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An Improved Multi-Objective Quantum-Behaved Particle Swarm Optimization for Railway Freight Transportation Routing Design

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ABSTRACT With the development of railway transportation, the railway transportation enterprises expand their freight transportation from station-to-station transportation to door-to-door transportation, which makes the routing design more complicated. The existing classical optimization algorithms are difficult to meet the needs of practical applications. Therefore, the paper introduces an Improved Multi-objective Quantum-behaved Particle Swarm Optimization algorithm (IMOQPSO). Then based on the continuous coding for the Railway Freight Transportation Routing Design, the proposed improved algorithm was applied to solve the problem to verify the performance of algorithm. Finally, the paper compared the performance of Improved Multi-objective Quantum-behaved Particle Swarm Optimization algorithm with other four continuous multi-objective swarm intelligence algorithms. The results shown that the proposed algorithm obtained the best Pareto front which is closer to the real Pareto front of Railway Freight Transportation Routing Design. Hence, the proposed Improved Multi-objective Quantum-behaved Particle Swarm Optimization algorithm can provide support for the railway transport enterprises routing design decisions to some extent.

INDEX TERMS IMOQPSO algorithm, routing design, swarm intelligence algorithm, multi-objective optimization.

I. INTRODUCTION

Railway is one of the most efficient and environmental-friendly way for transportation industry in China [1]. With the construction of railway infrastructure, the capacity of freight is increasing after separation of cargo lines from the passenger trains, the railway freight should gain more market share with its own advantages. However, in the process of the continuous growth of other modes of transportation and the increasing market competitiveness, the market share of the railway freight industry has declined year by year [2]. Therefore, the problems that how to optimize the organization of railway freight transportation enterprises and improve the efficiency and competitiveness of railway transportation. Railway freight door-to-door transportation is a complicated problem involves a range of issues, for example, firstly, the declining market share in freight transportation is a severe challenge to railway freight transport enterprises. Secondly, the essence of railway transportation service requires the railway transport enterprises continuously improving the service quality [3]–[5]. Thirdly, the railway freight door-to-door transportation involving more people and property which is also a new challenge for railway freight transportation routing design.

The railway freight transportation routing design (RFTRD) system optimization model can be used to comprehensive design the carload freight routing of multiple shippers received by railway transport enterprises. RFTRD system optimization model selected the optimal originating station and destination station for each shipper's cargo transportation, it not only can reduce the transportation cost and transportation time, but also can improve the service quality. The Quantum-behaved particle swarm optimization (QPSO) algorithm has the ability of diversity and the global search capability avoiding being stuck at local optima which has been verified in both theoretical and practical application.

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The QPSO algorithm has been widely welcomed and accepted since it proposed. There are numerous variants of QPSO algorithms which have been proposed by many researchers in recent years and used in various single-objective and multi-objective optimization problems. Hence, the paper proposed an improved QPSO algorithm based on the existing researches and applied it to the RFTRD system optimization model to verify the performance of the improved algorithm. The rest of paper is organized as follows. In section II, we provide the relative literature reviews for the swarm intelligence algorithms. In section III, we explain the proposed methodology, while section IV applied the proposed algorithm to the RFTRD experiment and compared with other particle swarm optimization algorithms. The section V presents the results analysis, and section VI concludes the paper.

