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Rail Consignment Path Planning Based on Multimodal Transport: Considering the Time Uncertainty Condition

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Abstract: Multimodal transport has emerged and applied to logistics work as single-mode transport was unable to meet the growing demand for logistics. Due to the difference in cost and time consumption between different modes of transportation, the path planning of multimodal transport is different from that of single-mode transport. This paper firstly established a multimodal railroad consignment path optimization model under the condition of transportation time uncertainty and then optimized the path and transportation mode with the particle swarm optimization (PSO) algorithm according to the path optimization model. In addition, the PSO algorithm was optimized by a genetic algorithm to avoid the optimization process of the PSO algorithm from falling into the locally optimal solution. Finally, simulation experiments were carried out on the improved PSO algorithm, and it was compared with the traditional PSO and genetic algorithms. The results showed that the improved PSO algorithm converged to stability after about 200 iterations, the traditional PSO algorithm converged to stability after about 240 iterations, and the genetic algorithm converged to stability after about 400 iterations; the total transport cost and time of railway transportation were USD 114,300 and 52.5 h; the total transport cost and time of the path obtained by the genetic algorithm were USD 60,400 and 35.6 h; the total transport cost and time of the path obtained by the traditional PSO algorithm were USD 37700 and 24.3 h; the total transport cost and time of the path obtained by the improved PSO algorithm were USD 3,1900 and 23.4 h.

Keywords: Multimodal transport, route optimization, uncertainty conditions, particle swarm optimization.

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1. Instruction

With the rapid development of society, the demand for various materials in the construction process is gradually increasing. It is obviously difficult to meet the demand by relying only on the materials produced in the nearby areas, so it is necessary to transport materials from other regions to local areas through logistics, and the materials produced locally can also be transported to other regions through logistics to promote the development of economic exchanges (Elbert et al., 2020). Transport methods that can be used in logistic transport include land, sea, and air transport. Land transport can be divided into highway transport and railway transport. There are various transport methods, and different types of transport methods have different advantages and disadvantages. For example, air transport is fast but costly; sea transport can carry a large cargo volume, but it is limited by the route and depends on a sufficient draught environment (Borocz, 2019). However, single-mode transport can no longer afford the gradually increasing volume of goods, both in terms of efficiency and transportation costs. For example, rail consignment in land transport can be realized by adding compartments to the train, but the train can only run on the tracks, resulting in a lack of freedom (Li et al., 2017). Multimodal transport combines waterway transport, highway transport, and railway transport, and selects the appropriate transport mode for the goods at different intermediate points in the whole logistic transport process, improving transport efficiency and reducing the cost. Based on the road impedance function of the public road bureau, Guo et al. (2020) improved the conditional value-at-risk, established a nonlinear programming model with generalized travel time as the objective function, and used the cellular ant colony algorithm to solve the model. The results of the empirical analysis verified the applicability of the proposed load redistribution method to such areas and the effectiveness of the algorithm. Ji et al. (2015) designed a transport mode combination optimization model based on the network characteristics of a multimodal transport system, used a genetic algorithm as an effective tool to solve the optimization problem, and finally verified the feasibility of the model by example. Gun et al. (2016) designed an effective method applicable to simulate multimodal transport systems affected by emergency situations and carried out a case study to verify the feasibility of applying the method. In the previous studies, the nonlinearities in the model were taken into account in the construction of the path planning model, and different optimization algorithms were used to find the optimal planning route based on the path planning model. The study aims to plan the routes in multimodal transportation to reduce the consignment cost and time. In the construction of the multimodal transport route planning model, by introducing the time triangle fuzzy number, the route planning model took into account the uncertainty of transportation time when planning the consignment route. The particle swarm optimization (PSO) algorithm was used to solve the path planning model, and the crossover and mutation operations in the genetic algorithm were used to improve the PSO algorithm to avoid falling into the locally optimal solution in the process of finding the optimal solution. Finally, a case in the multimodal transport network of Henan province was taken as the subject for simulation experiments, and the improved PSO algorithm was compared with the genetic and traditional PSO algorithms. The results showed that the PSO algorithm improved by the genetic algorithm was faster in path optimization. Then, the planned logistics path was compared with the actual planning path of the case, the single railroad planning path, and the paths obtained by the genetic and traditional PSO algorithms. The planning paths obtained by the three optimization algorithms were more advantageous than the actual planning path of the case in terms of transportation cost and time, which verified the effectiveness of the path planning models. The planning path obtained by the improved PSO algorithm consumed lower transportation costs and shorter time compared with the paths obtained by the other two algorithms, which verified the effectiveness of the improved PSO algorithm. The construction of the multimodal path planning model under uncertain time conditions and the improvement of the traditional PSO algorithm in this paper both provide effective references for the optimization of multimodal transport paths. The challenge in the research process is the existence of uncertainties in the construction of the path planning model, and this paper used the triangular fuzzy number of time to initially consider the impact of uncertain time on the path planning, but in reality, the uncertainties affecting the path planning are not only time, so the direction of the subsequent research is to consider more uncertainties in the construction of the path planning model.

