

Research Article

Urban Rail Transit Network Planning Based on Particle Swarm Optimization Algorithm

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In order to solve the problem that the urban rail transit network is affected by a large number of signals, resulting in poor control effect, and improve the living comfort of residents near urban rail transit, a study on urban rail transit network planning based on particle swarm optimization algorithm is proposed. The learning factor is dynamically adjusted according to the inertia weight parameters, and the particle swarm optimization parameters are selected in combination with the setting of the maximum velocity parameters. The individual optimal particle is selected by using the dominant relationship between the individual particles, and the optimization of the optimal particle is completed by combining the selection requirements of the global optimal particle. We design the v2x communication implementation scheme, obtain the traffic flow information of urban rail transit, build the signal input and output model based on particle swarm optimization algorithm, obtain the output feedback signal, and determine the planning scale of urban rail transit network, so as to build the urban rail transit network planning model and complete the urban rail transit network planning. The experimental results show that the proposed method can improve the utilization rate of urban rail transit network planning, effectively control the change of network signal amplitude, and reduce the repetition rate of urban rail transit network planning.

1. Introduction

The layout of the rail transit network should be consistent with the urban form, land use layout, and development direction. The planning and layout of the urban rail transit network should comply with the needs of the future land development of the city. The two restrict and depend on each other, and finally form a coincidence [1, 2]. Urban rail transit network planning is a special plan in urban comprehensive transportation planning, which refers to a system to determine the overall rationality and scientificity of urban rail transit system on the basis of urban overall planning and urban comprehensive transportation planning. Its significance and role are enormous. The backbone system of urban rail transit network shall conform to the dominant passenger flow direction of the city, form a complementary relationship with the urban road system, and smoothly connect with other urban public transport network systems to facilitate their conversion. The network planning shall reflect the

unity of stability, flexibility, and continuity. The network planning of the central urban area should be relatively stable, the urban fringe should leave room for development, and the entire network should be able to expand and develop with the adjustment and expansion of the city scale. The choice of urban rail transit mode should be based on local conditions, and the composition of functional levels should be reasonable and unified [3]. Just as the urban road system planning needs to define the road functions at different levels, the rail transit network also needs to be divided into different functional levels. The rail transit lines at this level adopt different standards and adopt flexible construction, operation, and traffic organization schemes to meet the traffic needs at all levels. The planning and construction of urban rail transit network should be combined with the current situation, taking into account the economic and social benefits and energy consumption, and should be based on the network planning, implementation, and gradual improvement [4–7]. Due to the nonrepeatability of

construction and huge project investment, the construction of each line must be based on the line network planning, carefully considered and decided according to the urban structure, urban function positioning, and construction needs, so as to avoid waste.

Relevant scholars have studied this, and reference [8] put forward the use of NetLogo to achieve the agent optimization matching of passenger demand and service supply of urban rail transit network. Passenger demand and service supply are one of the most important factors determining the performance of urban rail transit system. In this paper, the multi-agent dynamic interaction technology is used to transform the multi-criteria problem into a distributed artificial intelligence optimization problem. In terms of demand, the dynamic passenger transport demand with agent is modeled from the perspective of bounded rational travel decision. At the supply end, a train traffic dynamic service supply model based on Agent is established. The simulation results emphasize the importance of jointly/interactively representing the supply side and the demand side. These results are of great significance for formulating effective capacity utilization strategies of urban rail transit networks and policies to provide passengers with a high level of service. Reference [9] is put forward based on the influence of rail transit station, sustainability overlap multi-objective optimization of land use distribution, considering the multiple rail transit site overlapping influence the characteristic of land use, this article developed a new multi-objective land use allocation optimization model, to make sure every undeveloped land area city land use type and intensity. The pareto optimal land development scheme with minimum deviation is obtained by using non-dominated ranking genetic algorithms and ranking technology similar to ideal solution. The areas of influence of the two sites in the study area partially overlap, with many plots undeveloped. The results show that considering the comprehensive effect of multiple rail transit stations, the newly developed optimal land use allocation model can reasonably achieve the multi-objective coordination of urban sustainable development to the maximum extent.

Although some progress has been made in the above research, the tracking interval of urban transport trains is shortened significantly and the density of trains is increased significantly. In this situation, the difficulty of urban rail transit network planning and operation adjustment is further increased. Because of the great urban rail transit project investment, long construction period, especially the circuit and layout of urban land use, development pattern, and urbanization play an important role, so the research on urban rail transit network planning is of great importance, is proposed based on particle swarm optimization algorithm of urban rail transit line network planning study. Compared with other intelligent algorithms, particle swarm optimization algorithm has a simple algorithm principle, fast optimization speed, strong global and local convergence ability, and is very suitable for solving large-scale network planning problems. The experiment proves that the research content has good effect and strong feasibility. Using the dominant relationship between individual particles to select

the individual optimal particle, combined with the global optimal particle selection requirements to complete the optimization of the optimal particle; The V2X communication implementation scheme was designed to obtain the traffic flow information of urban rail, and the signal input and output model based on particle swarm optimization algorithm was constructed to obtain the output feedback signal and determine the planning scale of urban rail transit network, so as to complete the planning of urban rail transit network. The experimental results show that the proposed method can reduce the repetition rate of urban rail transit network planning.

