URSI AP-RASC, Sydney, Australia, 17 – 22 August 2025

RSUs Site Selection Optimization Method for Intelligent Transportation Systems in Complex Mountain Environment

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Abstract

In the complex mountain environment, the problem of difficult site selection and low accuracy of Roadside Unit (RSU) deployment is waste of resources caused by incomplete or overlapping coverage of RSUs deployment. Typical complex mountain environments are targeted by the ray tracing method to model and simulate the wireless channel transmission characteristics of the actual geographical environment. Multi-objective Particle Swarm Optimization (MOPSO) algorithms may not perform fine search for populations and are easy to fall into local optimization. An improved multi-objective particle swarm optimization algorithm based on adaptive parameter adjustment is proposed. Objective functions are network deployment coverage, total transmit power and communication quality. Decisions are made by using the ordinal preference method based on information entropy on the Pareto solution set, which solves the problem of site selection optimization of RSUs deployment in complex terrain environment. Compared with the competition-based multi-objective particle swarm algorithm, the convergence speed of the improved algorithm is significantly improved, along with the uniformity increased by 39.99%. Compared with the empirical site selection method, the network deployment coverage are increased by 31.66% and 23.01% and 23.01% respectively through the proposed method in this paper, and the communication system quality index are increased by 52.59% and 51.21% respectively, under the conditions of constraints or not.

1. Introduction

Collaborative Intelligent Transportation Systems (C-ITS), as the core development direction of next-generation intelligent transportation technology, closely connect various transportation elements and terminals through a new generation of communication technology. Collaborating to solve transportation problems and achieve integrated services under the same goal can greatly improve the safety, reliability, efficiency and comfort and convenience of transportation systems. The typical C-ITS application system structure is shown in Figure 1, information real-time transmission and sharing of vehicle-to-vehicle (V2V), vehicle-to-person (V2P), vehicle-to-infrastructure (V2I), vehicle-to-cloud (V2C), infrastructure-to-infrastructure (I2I) has become a key factor affecting the performance of C-ITS system (such as work efficiency, sustainability) [1-2].

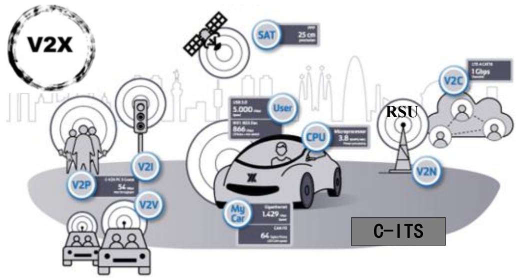

Figure 1 . Example of a typical application of C-ITS

The deployable location of RSUs is also affected by factors such as target coverage area, geological structure, and surface environment. Considering the cost of RSUs and the convenience of maintenance, RSUs should be deployed along roads as much as possible rather than areas such as dense woodlands, cliffs, and river flats. The combined constraints of these factors have brought more severe challenges to the deployment of RSUs in complex mountain environments, so the site selection optimization of C-ITS system RSUs designed for complex mountain application scenarios has become one of the key issues that must be faced in the field of intelligent transportation research in the future [3].

2. Acquisition of wireless communication performance

The location scenario of RSUs considered in this paper is shown in Figure 2, which equivalents vehicles traveling along the road in a mountainous environment as end points (EPs). Due to the limitations of complex terrain, RSUs need to be deployed along the road and communicate with multiple EPs in the coverage area. The ray tracing method was first used to model and simulate the actual terrain environment, and the sample dataset of wireless channel transmission characteristics of complex mountain environment was obtained. And the use of digital elevation model to model the actual geographical environment can intuitively avoid the geographical location that was not suitable for the deployment of RSUs. Therefore, RSU was mapped to the actual scene through latitude and longitude information, so as to realize the accurate deployment of

RSUs.

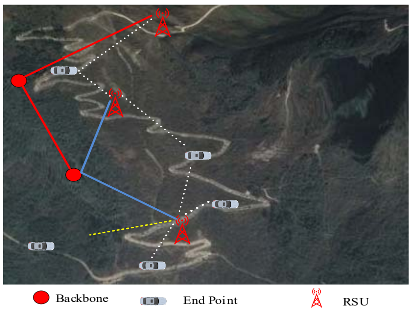

Figure 2. RSU deployment in complex environments

A. Model of Mountain Communication Environment

The environment modeling method was adopted, mainly for the terrain, vegetation covers and other factors to model the scene. For modeling the terrain environment, the model method of importing a digital elevation model (DEM) is often used [4]. In this work, a mountainous terrain on the outskirts of Mianyang City was selected as the research object to model and simulate the wireless channel environment. The effect after environmental modeling and communication equipment modeling is shown in Figure 3. To show the distribution of roads in different terrains, such as valleys, mountainsides, ridges, etc., in this modeling scenario, the road was modeled as the dark square in Figure 3, with a total of 123 points. The light-colored square is the site alternative point, a total of 644 points, which is the target coverage. In addition, a total of 394 alternative points met the road proximity threshold of 20m, and each point had a unique serial number and corresponding latitude and longitude values, so as to realize RSU positioning and actual scene.