2. Multimodal Transport under Uncertain Conditions

2.1. Multimodal Transport Path Optimization Model under Transport Time Uncertainty

Fig. 1 shows a sketch of a logistics network in the process of railroad consignment after the adoption of multimodal transport. It is a directional acyclic network. In Fig. 1, there are eight nodes, node 1 is the starting point, and node 8 is the end point; there are 11 paths, all of which can be finished by highway, railway, and waterway transport. Logistics often produce various uncertainties in the transportation process, influenced by external factors (Medvediev et al., 2020). For example, the transportation time cannot be fully maintained within the set time and will be affected by the transportation road conditions and weather; goods may also be temporarily increased or decreased in the intermediate nodes in the transportation process. Therefore, the uncertainties in the planning of multimodal rail consignment paths also need to be taken into account, but because of the various uncertain conditions that can affect transportation in the actual logistics, if the uncertain conditions are taken into account in the construction of the multimodal rail consignment path optimization model, it will greatly increase the computational complexity of the optimization model (Ahmadian et al., 2017). Therefore, in order to facilitate the study of multimodal transport path optimization under uncertain conditions, this paper only considered the uncertainty of logistics consignment time, i.e., before constructing the path optimization model, the following assumptions were set the following assumptions: (1) the same batch of goods will not be split during transportation; (2) there is only one path between adjacent nodes in the same mode of transportation; (3) the multimodal-transport logistics network is a directional acyclic network, and the same batch of goods will not pass the nodes and paths that have been passed during transportation; (4) every node in the logistics network has transshipment capability, and the cost is zero when the goods are transferred by the same transport mode; ⑤ the multimodal-transport logistics network is abstracted as $G = (N, A, M)$, where N is the set of nodes, A is the set of paths, and M is the set of transportation modes.

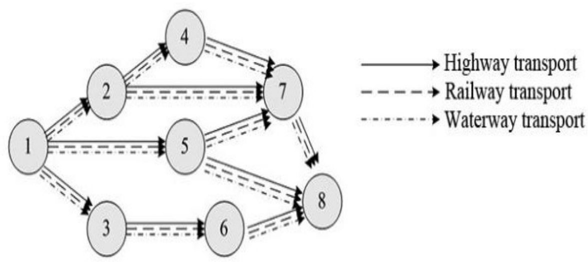

Fig. 1. Sketch of a Multimodal Transport Logistics Network

The rail consignment path optimization model for multimodal transport under transportation time uncertainty is as follows.

Eq. (1) is the target function of the optimization model, and its ultimate goal is to search for a path scheme so that both objective functions are minimal. Eqs. (2) and (3) are the constraints in the optimization model. Eq. (2) is used to ensure that the searched path meets the assumptions and the transformation of the transport mode in the path node. Eq. (3) is the chance constraint condition for the time fuzzy parameter (Adriano et al., 2021) in the model.

The objective function is:

$$\begin{cases} \min z_1 = \sum_{i\in N}\sum_{j\in N}\sum_{m\in M} q\cdot c_m\cdot d_{ijm}\cdot x_{ijm} \\ \qquad + \sum_{i\in N}\sum_{m\in M}\sum_{n\in M} q\cdot r_{imn}\cdot y_{imn} \\ \min z_2 = \sum_{i\in N}\sum_{j\in N}\sum_{m\in M} t'_{ijm} \\ \qquad + \sum_{i\in N}\sum_{m\in M}\sum_{n\in M} s'_{imn} \\ \qquad + \sum_{i\in N}\sum_{m\in M}\sum_{n\in M} w'_{imn} \end{cases} \tag{1}$$