2. Urban Rail Transit Network Planning Based on Particle Swarm Optimization Algorithm

2.1. Particle Swarm Optimization Algorithm. Particle swarm optimization algorithm is also translated into particle swarm optimization algorithm, particle swarm optimization algorithm, or particle swarm optimization algorithm. It is a stochastic programming algorithm based on group cooperation developed by simulating the foraging behavior of birds [10]. It is generally considered as a kind of cluster intelligence, which can be incorporated into multi-agent optimization system. The particle swarm optimization algorithm is initialized as a group of random particles (random solutions), and then the optimal solution is found through iteration. In each iteration, the particles update themselves by tracking two "extreme values" [11]. The first is the optimal solution found by the particle itself. This solution is called the individual extreme value p_{best} . The other extreme value is the optimal solution found by the whole population. This extreme value is the global extreme value g_{best} . In addition, we cannot use the whole population but only the neighbors of some of the optimal particles, so the extremum in all neighbors is the local extremum.

2.1.1. Selecting Particle Swarm Optimization Parameters. The design of urban rail transit network planning under particle swarm optimization algorithm needs to control some parameters, such as particle swarm size, learning factor, inertia weight, population topology, and maximum speed [12]. How to select particle swarm optimization parameters will have a direct impact on the optimization effect of urban rail transit network planning.

(1) Inertia Weight Parameters of Particle Swarm Optimization. The particle swarm inertia weight parameter G_c can measure the planning performance of the particle swarm optimization algorithm and make the algorithm distribute reasonably in the planning process of the whole urban rail transit network. As the inertia weight of particle swarm increases, the planning ability of the algorithm will be enhanced. As the inertia weight of particle swarm decreases, the algorithm will only have local planning ability [13]. Generally, the optimal range of particle swarm inertia weight parameter is $0 \sim 1.4$, but the convergence speed of the

algorithm will be accelerated when the value of particle swarm inertia weight parameter is $0.8 \sim 1.2$. When the inertia weight parameter of particle swarm optimization is set in the range of $0.8 \sim 1.2$, the convergence speed of the algorithm will be improved. Therefore, in order to enable the algorithm to have the ability of global planning of urban rail transit network at the initial stage of calculation and local planning at the end of calculation, the inertia weight of particle swarm optimization is set to decrease with the calculation of the algorithm [14]. Because the algorithm has two factors of calculation cost and effect, the linear reduction strategy of inertia weight is adopted to reduce the inertia weight value to about 0.4 as the optimal parameter of particle swarm inertia weight.

Particle swarm optimization algorithm has many advantages, but it will make the particle swarm follow the optimal particle to fly. After several iterations of the algorithm, the particle swarm will have a strong convergence, resulting in the slow convergence of the algorithm [15]. In order to overcome the shortcomings of the algorithm in iterative calculation, and considering the influence of inertia weight parameters on the algorithm performance, the inertia weight value is set to 0.7, and the inertia weight parameters are reduced to 0.4 with the increase of iterative calculation times. The change of inertia weight parameters is determined by

$$G_c = \frac{M_{\max} - M_{\min}}{T_{\max}} \quad (1)$$

In formula (1), M_{\max} represents the maximum weight parameter, M_{\min} represents the minimum weight parameter, and T_{\max} represents the longest calculation time.

(2) *Learning Factors x_1 and x_2* . The introduction of inertia weight parameter can improve the retrieval performance of the algorithm, but the learning factor also affects the planning performance of particle swarm optimization algorithm. The selection of learning factors x_1 and x_2 is through the trajectory of particle swarm, and $x_1 + x_2 \leq 4$ must be met at the same time. The learning factors x_1 and x_2 are the factors that control the particles to learn from the optimal individual, so as to control the approach to the best advantage in the particle swarm. If $x_1 = 0$, the particles do not have their own experience, and the convergence speed of the algorithm is relatively fast. However, when the algorithm is applied to problems with high complexity, it will make the algorithm very easy to enter the local optimal state. If $x_2 = 0$, it means that the particles only have their own experience, and there is no information shared by the particle swarm. Because there is no communication between the individual particles, the probability of the algorithm getting the solution is very small.

