door-to-door freight transportation. Similar to the flexible job shop scheduling problem, in order to ensure that each shipper's cargo station allocation is continuously rectified from 1 to the number of workable stations in the code, reference [43] is used for each shipper's cargo operation schedule (without considering the interaction between different shippers' cargo operations at the same station) for railway door-to-door freight transportation. The shipper ranks the stations in ascending order according to their cargo operation time. That is to say, the shipper's cargo operation schedules in Figure 7 starting station Table 1 and ending station Table 2 are sorted according to each shipper's cargo operation time, and the shipper's cargo sStation priority tables in starting station Table 3 and ending station Table 4 are obtained. Because the shipper's cargo departure and arrival stations need to be allocated separately, the coding is divided into two sub-coding parts: departure and arrival, which are used to allocate each shipper's cargo departure and arrival. In sub-coding, the location index assigns the station to the corresponding shipper number. The sub-codes of the start and end-to-stop assignments are decoded by the shipper's freight station priority tables of the start and end-to-stop Table 3 and Table 4, respectively, so that the start and end-to-stop of each shipper's goods can be obtained.

**Table 1: Originating station operation time**

<table>
<thead>
<tr>
<th>Consignor</th>
<th>Station 1</th>
<th>Station 2</th>
<th>Station 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.4</td>
<td>3.0</td>
<td>2.0</td>
</tr>
<tr>
<td>2</td>
<td>1.6</td>
<td>2.0</td>
<td>1.3</td>
</tr>
<tr>
<td>3</td>
<td>2.2</td>
<td>2.8</td>
<td>1.8</td>
</tr>
<tr>
<td>4</td>
<td></td>
<td>1.5</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>2.0</td>
<td>2.5</td>
<td>1.7</td>
</tr>
<tr>
<td>6</td>
<td>1.0</td>
<td>1.3</td>
<td>0.8</td>
</tr>
</tbody>
</table>

**Table 2: Destination station operation time**

<table>
<thead>
<tr>
<th>Consignor</th>
<th>Station 1</th>
<th>Station 2</th>
<th>Station 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.1</td>
<td>1.5</td>
<td>1.9</td>
</tr>
<tr>
<td>2</td>
<td>1.4</td>
<td>1.0</td>
<td>1.3</td>
</tr>
<tr>
<td>3</td>
<td>2.0</td>
<td>1.4</td>
<td>1.7</td>
</tr>
<tr>
<td>4</td>
<td>1.1</td>
<td></td>
<td>1.0</td>
</tr>
<tr>
<td>5</td>
<td>1.8</td>
<td>1.3</td>
<td>1.6</td>
</tr>
<tr>
<td>6</td>
<td>0.9</td>
<td>0.6</td>
<td>0.8</td>
</tr>
</tbody>
</table>

**Table 3: Originating station priority order**

<table>
<thead>
<tr>
<th>Consignor</th>
<th>Priority 1</th>
<th>Priority 2</th>
<th>Priority 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>S3</td>
<td>S1</td>
<td>S2</td>
</tr>
<tr>
<td>2</td>
<td>S3</td>
<td>S1</td>
<td>S2</td>
</tr>
<tr>
<td>3</td>
<td>S3</td>
<td>S1</td>
<td>S2</td>
</tr>
<tr>
<td>4</td>
<td>S2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>S3</td>
<td>S1</td>
<td>S2</td>
</tr>
<tr>
<td>6</td>
<td>S3</td>
<td>S1</td>
<td>S2</td>
</tr>
</tbody>
</table>

**Table 4: Destination station priority order**

<table>
<thead>
<tr>
<th>Consignor</th>
<th>Priority 1</th>
<th>Priority 2</th>
<th>Priority 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>S2</td>
<td>S3</td>
<td>S1</td>
</tr>
<tr>
<td>2</td>
<td>S2</td>
<td>S3</td>
<td>S1</td>
</tr>
<tr>
<td>3</td>
<td>S2</td>
<td>S3</td>
<td>S1</td>
</tr>
<tr>
<td>4</td>
<td>S3</td>
<td>S1</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>S2</td>
<td>S3</td>
<td>S1</td>
</tr>
<tr>
<td>6</td>
<td>S2</td>
<td>S3</td>
<td>S1</td>
</tr>
</tbody>
</table>