The constraint is:

$$\begin{cases} \sum_{i\in N}\sum_{m\in M} x_{oim} - \sum_{i\in N}\sum_{m\in M} x_{iom} = 1 \\ \sum_{i\in N}\sum_{m\in M} x_{ijm} = \sum_{h\in N}\sum_{m\in M} x_{jhm} \quad \forall j \in N/(o \cup d) \\ \sum_{i\in N}\sum_{m\in M} x_{idm} - \sum_{i\in N}\sum_{m\in M} x_{dim} = 1 \\ u_i - u_j + n\sum_{m\in M} x_{ijm} \le n-1 \quad \forall i,j \in N \\ y_{jmn} = \sum_{i\in N} x_{ijm} \cdot \sum_{h\in N} x_{jhm} \quad \forall m \ne n, j \in N \\ \sum_{i\in N}\sum_{m\in M} x_{ijm} \le 1 \quad \forall i \in N \\ \sum_{m\in M}\sum_{n\in M} y_{imn} \le 1 \quad \forall i \in N \\ x_{iim}, y_{imm} = 0 \quad \forall i \in N, m \in M \\ x_{iim}, y_{imm} \in \{0,1\} \quad i,j \in N \quad m,n \in M \end{cases} \tag{2}$$

$$\begin{cases} \sum_{i\in N}\sum_{j\in N}\sum_{m\in M}\left((1-\alpha_1)t_{ijmL} + \alpha_1 t_{ijmM}\right)x_{ijm} \\ \quad + \sum_{i\in N}\sum_{j\in N}\sum_{m\in M}((1-\alpha_1)s_{imnL} + \alpha_1 s_{imnM})y_{ijm} \\ \quad + \sum_{i\in N}\sum_{j\in N}\sum_{m\in M}((1-\alpha_1)w_{imnL} + \alpha_1 w_{imnM})y_{ijm} \le z_2 \\ ((1-\alpha_2)t_{ijmL} + \alpha_2 t_{ijmM})x_{ijm} \le t'_{ijm} \\ ((1-\alpha_2)t_{ijmU} + \alpha_2 t_{ijmM})x_{ijm} \ge t'_{ijm} \\ ((1-\alpha_2)s_{imnL} + \alpha_2 s_{imnM})y_{ijm} \le s'_{imn} \\ ((1-\alpha_2)s_{imnU} + \alpha_2 s_{imnM})y_{ijm} \ge s'_{imn} \\ ((1-\alpha_2)w_{imnL} + \alpha_2 w_{imnM})y_{ijm} \le w'_{imn} \\ ((1-\alpha_2)w_{imnU} + \alpha_2 w_{imnM})y_{ijm} \ge w'_{imn} \end{cases} \tag{3}$$

The meanings of symbols in these equations are shown in Table 1.

Table 1. Meanings of Symbols in Eqs. (1), (2), and (3)

Symbol	Meaning
z_1	The total consignment cost
z_2	The total consignment time
q	The amount of goods to be consigned
c_m	The unit transportation cost of transportation mode m
d_{ijm}	The distance of goods from point i to point j via transportation mode m
r_{imn}	The unit cost of goods to change from transportation mode m to n at point i
x_{ijm}	A decision variable that takes the value of 1 when the cargo travels from point i to point j via transport mode m and 0 vice versa
y_{imn}	A decision variable that takes the value of 1 when the transportation mode m is transformed to transportation mode n at point i and 0 vice versa,
o and d	The origin and destination
u_i	The serial number of the node i arranged on the path according to the forward order
$t_{ijmL}, t_{ijmM}, t_{ijmU}$	The triangular fuzzy numbers of the time taken to transport the cargo from point i to point j via transport mode m
$s_{imnL}, s_{imnM}, s_{imnU} s_{imnL}, s_{imnM}, s_{imnU}$	The triangular fuzzy numbers of the time required for the cargo to change from transportation mode m to transportation mode n at point i
$w_{imnL}, w_{imnM}, w_{imnU}$	The triangular fuzzy numbers of the time required for the cargo to waiting for changing from transportation mode m to transportation mode n at point i
$t'_{ijm}, s'_{imn}, w'_{imn}$	The real number variables of the respective corresponding link time
α_1	The confidence level of the objective function
α_2	The confidence level of the chance constraint

2.2. PSO-based Multimodal Transport Path Optimization

The multimodal logistics network becomes a directed acyclic network diagram after abstraction. Optimizing the multimodal rail consignment path is equivalent to selecting a path from the directed acyclic network diagram that can minimize transportation costs and time. The multimodal transport path optimization studied in this paper takes into account the uncertainty of transport time, so the triangular fuzzy numbers of transport, transshipment, and transshipment waiting time (Paula et al., 2015) are used instead of the clear time in the optimization model, and the chance constraints of the fuzzy numbers are also introduced. The final multimodal transport path optimization model under time uncertainty has shown in the last subsection. The path optimization model under uncertainty can use the optimization algorithm to calculate the optimal path, and the objective function of the path optimization model under uncertainty is the iterative convergence direction indication in the path optimization algorithm.