The two parameters of learning factor x_1 and x_2 have their own adjustment functions, but the adjustment of the two parameters is separated from each other, which weakens the unity of the algorithm in the process of urban rail transit network planning and is not conducive to the optimization and retrieval performance of the algorithm. Select the learning factor as the nonlinear function of the inertia weight parameter, and the calculation formula is as follows:

$$\begin{cases} x_1 = G_c^2 + G_c + 0.4, \\ x_2 = 0.4 + x_1. \end{cases} \quad (2)$$

The optimization algorithm of particle swarm optimization algorithm changes with the change of learning factors x_1 and x_2 , and the speed of particles will also change. When optimizing the parameters of learning factors x_1 and x_2 , $x_1 = x_2$ is usually selected, and the range of parameters is set between 0 and 4. In order to improve the unity of the algorithm, it is generally used to dynamically adjust the learning factor and set the maximum speed parameter through the inertia weight parameters to complete the selection of particle swarm optimization parameters.

2.1.2. *Optimizing Optimal Particles*. Particle Swarm Optimization (PSO) algorithm often ignores the improvement of updating the individual extremum of particles, and usually uses the dominant relationship between particles to extract the optimal individual of particles. During the evolution of particle swarm, the extreme value of particles cannot be updated. First, calculate the intensity Q_d of a single particle in the particle swarm, the fitness value S_y of a single particle, and the intensity Q_d of a single particle in the particle swarm can be calculated according to

$$Q_d = \frac{m_i}{O \times (x_1 + x_2)} \quad (3)$$

In formula (3), m_i represents the number of individual particles dominated by the i th particle in the particle swarm, and O represents the size of the particle swarm.

In a particle swarm, the fitness value S_y of a single particle is determined by the individual strength of all particles dominated by the population. The calculation formula is

$$S_y = \frac{Q_d}{R_{ab}} \quad (4)$$

In formula (4), R_{ab} represents the dominant relationship between particle individual a and particle b .

In addition to the selection of individual particles, the optimization of optimal particles also considers the selection of global optimal particles. Generally, a solution is randomly selected in the non-inferior solution set of particle swarm optimization as the global optimal particle. In order to improve the diversity of algorithm planning, the global optimal particles are optimized by dynamic weighting method. Calculate the fitness of each particle in the particle swarm according to formula (5). The calculation formula is

$$F_H = \frac{1}{V_b \times K} \quad (5)$$

In formula (5), V_b represents the position of the b th particle, and K represents the final position of the particle.

Using the dominant relationship between individual particles, combined with the selection requirements of individual optimal particles and global optimal particles, the optimization of optimal particles is completed, so as to

improve the update of individual extremum of particles; The specific process of optimizing optimal particles is shown in Figure 1.

According to the optimized particle flow, the implementation steps of particle swarm optimization algorithm are analyzed in detail:

Step 1: initialize the specific position of particles in particle swarm;

Step 2: calculate the average optimal position of particle swarm;

Step 3: calculate the fitness value of the current position of the particle, compare the fitness value calculated in the previous iteration, if it is less than the result of the previous iteration, it will be updated to the current position of the particle according to the historical position of the particle, and calculate the current global optimal position of the particle swarm;

Step 4: compare the results of the previous iteration with the current global optimal position of the particle. If the value of the current global optimal position of the particle is better than that of the previous iteration, the global optimal position of the particle swarm is used to update the position of the particle;

Step 5: calculate the optimal position of each dimension of the particle to obtain the random point position of a particle; Calculate the latest position of the particle;

Step 6: output the results to complete the optimal particle optimization.

To sum up, through the selection of parameters such as the learning factor and inertia weight of the particle swarm, the particle swarm optimization and the selection of the individual particle optimal position and the global optimal particle of the particle swarm are carried out to complete the optimization of the optimal particle; Finally, by optimizing the optimal particle flow design, the application of particle swarm optimization algorithm in urban rail transit network planning is realized.

2.2. Intelligent Control of Urban Rail Transit Signal Based on V2X Communication Technology. The intelligent control of urban rail transit signals based on V2X (vehicle to everything) network uses V2X technology to obtain vehicle operation status information, and controls urban rail transit signals according to the obtained information. Multiplexing cellular network is the main means for V2X communication system to realize information transmission. The structure of V2X communication system is shown in Figure 2.