II. LITERATURE REVIEW

The concept of Particle swarm optimization (PSO) was originally intent to simulate the social behaviors of bird flocking and fish schooling developed by Kennedy and Eberhart in 1995 [6]. In a PSO system, the position of each particle in search space is decided by its own experience and the best position of encountered particles [6], [7]. With the real-life application and extension, many researchers proposed numerous variants of PSO algorithms [8]–[22] to improve the robustness and global search capabilities of the algorithm for complicated real-life needs. For example, multi-phase particle swarm optimization (MPPSO) algorithm divided the particles swarm into multiple groups incorporates the idea of multiphase and hill-climbing which can increase the population diversity and spatial exploration ability of PSO algorithm [15]–[17]. QPSO algorithm inspired by the analysis of convergence of PSO and study the individual particle of a PSO system moving in a quantum multidimensional space [15]–[17]. Like Genetic Algorithms, the PSO is a population-based optimization method that searches multiple solutions. The existing PSOs, however, are not global-convergence-guaranteed algorithms, the QPSO algorithm outperforms traditional PSOs in search ability with less parameter [17]. The continuous swarm intelligent algorithms selected the variant of the PSO have been widely used to solve enormous real-word problems. Yao *et al.* [23] used the particle swarm optimization with self-adaptive inertia weight and local search strategy to solve the carton heterogeneous vehicle routing problem with a collection depot. Kumar *et al.* [24] considered that production and pollution routing problems with time window is a NP-hard problem of vehicle routing problem. Hence, they proposed a hybrid self-learning particle swarm optimization (SLPSO) algorithm in multi-objective framework to achieve the objectives with minimization of the total operational cost and minimization of the total emissions. Marinakis *et al.* [25] proposed a new hybridized version of Particle Swarm Optimization algorithm with Variable Neighborhood Search to solve the Constrained Shortest Path problem. In their proposed algorithm, a new velocities equation combined with the Particle Swarm Optimization with combined local and global expanding neighborhood topology was added. Okulewicz and Mańdziuk [26] believed that most of the problems in practice are dynamic and change in the process of optimization simultaneously, for example, the Dynamic Vehicle Routing Problem (DVRP). They presented and analyzed a Two-Phase Multi-Swarm Particle Swarm Optimizer (2MPSO) to solve the problem and the algorithm showed a strong result compared with the state-of-the-art literature result on a popular set of benchmark instances. Marinakis *et al.* [27] proposed a new variant of the Particle Swarm Optimization algorithm for the solution of the Vehicle Routing Problem with Time Widows. The proposed Multi-Adaptive Particle Swarm Optimization algorithm can used in three different adaptive strategies. Alinaghian *et al.* [28] proposed a Modified Random Topology Particle Swarm Optimization algorithm for the problem of time dependent competitive vehicle routing problem. They also considered an extension of the time dependent vehicle routing problem introduced the competition parameter and presented two improved algorithms based on PSO to solve the given problem. Chou *et al.* [29] developed a particle swarm carpool algorithm based on stochastic set-based particle swarm optimization. They introduced stochastic coding to augment traditional particles and used the particle position, particle view, particle velocity to represent a particle. The proposed algorithm provided satisfactory ride matches for the carpool service problem. Kachitvichyanukul *et al.* [30] proposed two solution for solving the pickup and delivery problem with time windows and the improved PSO algorithm was used in the generalized vehicle routing problem for multi-depot with multiple pickup and delivery request. The swarm intelligence algorithms also used in the location problem and can provide support. Roso *et al.* [31] considered that determining a suitable terminal location for an intermodal terminal is a critical element of the terminal establishment process, which is also a dependence for the entire intermodal freight distribution chain. Liu *et al.* [32] proposed an adaptive particle swarm optimization algorithm to solve the problem of electric vehicle charging station locating and sizing optimization. Li [33] applied the discrete PSO to solve the reverse logistics location of remanufacturing factory and the distribution of goods. Liu *et al.* [34] proposed a two-stage method to optimize railway freight center stations location and wagon flow organization. A heuristic algorithm that combined tabu search with adaptive clonal selection algorithm is applied to solve the problem. Hu *et al.* [35] considered that the location selection of the logistics distribution center for a supply and demand network enterprises directly affected the efficiency of the logistics system operation and the customer service. Hence, the paper applied an improved firefly algorithm to solve the logistic distribution center location selection problem for the supply and demand enterprises. Zhu [36] analyzed the key factors influencing the logistic distribution system and construct a logistic distribution center site selection model with the minimum total fee as objective.

The PSO algorithm was used to solve the proposed model. Hua *et al.* [37] used a novel approach of adaptive PSO algorithm to solve the proposed logistics distribution center location selection optimization model.

In quantum-behaved particle swarm optimization (QPSO), the potential position model of quantum mechanics (e.g. Delta potential well) is used to replace the position and velocity of the traditional PSO to generate the new position of particles. In QPSO algorithm, the new position of the particle is generated by the combination of the original position, the local attraction point, the global position, the contraction-expansion coefficient and the random parameters. The local attraction point is generated by the weighted average of the individual optimal position and the global optimal position. The global point (i.e. Mainstream Thought) is defined as the average of the optimal positions of all particles that is the mean best position [17]. In the process of QPSO, first calculate the average optimal position, then obtain the individual optimal position and the global optimal position to calculate the local attraction point, and then calculate the new particle position by the quantum mechanical potential field model, the new location fitness was obtained at last [15]–[17]. The QPSO algorithm has been applied in many real-life problems since the numerous variant QPSO proposed. Singh and Mahapatra [38] introduced the operator in genetic algorithm in QPSO and used the logistic mapping to generate chaotic numbers to solve the flexible job shop scheduling problem. Zhao *et al.* [39] Presented a novel evolutionary extreme learning machine based on improved quantum-behaved particle swarm optimization for radar target classification. Wang *et al.* [40] applied the QPSO algorithm in the hybrid energy storage system capacity optimization. Li *et al.* [41] Applied the discrete particle swarm optimization strategy in network clustering. For the complex network clustering, a quantum-behaved discrete multi-objective particle swarm optimization algorithm is proposed. Hu *et al.* [42] proposed a timing scheduling optimization algorithm based on QPSO to optimize the timing scheduling of traffic light. Li *et al.* [43] proposed an improved multi-objective QPSO algorithm based on spectral-clustering to detect the overlapping community structure in complex network, Tian and Ji [44] presented a multi-objective QPSO algorithm with sigma value to solve the flexible job-shop scheduling problems. Turgut [45] introduced the chaotic local search mechanism in the QPSO for thermal design of plate fin heat exchangers. Feng *et al.* [46] presented the multi-objective QPSO for economic environmental hydrothermal energy system scheduling.