The commonly used optimization algorithms are the genetic algorithm (Farshi et al., 2020), ant colony algorithm, and PSO algorithm, among which the PSO algorithm is simple to implement and can make the particles representing the path planning scheme gradually approach the optimal solution in the search space through iteration. In this paper, we choose the PSO algorithm to optimize the multimodal transport paths and improve it with crossover and mutation operations in the genetic algorithm to help it jump out of the locally optimal solution in the iterative process (Yu et al., 2018). The process of the improved PSO algorithm for planning a multimodal transport-based rail consignment path is shown in Fig. 2.

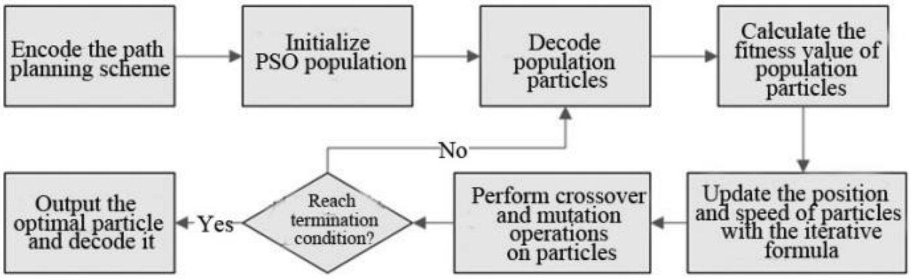

Fig. 2 The Basic Flow of the Improved PSO Algorithm

① The population is initialized, including the initial velocity and position of the particles. The position of a particle means a path planning scheme. The initialization of the PSO population means encoding the randomly generated path planning schemes, using the codes as the coordinates of the particle in the search space, and giving a random initial velocity. Taking the multimodal logistics sketch in Figure 1 as an example, there are three paths between two adjacent connected nodes: highway, railway, and waterway, but in order to facilitate the encoding of the planning scheme, the three paths between two nodes are combined into one path, and the problem of path planning becomes the selection of the transport mode in the path. The transport length and time of the path depend on the selected transport mode. Thus, the encoding of the particles for path planning is a matrix with a specification of $a \times 4$, where a represents the number of paths in the network. The connecting paths between two adjacent nodes are numbered. Every row in the matrix represents a connecting path of adjacent nodes. The first element of every row indicates the priority of the connecting path, the second element is the priority of selecting a highway in the path, the third element is the priority of selecting a railway in the path, and the fourth element is the priority of selecting waterway in the path. An encoding matrix represents a path-planning scheme. When transforming the encoding matrix into the positions of the particles, every priority within the path between every node is the coordinate of one axis of the particle, i.e., the dimension of the particle is $4a$. Also, when initializing a population particle, its priority takes a value in the range of (0, 1], and if a transport mode does not exist within the path, the priority of that transport mode is set as 0.

$$\begin{bmatrix} 0.124 & 0.111 & 0.147 & 0.214 \\ 0.369 & 0.547 & 0.025 & 0.126 \\ \cdots & \cdots & \cdots & \cdots \\ 0.263 & 0.364 & 0.421 & 0.457 \end{bmatrix}$$

Fig. 3. The Encoding Matrix in the Improved PSO Algorithm

② To calculate the population adaptation value, it is first necessary to decode the encoding matrix represented by the particles to obtain the path scheme given by the particles. The decoding of the encoding matrix is performed in the following way: starting from the starting node, the optimal path and the transportation mode are selected among the optional paths according to the priority so that the paths and nodes are gradually selected until the endpoint is reached. Then, according to the paths obtained by particle decoding, the fitness values of the particles are calculated by the objective function of the path optimization model in the last subsection.

③ The position and velocity of the particles within the population are updated by Eq. (4) (Zhang et al., 2020):

$$\begin{cases} v_i(t+1) = \varpi v_i(t) + c_1 r_1 (P_i(t) - x_i(t)) \\ \qquad + c_2 r_2 (G_g(t) - x_i(t)) \\ x_i(t+1) = x_i(t) + v_i(t+1) \end{cases} \tag{4}$$

where $v_i(t+1)$ and $x_i(t+1)$ are the velocity and position of particle i after one iteration, $v_i(t)$ and $x_i(t)$ are the velocity and position of particle i before the iteration, ϖ is the inertia weight of the particle, c_1 and c_2 are the learning factors, r_1 and r_2 are random numbers between 0 and 1 (Dang et al., 2022), $P_i(t)$ is the optimal position experienced by particle i (excluding particles that exceed the limit), and $G_g(t)$ is the best position experienced by the particle population after excluding particles that exceed the limit.