When the data transmitter of a V2X system is in the uplink transmission mode, it will affect the fixed base station, resulting in that the signals received by the base station are all interference signals with the same source. At this time, multiplexing problems are prone to occur in the network, resulting in data disorder in the transmission process [16]. In order to solve the above problems, the urban rail transit signal intelligent control method calculates the signal to interference ratio of the communication link, and analyzes

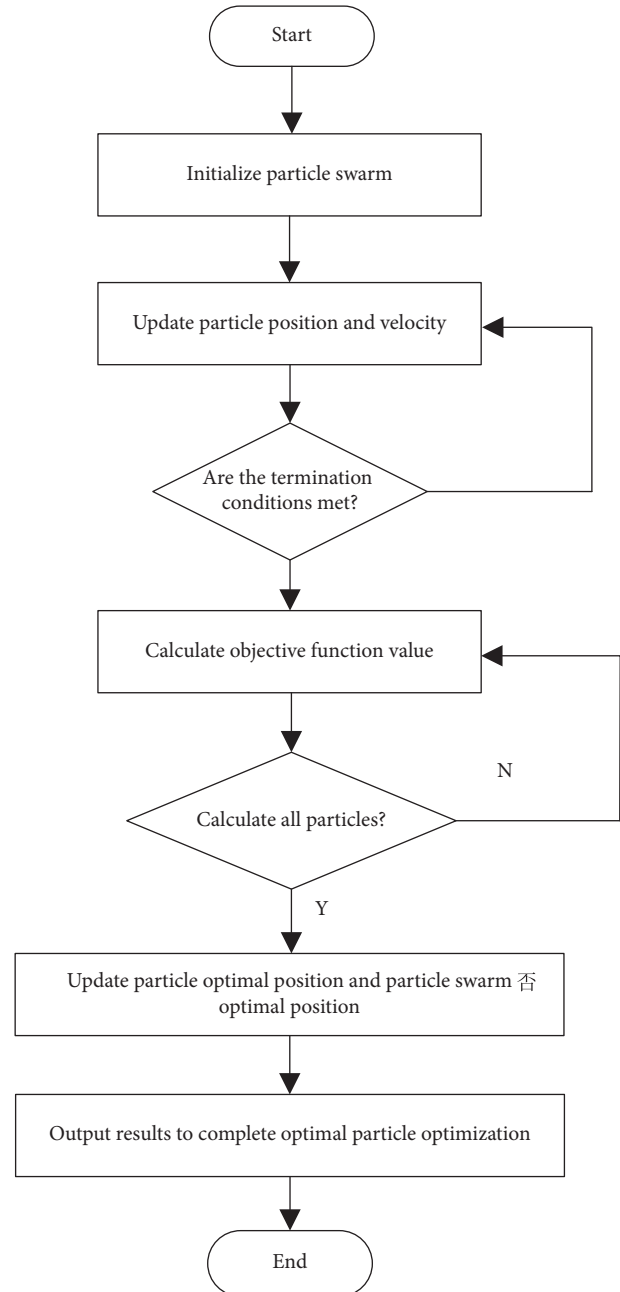


FIGURE 1: Flow chart of optimal particle optimization.

the multiplexing problem of the link in the communication process according to the calculation results.

If the data link multiplexing phenomenon in the communication network interferes with the signal transmission, most communication links will take measures to improve the signal reception quality, including reducing the bit error rate and improving the signal-to-noise ratio, which will affect other multiplexing terminals and interfere with the communication of other links. At this time, the original multiplexing terminal will receive the rebound interference, and such repetition will have an adverse impact. In order to solve the above problems, a communication implementation scheme is designed under the V2X communication technology, as shown in Figure 3.

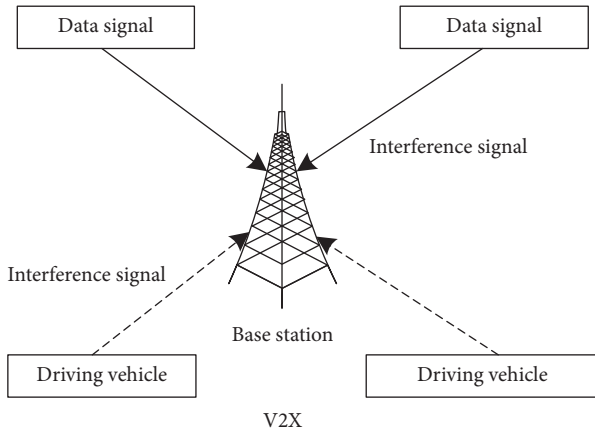


FIGURE 2: V2X communication system structure.

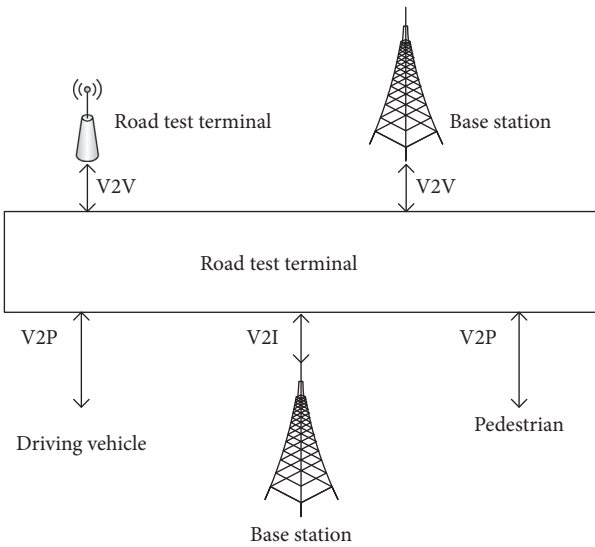


FIGURE 3: V2X communication implementation scheme.