The swarm intelligence algorithm has been applied to the problem of routing design optimization and various location selection such as logistics centers and railway freight stations. The QPSO algorithm is especially applied to various single-objective and multi-objective optimization problems in real-life. In the multi-objective optimization, the QPSO algorithm is widely used by researchers in recent years. In the process of application, the performance of the QPSO is improved by optimizing parameter setting and combining with other local search algorithms. Hence, in order to optimize the problem of railway freight transportation routing design, an improved QPSO algorithm was proposed in this paper and the detailed was as follows.

III. METHODOLOGY

In the multi-objective optimization problems, the goal is to find the pareto frontier. Therefore, it is necessary to extend the continuous swarm intelligence algorithm so that the algorithm can deal with multi-objective optimization problems to find the Pareto frontier. The improved QPSO algorithm was applied in the multi-objective RFTRD system and to solve the multi-objective optimization problems. The QPSO algorithm outperforms traditional PSOs in search ability with less parameter, which can improve the global searching capability to avoid being trapped in local optima. Based on the improvement of QPSO algorithm [38], [47] and its application in multi-objective algorithm [44], the paper proposed an improved multi-objective QPSO algorithm combined with a fast nondominated sorting approach [34].

The process of the improved multi-objective quantum-behaved particle swarm optimization (IMOQPSO) is as follows, after initializing the parameters and population, initializes the position of particle by chaotic mapping and calculates its fitness, then initializes the optimal position of the particle and its fitness and obtains the nondominated solution set of the initial population. After initializing the chaotic and mutated parameters of the particle position update formula, start the iteration to find the Pareto front of the optimization problem until the condition of the end loop is met. In the iterative process, firstly determine the mainstream thought, that is, the average of the optimal positions and obtain the contraction-expansion coefficient. Then enter the evolution of the individual particles. In the evolution process of individual particles at the current generation population, the random number of particle position update is determined by chaotic mapping and then the global optimal solution and local attraction point of the particle individual are determined. After that, the particle position is updated, the mutation operation is randomly performed and the fitness of new location was calculated. The current particle optimal position was updated at last. After completing the update of all individual locations in the current generation population, update and prune the global nondominated solution set. The flowchart of the IMOQPSO algorithm is shown in the Figure 1.

A. INITIALIZATION

In the initialization phase of the IMOQPSO algorithm, the position of the individual is initialized by the logistic mapping, that is, the initial position is generated by the logistic mapping within the range of values in the corresponding dimension. The optimal position and fitness of the particle is initialized to the initial position and fitness of the particle. In IMOQPSO algorithm, the nondominated solution was founded in the searching process has a nondominated solution set with capacity constraints. After initializing the popula-

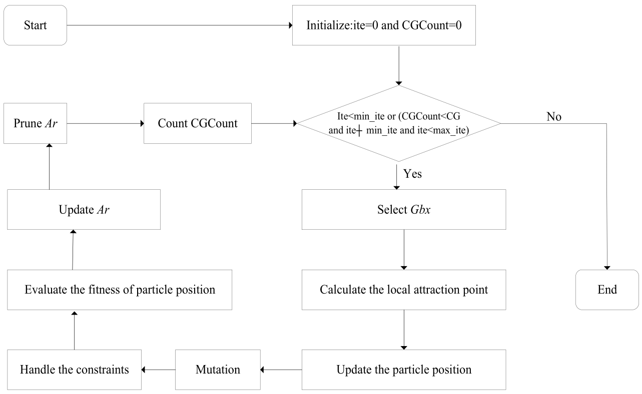

FIGURE 1. The flowchart of the IMOQPSO.

tion, the nondominated solution set is initialized. Finally, the initialization was used to generate the logistic map of k, u and θ.

B. GLOBAL OPTIMA

In the IMOQPSO algorithm, the nondominated solution set was founded by the nondominated solution set storage algorithm with the largest capacity limit and which is updated in the optimization process. In the optimization process, based on crowding-distance-based fitness proportionate selection (CD-FPS), each particle selects a global optimal position from the nondominated solution set to guide particle searching.