④ Crossover and mutation operations are performed on the particles within the population (Rizk-Allah et al., 2021). The crossover operation is to treat the $4a$ coordinate values of the particles as $4a$ gene fragments and randomly select twp particles according to the crossover probability to exchange the fragments of the same gene locus. The mutation operation is to randomly select a particle according to the mutation probability to change one of the gene fragments.

⑤ Whether the algorithm reaches the termination condition is determined. If the termination condition is reached, the best particle in the population is decoded to get the path planning scheme; if the termination condition is not reached, it returns to step ②. The termination condition is that the number of iterations reaches the preset maximum number or the fitness value converges to stability.

3. Simulation Analysis

3.1. Example Setup

Some multimodal transport logistics in Henan province were taken as the subject for simulation experiments. There are ten nodes in the selected logistics network, and the connecting paths between the nodes are shown in Fig. 4. The connecting path is obtained by abstracting three paths, including the highway path, the railway path, and the waterway path, and the length and transport time of the path will change with the selected transport mode. A survey on this logistics network in Henan province found that the ten nodes in the case all had sufficient transshipment capacity. In this logistics network, node 1 was the starting point, and node 10 was the endpoint. The case studied in the simulation experiment was a transport task in this logistics network. In this transport task, the cargo quantity was 180 tons, and there was no cargo splitting in the transport process, so it was suitable for the proposed multimodal transport path planning model. After investigating the logistics network in the case, the length and transport time of the paths of different transport modes is shown in Table 1. In the transport time, the uncertainty of the transport time was represented by the triangular fuzzy number. The waiting time before transforming one transport mode to another at different time points and the transformation time is shown in Table 2. The uncertainty of the transshipment time was represented by the triangular fuzzy number. In addition, the cost of transforming the transport mode is as follows. The cost of changing highway transport to railway transport was USD 0.44 /ton, the cost of changing highway transport to waterway transport was USD 0.76 /ton, and the cost of changing railway transport to waterway transport was USD 2.90 /ton.

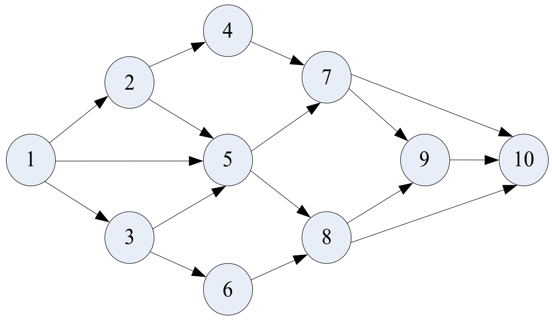

Fig. 4. Logistics Network Of Multimodal Transport

3.2. Algorithm Parameter Setting

The multimodal rail consignment path was optimized by the genetic algorithm-improved PSO algorithm, and the corresponding parameters are as follows. The population size was set as 20, both learning factors were set as 1.5, the maximum number of iterations was 1500, the inertia weight was 0.8, the crossover probability was set as 0.5, the mutation probability was set as 0.1, and the maximum number of iterations was 500.

To further verify the effectiveness of the improved PSO algorithm for path planning, it was compared with the traditional PSO algorithm and the genetic algorithm. Among them, the parameters of the traditional PSO algorithm are consistent with the improved PSO algorithm, except that there is no genetic operator. The parameters of the genetic algorithm are as follows. The population size was 20. The crossover probability of 0.5. The mutation probability was 0.1. The maximum number of iterations was 500.