**Table 7.** The example of discrete coding for railway freight transportation routing design

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5.2 Experimental example

The example of door-to-door transport of railway goods through design system optimization model is recorded as RFTRD example. Assuming that a railway transportation enterprise C receives the entrusted of 18 shippers' domestic railway door-to-door transport service, it needs to transport goods from A to B. The shipper's information is shown in Table 2, including the place of picking up goods at home, the place of delivery, the weight of delivery, the times of transfer and each time. The time required for the second transfer, as well as the start and end of the exceptional operation (that is, the shipper's goods cannot work at the station corresponding to the number). There are 6 start-up stations and 6 end-arrival stations in A and B, respectively. The information of start-up stations and end-arrival stations is shown in Tables 3 and 4, respectively, including location, operation speed, number of operation lines and unit operational cost. In the example of RFTRD, the number of cargo transit and the time needed for each transit, the unit operating cost of the starting and ending stations of each shipper are taken as the reference systems. The right-angle coordinate systems of the door-to-door pick-up, starting and ending stations and designated service locations are respectively constructed with the marshalling stations (logistics centers) in A and B as the origin points. The transport distance between them is assumed to be the Europeans between the two points. The distance between A and B marshalling stations (logistics centers) is set to $L_{AB} = 700 \text{km}$. 

<table>
<thead>
<tr>
<th>No.</th>
<th>Pick up location</th>
<th>Delivery location</th>
<th>Weight(t)</th>
<th>Transfer times</th>
<th>Transfer time(h)</th>
<th>Starting Station Exceptions</th>
<th>End-to-End Exceptions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(63, 52)</td>
<td>(67, 55)</td>
<td>1482</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>(65, 46)</td>
<td>(57, 48)</td>
<td>627</td>
<td>3</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>(61, 65)</td>
<td>(42, 72)</td>
<td>1763</td>
<td>3</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>(69, 60)</td>
<td>(58, 54)</td>
<td>2206</td>
<td>2</td>
<td>6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>(56, 71)</td>
<td>(38, 54)</td>
<td>1445</td>
<td>1</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>(47, 54)</td>
<td>(55, 54)</td>
<td>757</td>
<td>4</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>(69, 53)</td>
<td>(50, 53)</td>
<td>2020</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>(55, 49)</td>
<td>(41, 49)</td>
<td>1685</td>
<td>3</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>(50, 36)</td>
<td>(57, 37)</td>
<td>2407</td>
<td>3</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>(39, 54)</td>
<td>(43, 54)</td>
<td>1315</td>
<td>3</td>
<td>5</td>
<td>1.4</td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>(56, 54)</td>
<td>(61, 53)</td>
<td>1242</td>
<td>2</td>
<td>4</td>
<td>3</td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>(48, 54)</td>
<td>(69, 50)</td>
<td>1074</td>
<td>0</td>
<td>0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>(71, 54)</td>
<td>(56, 39)</td>
<td>482</td>
<td>3</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>(54, 52)</td>
<td>(48, 56)</td>
<td>1544</td>
<td>3</td>
<td>6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>15</td>
<td>(53, 47)</td>
<td>(70, 48)</td>
<td>424</td>
<td>3</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>16</td>
<td>(50, 68)</td>
<td>(55, 71)</td>
<td>1475</td>
<td>1</td>
<td>4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>(39, 57)</td>
<td>(51, 54)</td>
<td>649</td>
<td>5</td>
<td>5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>(55, 44)</td>
<td>(44, 53)</td>
<td>1804</td>
<td>4</td>
<td>5</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>No.</th>
<th>Location</th>
<th>Operation speed(t/h)</th>
<th>Operation line number</th>
<th>Cost per unit(yuan/vehicle)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(27, 24)</td>
<td>3391</td>
<td>6</td>
<td>299</td>
</tr>
<tr>
<td>2</td>
<td>(26, 35)</td>
<td>2706</td>
<td>4</td>
<td>298</td>
</tr>
<tr>
<td>3</td>
<td>(25, 27)</td>
<td>1743</td>
<td>2</td>
<td>291</td>
</tr>
<tr>
<td>4</td>
<td>(19, 26)</td>
<td>2890</td>
<td>4</td>
<td>314</td>
</tr>
<tr>
<td>5</td>
<td>(27, 24)</td>
<td>3684</td>
<td>6</td>
<td>304</td>
</tr>
<tr>
<td>6</td>
<td>(25, 35)</td>
<td>2507</td>
<td>4</td>
<td>285</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>No.</th>
<th>Location</th>
<th>Operation speed(t/h)</th>
<th>Operation line number</th>
<th>Cost per unit(yuan/vehicle)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(27, 24)</td>
<td>3391</td>
<td>6</td>
<td>299</td>
</tr>
<tr>
<td>2</td>
<td>(26, 35)</td>
<td>2706</td>
<td>4</td>
<td>298</td>
</tr>
<tr>
<td>3</td>
<td>(25, 27)</td>
<td>1743</td>
<td>2</td>
<td>291</td>
</tr>
<tr>
<td>4</td>
<td>(19, 26)</td>
<td>2890</td>
<td>4</td>
<td>314</td>
</tr>
<tr>
<td>5</td>
<td>(27, 24)</td>
<td>3684</td>
<td>6</td>
<td>304</td>
</tr>
<tr>
<td>6</td>
<td>(25, 35)</td>
<td>2507</td>
<td>4</td>
<td>285</td>
</tr>
</tbody>
</table>
5.3 Operation parameters

Operational parameters for calculating transportation costs and time (see Table 5). Among them, the whole vehicle is measured by the vehicle with the standard weight $\gamma = 60 t$, and the speed of highway transportation is $v_3 = 60 \text{ km/h}$. Estimation parameters of job delay time in start $\alpha = 1$ and end $\beta = 3$ stations are set to sum.