According to Figure 3, the V2X communication implementation scheme establishes a wireless multi hop connection by combining the global positioning system and wireless communication technologies, such as wireless LAN, cellular network, to provide high-speed data access services for vehicles in high-speed mobile state, so as to realize the information interaction between V2X.

2.3. Research on Urban Rail Transit Network Planning

2.3.1. Determining the Planning Scale of Urban Rail Transit Network. Before determining the planning scale of urban rail transit network, it is necessary to establish the planning scale index of urban rail transit network, including the total length index of urban rail transit route, traffic density index, and transportation capacity index [17]. The total length of urban rail transit lines is

$$L_z = \sum L_i \times F_H. \quad (6)$$

In formula (6), L_i represents the length of the i traffic line, and L_z can indirectly describe the overall size of urban rail transit planning scale, which is a key index to evaluate the passenger flow transmission capacity and traffic equipment demand of urban rail transit.

The formula for calculating the transportation capacity index of urban rail transit is

$$H_J = \sum_{i=1}^m M_i \times L_z. \quad (7)$$

In formula (7), M_i represents the passenger flow transmission capacity of the i traffic line, and the urban rail transit transmission capacity index H_J can reflect the impact of urban rail transit on the passenger transport system.

In the process of determining the total length L_z of urban rail transit lines according to urban population size and land resources, considering that there is a certain close correlation between the scale of urban rail transit and land area and total population [18], a signal input-output model based on particle swarm optimization algorithm can be established as shown in Figure 4, the model refers to the structure that describes the characteristics of the system with the external characteristics of the input and output variables of the system.

It can be seen from Figure 4 that on this basis, the asynchronous in-phase control method is adopted to limit the control target parameters. When the output signal of the model satisfies the Gaussian stationarity, the feedback result at the output is consistent with the filter transmission result of the model signal.

The results of the signal input-output model based on particle swarm optimization algorithm are used to calculate the total amount of urban rail transit. The calculation formula is as follows:

$$Z_l = Z_z \times Q_{cb} \times B_{xc} \times H_J. \quad (8)$$

In formula (8), Z_z represents the total amount of urban rail transit, Q_{cb} represents the per capita travel rate, and B_{xc} represents the expected value of the population.

The planning scale of urban rail transit network is obtained through the determination of three indicators, namely, the total length indicator of urban rail transit route, the transmission capacity indicator, and the total amount indicator of urban rail transit, so as to eliminate the impact of traffic structure on urban rail transit network planning and determine the planning scale of urban rail transit network.

2.3.2. Construction of the Urban Rail Transit Network Planning Model. Just as previous studies on urban space [19–23], the passenger flow distribution points shall be marked on the urban rail transit lines, and the alternative stations shall be marked one by one along the passenger flow distribution points at the urban rail transit stations. The final planning scheme of the transportation network shall be determined according to the passenger flow coverage of each transportation station. If there are alternative stations in the

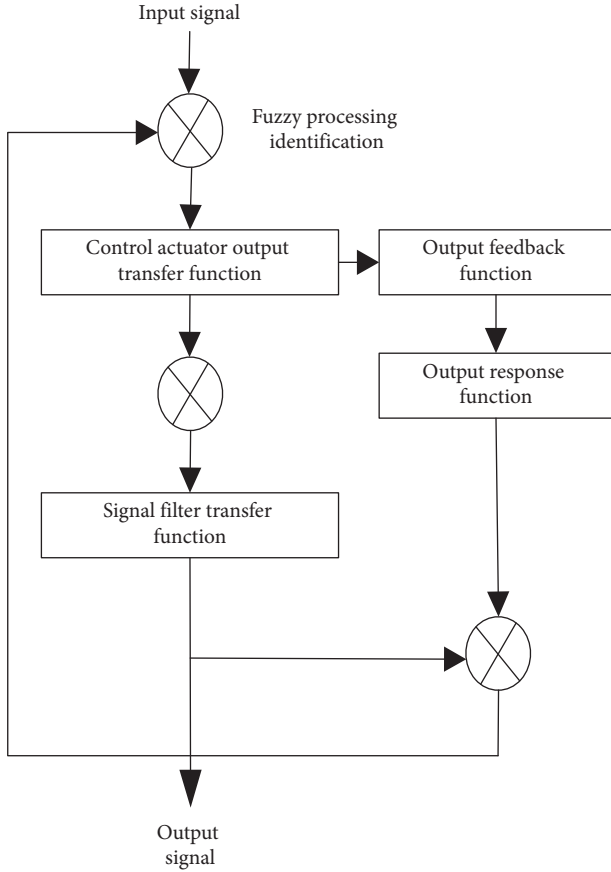


FIGURE 4: Signal input and output model based on particle swarm optimization algorithm.