Table 2. Distance of Different Transportation Modes Within the Effective Path

Inter-node paths	Transportation distance/km			Transportation time/h $(t_{ijmL}, t_{ijmM}, t_{ijmU})$		
	Highway	Railway	Waterway	Highway	Railway	Waterway
1→ 2	120	250	300	(3.1,3.5,4.1)	(4.1,4.2,4.9)	(6.1,6.2,6.8)
1→ 5	235	125	420	(4.1,4.5,5.1)	(3.3,3.6,4.2)	(5.2,5.5,5.9)
1→ 3	/	350	320	/	(4.1,4.6,5.2)	(7.1,7.5,7.9)
2→ 4	980	560	740	(5.1,5.5,6.1)	(6.1,6.3,6.7)	(7.1,7.6,8.1)
2→ 5	580	780	/	(8.1,8.5,9.2)	(7.1,7.3,7.5)	/
3→ 5	630	750	520	(4.3,4.5,5.0)	(4.1,4.7,5.3)	(6.1,6.5,6.9)
3→ 6	550	/	470	(4.1,4.5,5.1)	/	(6.2,6.5,6.8)
4→ 7	860	740	690	(8.2,8.7,9.1)	(9.1,9.5,10.1)	(5.1,5.5,6.1)
5→ 7	740	650	/	(4.1,4.8,5.4)	(5.1,5.4,6.1)	/
5→ 8	1020	750	470	(4.1,4.6,5.3)	(5.1,5.5,6.1)	(3.1,3.5,4.1)
6→ 8	860	790	450	(7.1,7.4,7.7)	(3.1,3.5,4.1)	(6.4,6.7,7.1)
7→ 9	630	/	460	(7.1,7.5,8.3)	/	(4.1,4.7,5.5)
7→ 10	960	750	670	(4.1,4.7,5.9)	(7.1,7.5,8.1)	(3.1,3.5,4.1)
8→ 9	650	740	630	(6.1,6.5,7.1)	(3.1,3.5,4.1)	(7.1,7.5,8.1)
8→ 10	/	940	750	/	(8.1,8.4,8.8)	(3.1,3.5,4.1)
9→ 10	760	850	920	(8.1,8.7,9.3)	(3.1,3.5,4.1)	(9.1,9.5,10.1)

Table 3. Waiting and Handling Time for the Transshipment of Goods in the Node

Nodes	Transshipment waiting time (h) (w_{imnL}, w_{imnM}, w_{imnU})			Handling time (h) (s_{imnL}, s_{imnM}, s_{imnU})		
	Highway-railway	Highway-waterway	Railway-waterway	Highway-railway	Highway-railway	Railway-waterway
1	(0.5,0.8,1.1)	(0.2,0.5,0.8)	(0.3,0.7,1.2)	(0.3,0.6,1.1)	(0.5,0.8,1.5)	(0.6,0.9,1.3)
2	(0.3,0.6,1.1)	(0.5,0.8,1.5)	(0.6,0.9,1.3)	(0.7,0.9,1.4)	(0.5,0.8,1.3)	(0.5,0.9,1.6)
3	(0.7,0.9,1.4)	(0.5,0.8,1.3)	(0.5,0.9,1.6)	(0.5,0.7,1.1)	(0.5,0.8,1.5)	(0.5,0.8,1.1)
4	(0.4,0.8,1.2)	(0.6,0.9,1.7)	(0.5,0.8,1.1)	(0.5,0.9,1.3)	(0.2,0.4,1.0)	(0.7,0.9,1.3)
5	(0.5,0.8,1.5)	(0.5,0.8,1.1)	(0.5,0.7,1.1)	(0.2,0.4,1.0)	(0.7,0.9,1.3)	(0.5,0.9,1.3)
6	(0.2,0.4,1.0)	(0.7,0.9,1.3)	(0.5,0.9,1.3)	(0.5,0.8,1.1)	(0.1,0.5,1.0)	(0.5,0.8,1.2)
7	(0.5,0.8,1.1)	(0.1,0.5,1.0)	(0.5,0.8,1.2)	(0.6,0.9,1.7)	(0.5,0.8,1.5)	(0.5,0.8,1.1)
8	(0.6,0.9,1.7)	(0.5,0.8,1.5)	(0.5,0.8,1.1)	(0.2,0.4,1.0)	(0.7,0.9,1.3)	(0.5,0.9,1.3)
9	(0.5,0.8,1.1)	(0.5,0.9,1.6)	(0.7,0.9,1.3)	(0.7,0.9,1.4)	(0.5,0.8,1.3)	(0.5,0.9,1.6)
10	(0.3,0.7,1.2)	(0.5,0.8,1.1)	(0.6,0.9,1.7)	(0.6,0.9,1.7)	(0.5,0.8,1.5)	(0.5,0.8,1.1)

In addition to comparing the performance of improved PSO, conventional PSO, and genetic algorithms, this paper also compared the multimodal rail consignment path planned by the improved PSO algorithm with the rail consignment path without multimodal transport, which only adopted railway transportation mode and was optimized by the improved PSO algorithm.