### Table 5. The parameters of operation.

<table>
<thead>
<tr>
<th>No.</th>
<th>Name</th>
<th>Unit</th>
<th>Numerical value</th>
<th>No.</th>
<th>Name</th>
<th>Unit</th>
<th>Numerical value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$\gamma$</td>
<td>t/car</td>
<td>60</td>
<td>7</td>
<td>$\zeta_1$</td>
<td>%</td>
<td>9</td>
</tr>
<tr>
<td>2</td>
<td>$\lambda$</td>
<td>%</td>
<td>5</td>
<td>8</td>
<td>$\zeta_2$</td>
<td>%</td>
<td>7</td>
</tr>
<tr>
<td>3</td>
<td>$\epsilon$</td>
<td>%</td>
<td>40</td>
<td>9</td>
<td>$\zeta_3$</td>
<td>%</td>
<td>6</td>
</tr>
<tr>
<td>4</td>
<td>$\omega_1$</td>
<td>t</td>
<td>23.5</td>
<td>10</td>
<td>$\zeta_4$</td>
<td>%</td>
<td>35</td>
</tr>
<tr>
<td>5</td>
<td>$\omega_2$</td>
<td>t</td>
<td>145</td>
<td>11</td>
<td>$v$</td>
<td>km/h</td>
<td>45</td>
</tr>
<tr>
<td>6</td>
<td>$\sigma$</td>
<td>t</td>
<td>3150</td>
<td>12</td>
<td>$v_3$</td>
<td>km/h</td>
<td>60</td>
</tr>
</tbody>
</table>

The unit operating cost corresponding to the standard (see Table 6) and the unit transportation cost of road freight transportation are set at $C_{51} = C_{52} = 0.8 \text{ yuan/(t.km)}$.

### Table 6. The unit activity cost of workload indices

<table>
<thead>
<tr>
<th>No.</th>
<th>Name</th>
<th>Unit</th>
<th>Numerical value</th>
<th>No.</th>
<th>Name</th>
<th>Unit</th>
<th>Numerical value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$C_{12}$</td>
<td>140</td>
<td>5</td>
<td>9</td>
<td>$C_{32}$</td>
<td>140</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>$C_{21}$</td>
<td>46</td>
<td>6</td>
<td>10</td>
<td>$C_{32}$</td>
<td>140</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>$C_{22}$</td>
<td>0.028</td>
<td>7</td>
<td>11</td>
<td>$C_{53}$</td>
<td>0.8</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>$C_{23}$</td>
<td>0.0042</td>
<td>8</td>
<td>12</td>
<td>$C_{52}$</td>
<td>0.8</td>
<td></td>
</tr>
</tbody>
</table>

5.4 experimental result

In the example experiment, the parameter settings of all algorithms are the same as those of algorithm verification. Figure 8 depicts the Pareto frontier convergence of the selected discrete swarm intelligence algorithm in the RFTRD example, while the statistical analysis of the average population diversity, running time and iteration times of 30 independent experiments is shown in Figure 9. The statistical analysis of SC and ISC of the selected discrete swarm intelligence algorithm in the RFTRD example in 30 independent experiments is shown in Table 7. The "subject" and "object" columns in Table 7 represent the algorithm for which the number corresponds to the "algorithm name" column.
FIGURE 8: The Pareto front convergences and population entropy of the discrete SI for the RFTRD example

In Figure 8(a), we can see that the Pareto frontier convergence of Random Frog Leaping algorithm is the best, while the Pareto frontier uniformity of RMN-MOSFLA-PR algorithm is obviously better than that of MOSFLA algorithm; the effect of intelligent water drop algorithm is not good, and the improved intelligent water drop algorithm is worse. In Figure 8(b), it can be seen that the population diversity of Random Frog Leaping algorithm has declined more obviously, the population diversity of MOSFLA algorithm has declined fastest, and the population diversity of RMN-MOSFLA-PR algorithm has declined more evenly, and has reached the maximum number of iterations, which means that the population diversity of RMN-MOSFLA-PR algorithm has declined more evenly. If the maximum number of iterations is increased, the algorithm can continue to evolve to obtain better optimization results, while the population diversity of intelligent water droplet algorithm is basically unchanged, indicating that its convergence effect is poor.