urban rail transit station set, if stations are selected from the central city, the total number of stations can be expressed as

$$Z_{ZD} = \ln\left(\frac{L}{\bar{l}_i}\right) \times Z_l. \quad (9)$$

In formula (9), Z_{ZD} represents the total number of stations on the urban rail transit line, \ln represents the rounding function, and \bar{l}_i represents the average length of the distance between the optimal traffic stations.

Take the starting point of the urban rail transit line as the center of the circle and d_{\min} and d_{\max} as the radius to make a circle. When the urban rail transit line intersects at two points, the traffic station between the two intersections is the alternative station. If there is only one traffic alternative station, the selection of this station is unique. If there are multiple alternative stations, it indicates that there are multiple urban rail transit network planning schemes. Each alternative station is rounded in the above way until the last traffic station, and then the alternative stations and multiple alternative schemes are obtained, as shown in Figure 5.

Although urban rail transit stations can be selected in the above steps, the determination of d_{\min} and d_{\max} are difficult, and there is no fixed value between d_{\min} and d_{\max} . When selecting urban rail transit stations, the distance difference between d_{\min} and d_{\max} are very large, which increases the number of options finally obtained.

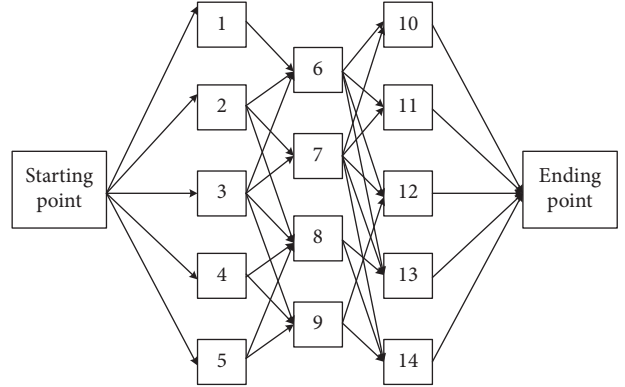


FIGURE 5: Schematic diagram of the formation of urban rail transit stations.

Based on the passenger flow distribution range of urban rail transit stations, the urban rail transit network planning model is calculated as follows:

$$E_{ij} = P \times (1 - r) \times (d_{\max} - d_{\min}). \quad (10)$$

In formula (10), P represents a constant, and r represents the weighted sum of population density and travel density.

According to the established model, the traffic station coverage in urban rail transit network planning can be obtained, so as to analyze the coverage of bus stations and select the planning scheme with the largest traffic station coverage. Therefore, the passenger flow coverage of urban rail transit lines with the best planning scheme can be obtained.

Here, the optimal planning scheme is found among the planning schemes with the same number of transport stations, and the urban rail transit network planning is realized by calculating the passenger flow coverage of urban rail transit planning stations.

3. Experimental Analysis

In order to test the application performance of urban rail transit network planning based on particle swarm optimization algorithm, the simulation experiment is carried out. The experiment is designed by Matlab, and a simulation platform is established. The signal acquisition frequency on the platform is 25 KHz, the sampling time is 1500 s, and the baud interval width is 15 BPs. Set the node coverage of particle swarm to 500×500 , the optimal number of sub nodes is 64, the information communication coverage radius of relay transmission node is $R = 1.25$, the total node size is 1000, the improvement duration is set to 60 min (lasting for 15 sampling points), the time sampling interval of sampling points is 10 min, and the maximum iteration round is 1500. See Table 1 for other parameter settings.

According to the above environment and the parameter settings in Table 1, the urban rail transit network planning test under the particle swarm optimization algorithm is carried out. Taking a city rail train as the research object, the city rail supports the interconnection between equipment of different signal manufacturers. The total length of the urban

TABLE 1: Experimental parameter settings.

Parameter name	Parameter size	Parameter name	Parameter size
Iterations	30	Inertia weight	0.7298
Spatial dimension	6	Simulation area	200 × 200
Routing and forwarding protocol	IEE802.15.4	Penalty coefficient	2000
Smoothness weight	0.3	Traffic line weight	0.7

rail transit line is 16 kilometers, and the airport can be reached through the railway station.

The studied urban rail transit network planning method based on particle swarm optimization algorithm, reference [8] method and reference [9] method are used for comparison, and the comparison results of urban rail transit network planning utilization are obtained, as shown in Figure 6.