In the optimization model of multimodal transport-based rail consignment under logistics time uncertainty, the freight volume was set as 180 tons. The confidence level in the objective function and chance constraint function within the optimization model were: $\alpha_1 = 0.9$, $\alpha_2 = 0.8$.

3.3. Experimental Results

Fig. 5 shows the iterative convergence curves during the optimization of the rail consignment path under uncertainty using the three path optimization algorithms. It was seen from Fig. 5 that as the number of iterations increased, the average fitness values of the paths planned by the three algorithms decreased and eventually converged to stability. Comparing the convergence curves of the three path optimization algorithms, it was seen intuitively that the improved PSO algorithm converged to stability faster, and the average fitness value of the population converged to stability after about 200 iterations; the traditional PSO algorithm converged relatively slowly, reaching stability after about 240 iterations, and the average fitness value at stabilization was slightly higher than that of the improved PSO algorithm; the genetic algorithm converged the slowest and converged to stability after about 400 iterations, and the average fitness value at stabilization was higher than that of the traditional PSO algorithm.

Table 4 shows the planned paths for rail consignment logistics without multimodal transport and the paths under the three path optimization algorithms when multimodal transport was used and also shows the transportation cost and total time consumed for the corresponding paths. Some multimodal transport logistics in Henan province were taken as the subject for simulation experiments. There are ten nodes in the selected logistics network, and the connecting paths between the nodes are shown in Fig. 4. The connecting path is obtained by abstracting three paths, including the highway path, the railway path, and the waterway path, and the length and transport time of the path will change with the selected transport mode. A survey on this logistics network in Henan province found that the ten nodes in the case all had sufficient transshipment capacity. In this logistics network, node 1 was the starting point, and node 10 was the endpoint. The case studied in the simulation experiment was a transport task in this logistics network. In this transport task, the cargo quantity was 180 tons, and there was no cargo splitting in the transport process, so it was suitable for the proposed multimodal transport path planning model. After investigating the logistics network in the case, the length and transport time of the paths of different transport modes is shown in Table 1. In the transport time, the uncertainty of the transport time was represented by the triangular fuzzy number. The waiting time before transforming one transport mode to another at different time points and the transformation time is shown in Table 2. The uncertainty of the transshipment time was represented by the triangular fuzzy number. In addition, the cost of transforming the transport mode is as follows. The cost of changing highway transport to railway transport was USD 0.44 /ton, the cost of changing highway transport to waterway transport was USD 0.76 /ton, and the cost of changing railway transport to waterway transport was USD 2.90 /ton.

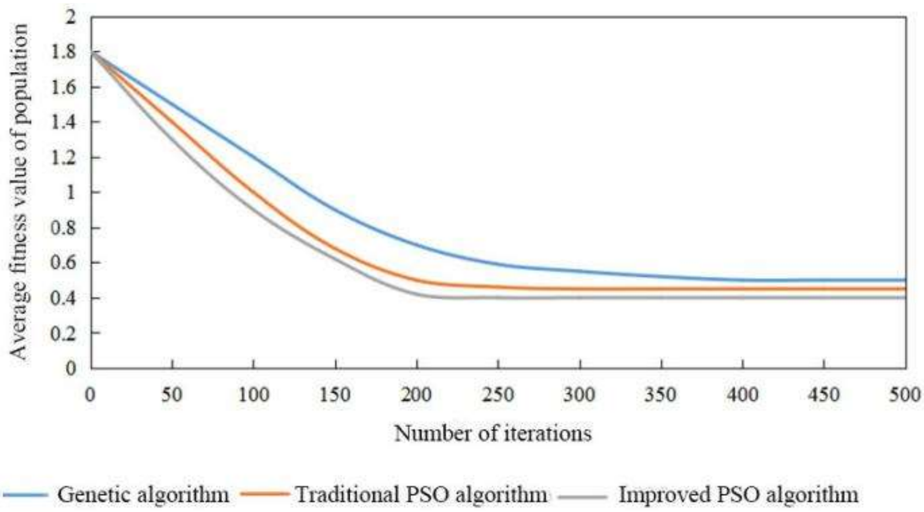

Fig. 5. Convergence Curves of Three Path Optimization Algorithms

Table 4. Paths Planned by Single Rail Consignment, Paths Planned by Three Algorithms under Multimodal Transport, and the Path Of The Actual Case