FIGURE 9: The statistical analysis of the discrete swarm intelligence algorithm on running time and iterations

When it comes to Figure 9, obviously, the Random Frog Leaping algorithm has achieved better optimization results, its running time \( f(I) \) is obviously longer than that of the intelligent water drop algorithm \( T[I] \) even if iteration number \( I \) increases, that is \( T[I]=O(f(I)) \); the two stochastic frog leaping algorithms have reached the maximum number of iterations set, which shows that increasing the number of iterations can continue to optimize, while the intelligent water droplet algorithm has not reached the maximum number of iterations set.

TABLE 7: The computational statistics of the discrete swarm intelligence on SC and ISC in the RFTRD example

<table>
<thead>
<tr>
<th>Question No.</th>
<th>No.</th>
<th>Algorithm name</th>
<th>GD</th>
<th>IGD</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Min</td>
<td>Max</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>RMN-MOSFLA-PR</td>
<td>0</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>MOSFLA</td>
<td>0</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>RMN-MO1WD1-PR</td>
<td>0</td>
<td>0.5</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>RMN-MO1WD2-PR</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>
In this paper, the improved discrete multi-objective swarm intelligence algorithm is applied to solve the optimization model of door-to-door freight transportation. We apply the improved discrete multi-objective swarm intelligence algorithm to solve the door-to-door transport design problem of railway freight, and provide decision support for the design of door-to-door transport of railway freight. The Pareto frontier obtained by RMN-MOSFLA-PR algorithm in the RFTDRD example can provide decision support for railway transportation enterprises to arrange their cargo starting and ending stations for multiple shippers systematically and synthetically based on the optimized results obtained by the improved discrete multi-objective swarm intelligence algorithm, especially the best optimization results obtained by RMN-MOSFLA-PR algorithm.

(2) Different discrete clustering intelligent algorithm have different performance in solving the design problem of railway door-to-door freight transportation. In RFTDRD example, RMN-MOSFLA-PR algorithm achieves the best optimization results, and achieves the Pareto front which is closer to the real Pareto front of RFTDRD example. However, the Pareto front obtained by MOSFLA algorithm is close to that of RMN-MOSFLA-PR algorithm, while the Pareto front is not as effective as that of RMN-MOSFLA-PR algorithm.

(3) When the improved discrete swarm intelligence algorithm is applied to solve benchmark cases, it achieves better performance than the original algorithm. However, when it comes to complex practical problems, the above phenomenon is not always appearing. In the intelligent water droplet algorithm, two kinds of intelligent water droplet algorithm have achieved better results than the original algorithm in the benchmark example, but in the RFTDRD example, the Pareto frontier obtained by the original algorithm MOIWD1 is closer to the real Pareto frontier of the RFTDRD example than the other three intelligent water droplet algorithms.
VI. CONCLUSION AND FUTURE WORK

With the perspective of complex system and multi-agent modeling, the door-to-door transport process of railway freight is analyzed in detail. We divide it into five operation links: sending, operation, transit, arrival and service at both ends, and point out the key factors: transportation cost and transportation time. Then, we take the transport cost and time as optimization object and propose an improved multi-objective random frog leaping algorithm and multi-objective intelligent water drop algorithm. To the end, the numerical examples are compared and analyzed from the quantitative and qualitative perspectives. Object-to-door transportation optimizes the performance of the model through a design system. Based on the improved multi-objective swarm intelligence algorithm, this paper solves and analyses the optimization model of door-to-door railway freight transportation through design system, and draws some conclusions. However, the article also has its shortcomings and can be further studied in the next step:

1. The optimization model of door-to-door railway freight transportation system constructed in this paper simplifies the transit link in the process of railway freight transportation and replaces it with the number and time of transit given by experience. Therefore, the next step of in-depth study can be considered in detail.

2. Railway door-to-door freight transportation is a complex transportation system, which involves complex transportation resources. In the process of building the optimization model through design, this paper simplifies the process, such as estimating the transportation time of highway and railway. The next step is to refine the estimation of the transportation time of each link.

3. Cluster intelligence algorithms perform differently in solving different optimization problems. Generally, with the increasing complexity of the problem, the performance decreases. Especially in high-dimensional problems, the performance is not good and the search time increases significantly. Therefore, the next step is to study how to further improve its performance, especially in complex optimization problems.

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REFERENCES


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Borut Buchmeister received his M. Sc. and Dr. Sc. degrees in Mechanical Engineering at the Faculty of Mechanical Engineering, Maribor, in 1990 and in 1996. He is Head of two laboratories: Laboratory for Production & Operations Management and Laboratory for Discrete System Simulation. Since 2002 he is the Editor-in-Chief of the International Journal of Simulation Modelling (IJSIMM). He is active in the area of production & operations management. His current research activity concerns computer-aided process planning solutions, production planning and scheduling, performance evaluation methods, layout planning, inventory control, discrete optimization techniques, discrete-event simulation.