It can be seen from the experimental results in Figure 6 that when reference [9] method is used to plan the urban rail transit network, the method does not know the overall scale of the urban rail transit network planning in advance, which makes the utilization rate of the urban rail transit network planning low; Reference [8] method in the planning process, the utilization rate of urban rail transit planning is higher than that of the planning optimization method in reference [9], and is relatively stable. With the increase of urban rail transit network planning area, the utilization rate of urban rail transit network planning tends to be stable, but the utilization rate is still not ideal; When using the planning optimization method in this paper to plan the urban rail transit network, this method not only determines the network planning scale but also establishes the urban rail transit network planning model, which simplifies the calculation process and effectively improves the utilization rate of urban rail transit network planning. The reason is that before the planning scale of urban rail transit network is determined, the planning scale index of urban rail transit network is established, including the total length index of urban rail transit route, traffic density index, and transport capacity index, which is beneficial to improve the planning of urban rail transit network line to a certain extent.

In this experimental case, the signal amplitude change of the original integrated communication network of urban rail transit network planning is shown in Figure 7.

It can be seen from Figure 7 that the signal amplitude changes regularly under normal running conditions, and the fluctuation range is [-1, 1]. Based on this, the urban rail transit network planning method based on particle swarm optimization algorithm is used to analyze whether the signal amplitude change of urban rail transit dedicated communication integrated network is consistent with the normal running of trains. The results are shown in Figure 8.

It can be seen from Figure 8 that the network signal amplitude changes regularly using the urban rail transit network planning method based on particle swarm optimization algorithm, in which the change amplitude is [-1, 1]. It is basically consistent with the signal amplitude change of the original communication integrated network, and it is more perfect at 1.2 s and 1.5 s. The comparison results show that the research planning method

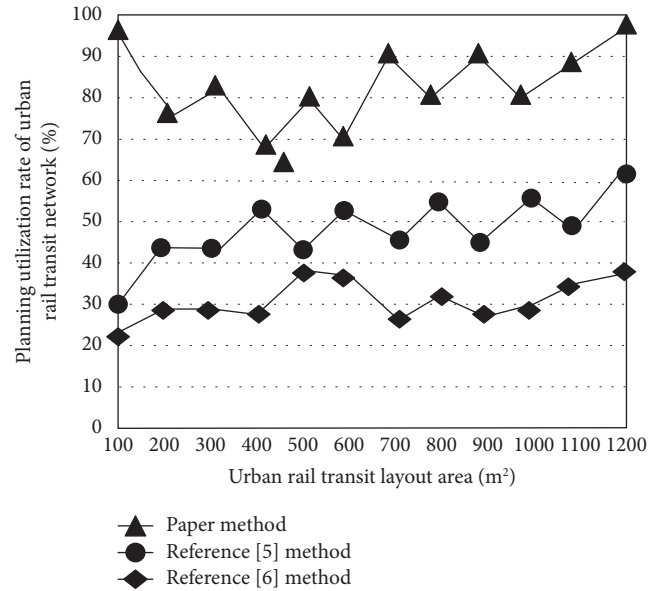


FIGURE 6: Planned utilization rate of urban rail transit network.

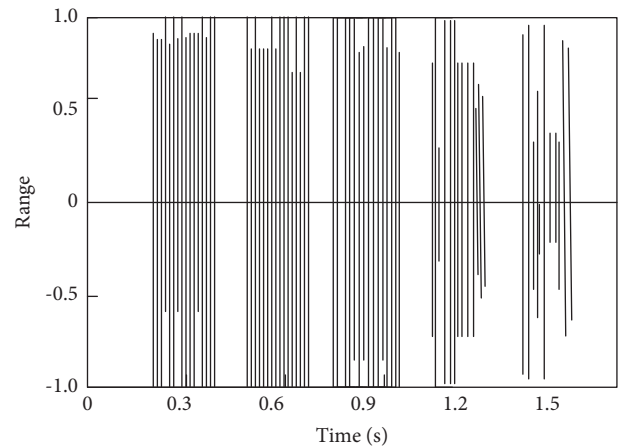


FIGURE 7: Amplitude change of original communication integrated network signal.

can effectively control the amplitude change of network signal. The reason is that the method in this paper adopts V2X technology to obtain vehicle operating status information, and control urban rail transit signals based on the obtained information, which is conducive to controlling signal amplitude changes to a certain extent.