C. MAINSTREAM THOUGHT

Sun *et al.* [47] believed that the mainstream thought determines the search scope and creativity of particles. The definition of mainstream thought as the mean of the personal best position is somewhat reasonable, however, is something of paradox, compared with the evolution of social culture in real world. Therefore, in the IMOQPSO algorithm, the average optimal position is calculated based on the fast nondominated sorting approach [48]. After sorting the current population by the fast nondominated sorting, the individuals in the population are distributed on different nondominated frontier surfaces and the average best position on each frontier surface is the same. In order to ensure a better convergence of the algorithm, the average best position of the current nondominated frontier k is the mean of the best position of the individual before the current nondominated frontier k (including k).

$$Mbests_i = Mbests(fns.frontIndex(i)) \tag{1}$$

$$Mbests_k = mean(Pbx_k) \tag{2}$$

$$Pbx_k = Pbx(fns.frontIndex <= k, :), \quad k \in [1, fns.Nf] \tag{3}$$

$$[fns] = fastNondo\min atedSort(s, f) \tag{4}$$

where *fastNondominatedSort* is the fast nondominated sorting function of the structure that returns the output result after sorting, including the number of frontier faces *Nf* and the nondominated frontier face of the individual *frontIndex*, k is the kth nondominated frontier surfaceand $mean(.)$ is a function of the calculated parameter.

D. PARTICLE POSITION UPDATE

In IMOQPSO algorithm, the position is updated by the quantum behavior of the particle. Firstly, the k, u and θ position updated parameters are generated by the logistic mapping [38]. After selecting the global optimal position and calculating the average optimal position based on the CD-FPS, the local attraction points are calculated, and the particle position is updated. In order to improve the convergence of the IMOQPSO algorithm, the particle update with a 50% probability will adopt the value of the corresponding dimension of the individual optimal or global optimal position, that is, each dimension has a 25% probability with the value of individual optimal position or 25% probability with the value of the global optimal position. Hence, the particle position update formula is as follows:

$$x(i,j) = \left\{ \begin{array}{c} Pi(i,j) - \beta(Mbests_i(j) - x(i,j)) \ln(1/u), k \leq 0.25 \\ Pi(i,j) + \beta(Mbests_i(j) - x(i,j)) \ln(1/u), 0.25 < k \leq 0.25 \\ Pbx(i,j), 0.5 < k \leq 0.75 \\ Gbx(j), k > 0.75 \end{array} \right\} \tag{5}$$

After updating the position, the optimal position of the particle is updated. Considering the need for continuous optimization of the algorithm, update the particle optimal position as long as the current position of the particle is not dominated by its historical optimal position.

E. MUTATION OPERATION

In order to improve the performance of the algorithm and consider its convergence, the IMOQPSO algorithm introduces mutation operations [49]. In the IMOQPSO algorithm, the variation parameter [49] is introduced to control the rate of decline in the possibility of mutation. As the number of iterations increases, the possibility of mutation becomes smaller which means the influence of the mutation operator is gradually reduced [49].

F. CONSTRAINT HANDLING

In IMOQPSO algorithm, the constraints handling of optimization problem adopted the method of not allowing individuals to fly out of the feasible area. Four kinds of handling methods include of the randomly generated in the feasible region, set as the individual optimal, global optimal and corresponding dimensional boundary values, are adopted with equal probability to replace the value of the particle flying out of the feasible region dimension.

G. PRUNE A SET OF NONDOMINATED SOLUTIONS

In the IMOQPSO algorithm, when the storage of nondominated solution set found in the optimization process reaches the maximum capacity limit, it is necessary to prune the nondominated solution out of the capacity limit.

TABLE 1. The information of consignor.

No	Pick-up location	Destination	Weight(t)	Transfers times	Transfers time(h)	Originating station (exception)	Destination station (exception)
1	(63, 52)	(67, 55)	1482	0	0		
2	(65, 46)	(57, 48)	627	3	5		
3	(61, 65)	(42, 72)	1763	3	5		
4	(69, 60)	(58, 54)	2206	2	6		
5	(56, 71)	(38, 54)	1445	1	5		
6	(47, 54)	(55, 54)	757	4	5		
7	(69, 53)	(50, 53)	2020	0	0		
8	(55, 49)	(41, 49)	1685	3	4		
9	(50, 36)	(57, 37)	2407	3	5		
10	(39, 54)	(43, 54)	1315	3	5	1,4	
11	(56, 54)	(61, 53)	1242	2	4		3
12	(48, 54)	(69, 50)	1074	0	0		
13	(71, 54)	(56, 39)	482	3	4		
14	(54, 52)	(48, 56)	1544	3	6		
15	(53, 47)	(70, 48)	424	3	5		
16	(50, 68)	(55, 71)	1475	1	4		
17	(39, 57)	(51, 54)	649	5	5		
18	(55, 44)	(44, 53)	1804	4	5		

There are different strategies for selecting the optimal solution from the non-dominated solution set, but all the solutions with the lowest probability of being selected are deleted from the solution until the capacity limit is met. It can guarantee a better global optimal solution and a better nondominated frontier in the evolution of the algorithm, which can reduce the time to select and update the non-dominated solution set at the same time.