	Single rail consignment	Genetic algorithm	Traditional PSO algorithm	Improved PSO algorithm	The actual case
Planned path	① ② ⑤ ⑦ ⑨ ⑩	① ② ④ ⑦ ⑨ ⑩	① ③ ⑤ ⑧ ⑨ ⑩	①⑤⑦⑩	①②⑤⑧⑨⑩
Shipping method	Railway	Railway-waterway-railway-waterway-railway	Railway-highway-railway-railway-highway	Railway-railway-waterway	Highway-railway-waterway-waterway-railway
Total transportation cost/ten thousand USD	80.12	42.36	26.45	22.34	9.01
Total transport time/h	52.5	35.6	24.3	23.4	42.3

The comparison between the path of the single rail consignment and the paths obtained by three algorithms suggested that compared to the path of the single rail consignment, the paths of the multimodal transport-based rail consignment were less in terms of transportation cost and time. Among the three path optimization algorithms for multimodal transport, the path obtained by the genetic algorithm cost the most and took the longest time, followed by the traditional PSO algorithm, and the path obtained by the improved PSO algorithm consumed the least transportation cost and time.

4. Discussion

For people engaged in the logistics industry, logistics costs and time should be minimized. Traditional logistics transportation uses a single means of transport, limiting the volume of goods transported and the path. In order to make more choices in logistics path planning, multiple transportation modes are combined to form multimodal logistics. Compared with the traditional path planning of single railway logistics, the path planning of multimodal transportation is more diverse in terms of path selection, i.e., the candidate paths are greatly increased. In this paper, in order to quickly plan the multimodal transport paths, the PSO algorithm improved by the genetic algorithm was used to plan the paths, and triangular fuzzy numbers were introduced to reflect the uncertainty of transport time and transport mode transformation time when building the multimodal transport path planning model, so that the path planning model was relatively close to the actual situation. Finally, a cargo transport task in the multimodal logistics in Henan province was used as a case for simulation experiments, and the improved PSO algorithm was compared with the genetic and traditional PSO algorithms. The final results are shown above.

Among the three algorithms for multimodal path planning, the improved PSO algorithm had the highest convergence speed, the PSO algorithm was the second, and the genetic algorithm was the lowest. The path fitness value of the improved PSO algorithm was the smallest after the convergence was stabilized. The reason is that the improved PSO algorithm used crossover and mutation operations of the genetic algorithm to adjust the particle coding. The mutation operation made the particles “jump” in the search space to get rid of the defect that the traditional PSO algorithm falls into the locally optimal solution in the iterative process.

The path transportation costs and time obtained by the three path planning algorithms were compared, and they were also compared with the path of the single railway transport and the original planned path of the case. The results of the comparison suggested that the path of the single railway transport was not only the most expensive but also the most time-consuming, while the path of the case used multimodal transport to reduce the transport cost and time by taking advantage of different transport modes. The paths calculated by the three path planning algorithms were less costly and time-consuming than the original path, which verified the effectiveness of the constructed multimodal path planning model. The comparison between the three path planning algorithms showed that the path obtained by the improved PSO algorithm had the lowest transportation cost and transportation time, which was because the PSO algorithm introduced with crossover and mutation operations made the particles get rid of the locally optimal solution by "jumping" as much as possible.

5. Conclusion

This paper firstly established a multimodal rail consignment path optimization model under transportation time uncertainty, then optimized the path and transportation mode with the PSO algorithm according to the path optimization model, improved the PSO algorithm with the genetic algorithm to avoid falling into the locally optimal solution, conducted simulation experiments on the improved PSO algorithm, and compared it with the traditional PSO and genetic algorithms. The results demonstrated that the improved PSO algorithm converged to stability faster when searching the optimal path, and the fitness value after stabilization was the smallest; the paths obtained by the three path optimization algorithms were more excellent than the path of the single rail consignment and the original path of the case, and the transportation cost and time of the path obtained by the improved PSO algorithm was the smallest.

In this paper, the triangular fuzzy number was introduced in the process of constructing the path-planning model of multimodal transportation, so the time parameter in the path-planning model was uncertain, which made the constructed model close to the actual situation, and the path-planning model was solved by using the improved PSO algorithm improved by the genetic algorithm. The work provides an effective reference for rational planning of multimodal transport paths. The limitation of this paper is that although the uncertainty of time is reflected by introducing triangular fuzzy numbers when constructing the path planning model, the uncertainty in the actual situation is not only time, and the actual logistics may not fully comply with the assumptions of the model, so the future research direction is to construct the model assumptions as close as possible to the actual situation and take into account the uncertainties other than time.

Author Contributions

Haolin Tong contributes to conceptualization, methodology, validation, analysis, investigation, data collection, draft preparation, manuscript editing, visualization, supervision, and project administration.

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