In order to further improve the feasibility of the research method, the research method, reference [8] method, and reference [9] method are, respectively, used to carry out the

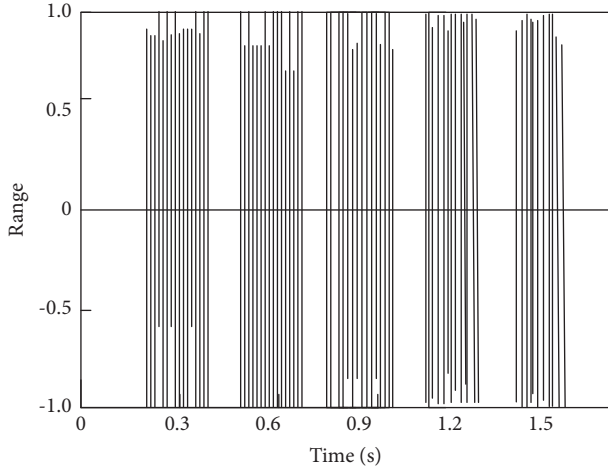


FIGURE 8: Signal amplitude change analysis.

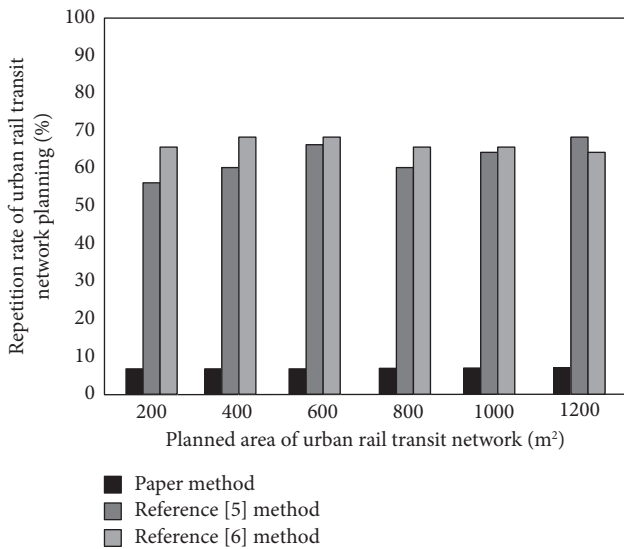


FIGURE 9: Comparison results of repetition rate of urban rail transit network planning.

comparison experiment on the repetition rate of urban rail transit network planning. The results are shown in Figure 9.

It can be seen from the experimental results in Figure 9 that when the planning optimization method in this paper is adopted, the repetition rate of urban rail transit network planning is far lower than that of the other two methods with the change of urban rail transit network planning area. In contrast, the planning methods in reference [8] and reference [9] have high repetition rate in urban rail transit network planning, resulting in poor planning effect of urban rail transit network layout. The reason is to mark the passenger flow distribution points on the urban rail transit line, mark the alternative stations along the passenger flow distribution points one by one in the urban rail transit station, and determine the final planning scheme of the transportation line network according to the coverage of the passenger flow of each traffic station, so as to benefit and reduce the planning repetition rate of the transportation line network.

Based on the above experimental results, it can be seen that the proposed method has a good effect on improving the utilization rate of urban rail transit network planning and the repetition rate of urban rail transit network planning, comprehensively improving the planning effect of urban rail transit network, and the network signal amplitude changes regularly.

4. Conclusion and Prospect

4.1. Conclusion

- (1) When using the planning optimization method in this paper to plan the urban rail transit network, this method not only determines the network planning scale but also establishes the urban rail transit network planning model, which simplifies the calculation process and effectively improves the utilization rate of urban rail transit network planning.
- (2) The amplitude variation of network signal using the method studied is regular, and the amplitude variation is $[-1, 1]$. It is basically consistent with the signal amplitude change of the original communication integrated network. It is more perfect at 1.2 s and 1.5 s to effectively control the signal amplitude change of the network.
- (3) When using the planning optimization method in this paper, with the change of urban rail transit network planning area, the repetition rate of urban rail transit network planning is low, which has a good effect.

4.2. *Prospect.* In the research of urban rail transit network planning based on particle swarm optimization algorithm studied in this paper, there are still the following problems to be solved, which need to be further studied and improved:

- (1) Considering the complexity of urban rail transit network planning, some factors need to be simplified in the modeling process, and a single objective optimization model is established. In the next study, all factors and optimization indexes should be considered as much as possible to establish a more accurate multi-objective optimization model for urban rail transit network planning.
- (2) The train operation adjustment simulation system mainly starts from ATS system. It needs to realize the simulation function of urban rail transit network planning based on particle swarm optimization algorithm, and fully consider the information interaction with the planning system. In order to make it practical, more perfect function modules should be designed in combination with the actual situation on-site.
- (3) More practical applications are needed to prove that it is feasible to solve the urban rail transit network planning problem based on particle swarm optimization algorithm, and the performance comparison with other intelligent methods will be realized in further research.

Data Availability

Requests for access to the data used to support the findings of this study should be made to Ning Yu (yun@qghru.edu.cn).

Conflicts of Interest

The author declares no conflicts of interest.

Authors' Contributions

Ning Yu performed conceptualization and formal analysis and developed the methodology and wrote the draft.

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