IV. EXPERIMENTS

A. THE RFTRD EXAMPLE

The railway freight transportation routing design system optimization model can be recorded as RFTRD. Suppose a railway transport enterprise C, which has received 18 shippers' domestic door-to-door transportation service for full-loaded freight and needs to transport goods from A to B. the shippers information as shown in Table 1 which includes of the pick-up location, the destination, the weight of goods, the number of transfers, the time required for each transfer, and the originating station and destination stations with the exception operation (i.e., the shipper's goods cannot be delivered to the corresponding stations). There are 6 originating stations and 6 destination stations in A and B respectively. The information of the originating stations and the destination stations are shown in Table 2 and Table 3 respectively, which includes of the information of location, operating speed, number of lines and unit operating costs. In the RFTRD example, the Cartesian coordinate system constructed with the origin of A and B stations (logistics centers) as the reference system. The distance between the stations of A and B is set to $L_{AB} = 700$km.

TABLE 2. The information of originating station.

No	Location	Operating speed(t/h)	Line number	Unit cost(yuan/load)
1	(27, 24)	3391	6	299
2	(26, 35)	2706	4	298
3	(25, 27)	1743	2	291
4	(19, 26)	2890	4	314
5	(27, 24)	3684	6	304
6	(25, 35)	2507	4	285

TABLE 3. The information of destination station.

No	Location	Operating speed(t/h)	Line number	Unit cost(yuan/load)
1	(27, 25)	1746	2	211
2	(26, 19)	2895	4	208
3	(24, 28)	3671	6	214
4	(18, 24)	2510	4	204
5	(27, 35)	2460	3	186
6	(27, 27)	2341	3	204

TABLE 4. The parameters of operation.

No	Name	Unit	Value	No	Name	Unit	Value
1	γ	t/load	60	7	ς_1	%	9
2	λ	%	5	8	ς_2	%	7
3	ε	%	40	9	ς_3	%	6
4	ω_1	t	23.5	10	ς_4	%	35
5	ω_2	t	145	11	v	km/h	45
6	σ	t	3150	12	v_3	km/h	60

TABLE 5. The unit activity cost of workload indices.

No	Name	Value	No	Name	Value	No	Name	Value
1	C_{12}	140	5	C_{24}	0.0061	9	C_{32}	140
2	C_{21}	46	6	C_{25}	0.0087	10	C_{42}	140
3	C_{22}	0.028	7	C_{26}	140	11	C_{51}	0.8
4	C_{23}	0.0042	8	C_{31}	118	12	C_{52}	0.8

Calculate the operational parameters for transportation costs and transportation time (see Table 4). Among them, the weight for each carloadis $\gamma = 60$t, and the speed of road transportation is $v_3 = 60$km/h. The estimation parameter of operational delay time in the originating station and the destination station is set to$\alpha = 1$ and $\beta = 3$.

The setting of unit activity cost of workload indices shown in Table 5, the unit transportation cost for cargo freight is set to $C_{51} = C_{52} = 0.8$ yuan/(t·km).

B. CODING AND DECODING

In the example of RFTRD, the real-code system [38] was introduced to encode the problem of door-to-door railway freight transportation routing design to verify the practical application of the continuous swarm intelligence algorithm in this problem. In the problem of RFTRD, it is necessary to allocate the originating station and the destination station for each shipper's goods.Different from the flexible job shop scheduling problem, the order of the cargo operations for different shippers in the same station is not considered. An example of continuous coding for RFTRD shown in Figure 2.

In order to ensure search space of the swarm intelligence algorithm is continuous, a priority table is introduced (see Table 3 originating station and Table 4 destination station in Figure 2), and the real-code system is used for the example of RFTRD [38]. In order to reduce the search space and improve the performance of algorithm, the open interval (0,1) coding mode is adopted. The value range corresponding to each shipper dimension is within the open interval (0,1) before the decoding, and the number of stations Ns_i corresponding to each shipper is not considered. The number of stations Ns_i corresponding to each shipper was considered in the process of decoding. The code value is converted into the value corresponding to the open interval $(0, Ns_i)$, and then the method of decoding for machine distribution in the flexible job shop scheduling problem is adopted to obtain the station priority of each shipper's cargo operation. According to the priority table (see Table 3 originating station and Table 4 destination station in Figure 2), the originating station and the destination station of the shipper's goods are correspondingly allocated. In the code of RFTRD, S is divided into two parts includes of the originating station and the destination station, which are used to assign the originating station and the destination station of each shipper's cargo operations.

TABLE 6. The parameter setting of the IMOQPSO.

No	Name	Value	No	Name	Value	No	Name	Value
1	Ns	100	4	min_ite	1000	7	β_{min}	0.4
2	Na	100	5	max_ite	3000	8	α	5
3	CG	10	6	β_{max}	1			

TABLE 7. The parameter setting of the IMOMPPSO.

No	Name	Value	No	Name	Value	No	Name	Value
1	Ns	100	5	max_ite	900	9	VC_ma	15
2	Na	100	6	ph	2	10	VC_mir	5
3	CG	10	7	pcf	5	11	α	10
4	min_ite	300	8	g	2			

C. PARAMETER SETTING

The multi-objective multi-phase particle swarm Optimization (MOMPPSO) [13], the multi-objective quantum-behaved particle swarm optimization (MOQPSO) [38], the bare-bones multi-objective particle swarm optimization algorithm (BBMOPSO) [49] and the multi-objective particle swarm optimization algorithm (MOPSO) [50] Improved multi-objective multi-phase particle swarm optimization (IMOMPPSO) are selected as comparative objects.

According to the experiment of [17], [38], the parameter setting of IMOQPSO is shown in Table 6, all of the parameter setting of MOQPSO is same to the IMOQPSO except the $MAXT = 10$. The parameter setting of IMOMPPSO is shown as TableVII according to the experiment in [13]. The parameter setting of MOMPPSO is same to the IMOMPPSO except the $VC = 10$. The $\alpha = 8$ in the BBMOPSO algorithm and $w = 0.4$ and $tp = 0.01$ in the MOPSO algorithm, the other parameter setting is same to other algorithms except the $min\_ite = 600$ and $max\_ite = 1800$.

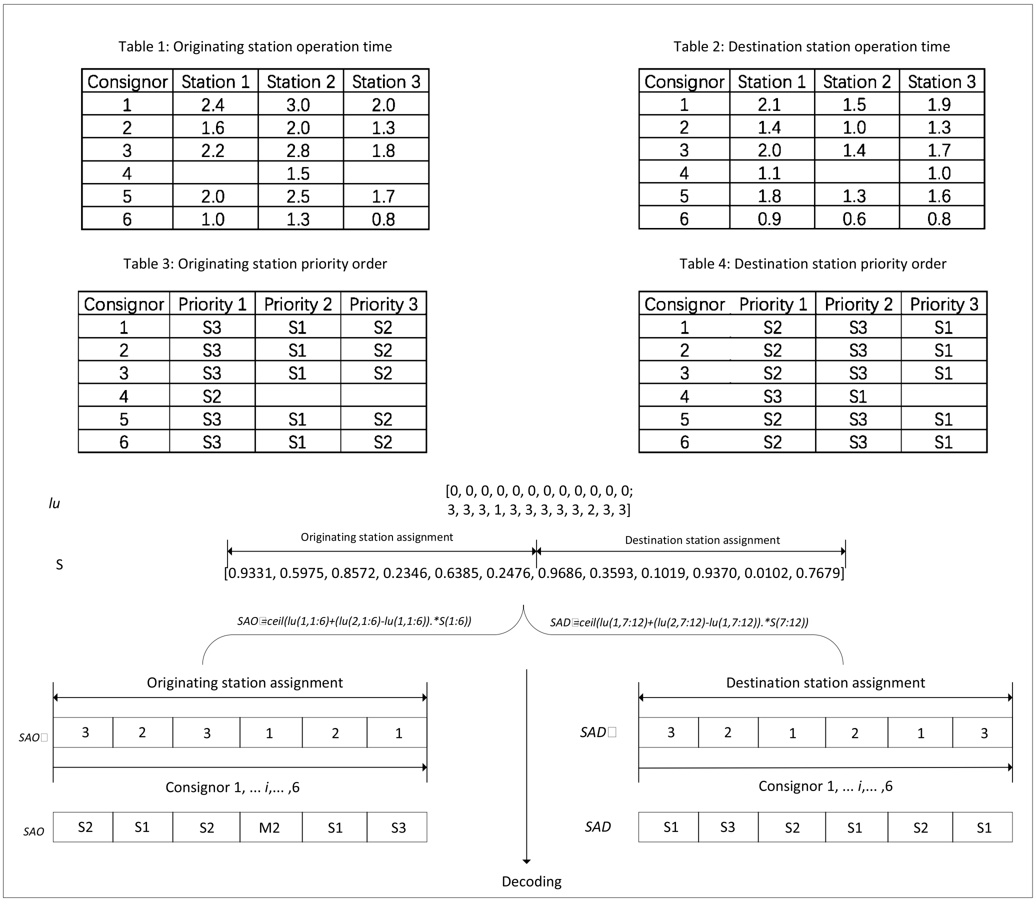
Table 1: Originating station operation time

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

Table 2: Destination station operation time

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

Table 3: Originating station priority order

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

Table 4: Destination station priority order

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

FIGURE 2. The example of continuous coding for railway freight transportation routing design.

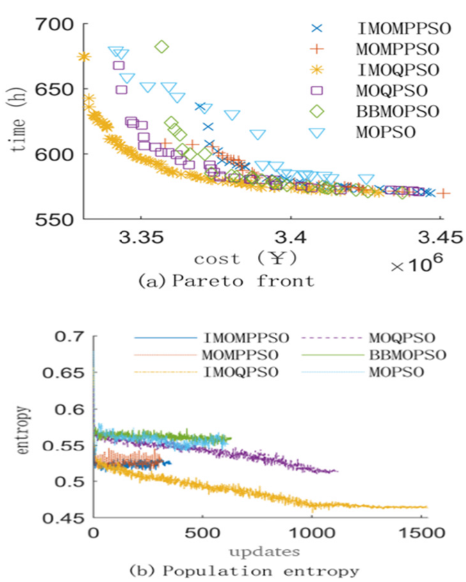

FIGURE 3. The Pareto front convergences and population entropy of the continuous SI for the RFTRD example.

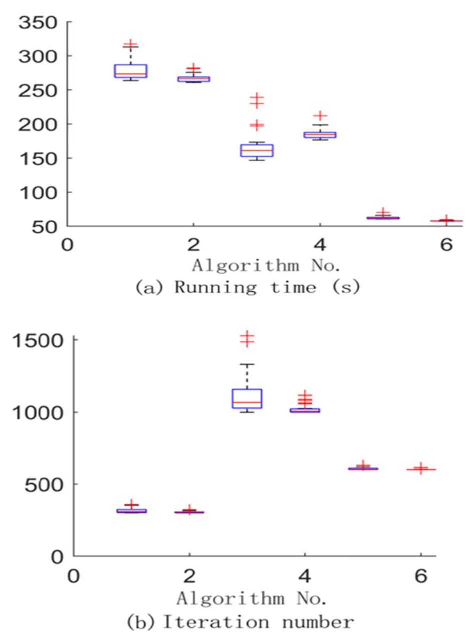

FIGURE 4. The statistical analysis of the continuous SI on running time and iteration number for the RFTRD example.

V. RESULTS ANALYSIS

The Pareto front convergences and population entropy of the continuous swarm intelligencein 30 independent experiment for the RFTRD exampleas shown in Figure3. The statistical analysis of the continuous swarm intelligence(SI) on running

TABLE 8. The computational statistics of the continuous SI on SC and ISC for the RFTRD example.

Subject	Object	Name	SC				ISC			
			Min	Max	Mean	Std	Min	Max	Mean	Std
1	2	MOMPPSO	17.24	80	50.98	15.88	**-53.03**	**66.21**	**12.17**	**29.46**
	3	IMOQPSO	0	1.96	0.17	0.52	-100	-82.14	-95.79	5.13
	4	MOQPSO	5	83.78	42.77	18.4	**-70.99**	**83.78**	**4.26**	**37.15**
	5	BBMOPSO	3.33	65.79	33.72	17.67	-91.41	31.76	-23.05	35.65
	6	MOPSO	18.92	76.32	45.96	15.47	**7.81**	**73.62**	**41.26**	**19.88**
2	1	IMOMPPSO	13.79	70.27	38.82	15.65	-66.21	53.03	-12.17	29.46
	3	IMOQPSO	0	7.14	0.33	1.38	-100	-79.53	-96.65	4.74
	4	MOQPSO	10	78.38	39.47	16.96	-74.62	73.12	-4.9	36.95
	5	BBMOPSO	0	55.26	27.7	14.53	-93.75	26.69	-35.49	29.52
	6	MOPSO	18.92	84.21	48.24	17.64	**0.98**	**81.82**	**41.83**	**23.49**
3	1	IMOMPPSO	82.14	100	95.96	4.89	**82.14**	**100**	**95.79**	**5.13**
	2	MOMPPSO	85.19	100	96.97	3.91	**79.53**	**100**	**96.65**	**4.74**
	4	MOQPSO	96.67	100	99.43	1.16	**96.67**	**100**	**99.43**	**1.16**
	5	BBMOPSO	88	100	96.97	3.63	**87.01**	**100**	**96.82**	**3.81**
	6	MOPSO	100	100	100	0	**100**	**100**	**100**	**0**
4	1	IMOMPPSO	0	81.25	38.51	19.75	-83.78	70.99	-4.26	37.15
	2	MOMPPSO	5.26	84.62	44.37	21.09	**-73.12**	**74.62**	**4.9**	**36.95**
	3	IMOQPSO	0	0	0	0	-100	-96.67	-99.43	1.16
	5	BBMOPSO	0	78.79	28.51	22.91	-91.67	70.36	-21.39	43.06
	6	MOPSO	27.03	100	74.65	23.78	**-12.63**	**100**	**68.39**	**33.59**
5	1	IMOMPPSO	24.14	94.74	56.77	19.05	**-31.76**	**91.41**	**23.05**	**35.65**
	2	MOMPPSO	28.57	93.75	63.19	15.61	**-26.69**	**93.75**	**35.49**	**29.52**
	3	IMOQPSO	0	1.79	0.15	0.46	-100	-87.01	-96.82	3.81
	4	MOQPSO	7.69	91.67	49.9	20.95	**-70.36**	**91.67**	**21.39**	**43.06**
	6	MOPSO	18.92	81.58	48.95	12.85	**13.66**	**81.58**	**46.3**	**15.45**
6	1	IMPMPPSO	0	18.75	4.7	6.06	-73.62	-7.81	-41.26	19.88
	2	MOMPPSO	0	27.59	6.41	8.05	-81.82	-0.98	-41.83	23.49
	3	IMOQPSO	0	0	0	0	-100	-100	-100	0
	4	MOQPSO	0	42.86	6.26	11.03	-100	12.63	-68.39	33.59
	5	BBMOPSO	0	24.14	2.66	6.05	-81.58	-13.66	-46.3	15.45

time and iteration number in 30 independent experiment for the RFTRD example as shown in Figure 4. The computational statistics of the continuous SI on space complexity (SC) and the improved two-set coverage (ISC) in 30 independent experiment for the RFTRD example is shown in Table 8.

From the Pareto front convergence of the continuous swarm intelligent algorithms in the RFTRD (see Figure 3a), it can be seen that the IMOQPSO algorithm, obtains better Pareto front convergence than other algorithms. The performance of BBMOPSO algorithm on Pareto frontier convergence is next; then is the multiphase particle swarm optimization algorithm, the MOPSO algorithm has the worst Pareto front convergence performance. From the population entropy of the continuous swarm intelligence in 30 independent experiment for the RFTRD example (see Figure 3b), it can be seen that as the number of iterations increases, the population diversity of the IMOQPSO algorithm decreases, which shows that the algorithm has better convergence in the process of optimization. However, the decline trend of population diversity of other algorithms is not obvious, that is, the convergence ofother algorithms is not obvious in the optimization process.

From the statistical analysis of the continuous SI on running time and iteration number in 30 independent experiment for the RFTRD example (see Figure 4), it can be seen that the multiphase particle swarm optimization algorithm has the longest running time, and its running time is about twice of the QPSO algorithm, and the corresponding Pareto front convergence effect is relatively insignificant. The running time of QPSO algorithm is second longest, but the Pareto front convergence effect is the relatively best. Especially for the IMOQPSO, there is a large fluctuation on the number of iterations of IMOQPSO, which means the algorithm can obtains better optimization results by increase appropriately the minimum number of iterations.

From the computational statistics of the continuous SI on SC and ISC in 30 independent experiment for the RFTRD example (Table 8) can be seen, the IMOQPSO algorithm obtain the best optimization results, followed by the BBMO-POSO algorithm and then the IMOMPPSO algorithm, the MOQPSO algorithm, MOMPPSO algorithm and MOPSO algorithm shown a relatively worse results compared with the IMOQPSO.

VI. CONCLUSION AND FUTURE RESEARCH

The paper proposed an improved QPSO algorithm for solving the problem of RFTRD and the good performance of the IMOQPSO algorithm can provides decision support for the railway freight transportation routing design. This paper also compares the effects of different continuous swarm intelligent algorithms in the example of RFTRD with the IMOQPSO algorithm. The proposed IMOQPSO algorithm obtains the real Pareto front which is closer to the RFTRD example and achieves better results than other algorithms. Based on the proposed IMOQPSO algorithm used in the RFTRD example, the Pareto front obtained by the IMOQPSO algorithm can be used for the railway transportation enterprises. It can provide the decision support to arrange the cargos for multiple shippers from originating station to the destination station, optimize the existing transportation resources, reduce the transportation cost and transportation time of the system and improve the quality of the service. In the future research, considering that resources can be expanded, assuming that the location of the originating station and the destination station are unknown or to be determined, the resource-expandable railway freight transportation routing design (RERFTRD) system optimization model will be constructed. The IMOQPSO algorithm will be applied to solve the problem.

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