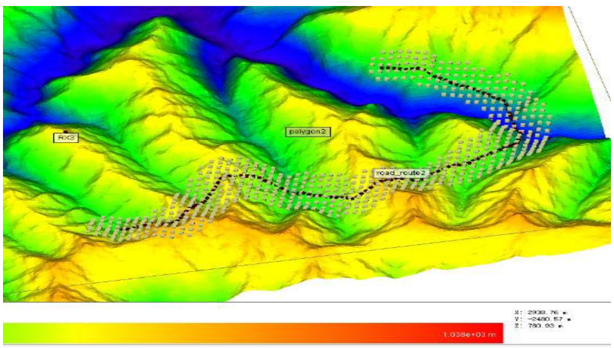

Figure 3. Modeling simulation scenario

B. Wireless Insite (WI)-based communication simulation modeling

To bring the communication equipment closer to the performance of the actual equipment, we focused on three parameters when modeling the communication equipment: i) Transmission frequency band, ii) Signal bandwidth, iii) Transmit power. The simulation parameters of WI are set as shown in Table I.

Table I WI simulation related parameters

No.	Parameters	Value	No.	Parameters	Value
1	Waveform	Sinusoid	9	Sites pitch	Adjusted for simulation
2	Carrier frequency	5900MHz	10	Antenna altitude	2m
3	Antenna type	Half-wave dipole	11	X-axis range	4793.54~4664.39m
4	Rays pitch	0.25°	12	Y-axis range	3463.80~3395.68m
5	Transmit power	47dBm	13	Z-axis range	466.00~592.48m
6	Number of reflections	6	14	Soil conductivity	0.02 S/m
7	Scattering times	0	15	Soil dielectric constant	25.00
8	diffraction times	1			

WI-based simulation can obtain the path loss of each point in the target scene relative to any other point, and the RSU site optimization in the following is based on the path loss parameters obtained from this.

3. RSUs siting optimization algorithm based on multi-target particle swarm

A. RSUs site selection optimization: target setting

To meet the requirements of C-ITS for network coverage, site deployment cost, and service quality, this work considered the location optimization of RSUs under the condition of *t* EPs and *n* RSU site selection points. In order to meet the calculation of the optimized objective function, the received power of EP was calculated based on the path loss parameter. Set the *m* RSUs alternative points in the simulation scenario, and the corresponding formula is as follows:

$$P_r(RSU_i, EP_j, k) = P_t(RSU_i, EP_j, k) - P_{loss}(RSU_i, EP_j), \quad i \le m, j \le t, 0 < k \le K \tag{1}$$

Where, $P_r(RSU_i, EP_j, k)$ is the receive power of the *j*th *EP* at the *k*th transmit power conditions relative to the RSUs *i*th, $P_t(RSU_i, EP_j, k)$ is the transmit power of the *i*th RSU for the *j*th *EP*, $P_{loss}(RSU_i, EP_j)$ is the path loss between RSU_i and EP_j, which was simulated by the ray tracing method. *K* is the number of randomized transmission power, which is determined by the simulation accuracy of the actual scene. Three indicators are selected as the objective function, such as Communication network coverage, Total transmit power and Communication System Quality Objective [23]. Constraints are road and Maximum transmit power.

Aiming at the shortcomings that particle swarm algorithms cannot perform fine search for populations, an improved multi-objective particle swarm optimization algorithm method based on inertia weights and learning factors of convergence contribution (IMOPSO) is proposed to achieve the purpose of fine adjustment of algorithm parameters. In view of the shortcomings that it is easy to fall into local optimum, a cross-variation method based on the variance of the optimal memory interval of individual particles is proposed to improve it [5].

B. Improved multi-objective particle swarm algorithm

Aiming at the shortcomings that particle swarm algorithms cannot perform fine search for populations, an improved multi-objective particle swarm optimization algorithm method based on inertia weights and learning factors of convergence contribution (IMOPSO) is proposed to achieve the purpose of fine adjustment of algorithm parameters. In view of the shortcomings that it is easy to fall into local optimum, a cross-variation method based on the variance of the optimal memory interval of individual particles is proposed to improve it.

Algorithms 1 Adaptive Cross-Variation Methods

```
CrossMutation ( δ_i^2 , δ_min^2 , p_c , p_m , P_g^t )
if δ_i^2 < δ_min^2 then
    r_id ← initial() /* Particles are assigned random numbers in each dimension */
    for j = 1 → d do
        if r_id(j) < p_m /* Mutate particles */
            x_id ← initial()
        end if
        if r_id(j) < p_c /* Cross particles*/
            x_i(j) ↔ P_g^t(j)
        end if
    end for
end if
return x_i
end function
```

C. Solving of RSUs site selection optimization based on ray tracing method

This section will elaborate on the solution process of RSU site optimization method proposed in this paper. Modeling the actual terrain environment by the ray tracing method will obtain more accurate path loss parameters than the traditional channel model. The IMOPSO algorithm first encodes the particle using this parameter as a data source for subsequent computation of the objective function.
Before optimizing the algorithm, particles need to be encoded using (2).

$$X = [S_1, P_t(RSU_1, EP), S_2, P_t(RSU_2, EP), \cdots, S_n, P_t(RSU_n, EP)] \quad (2)$$

Where, $S_i, (i = 1, 2, \cdots, n)$ represents the serial number of the RSU site selection point, *n* represents the number of RSU site selection points, and $P_t(RSU_i, EP)$ represents the transmission power of the *i*th RSU site selection points. In this paper, the solution method of RSUs site selection optimization based on ray tracing method is as follows:

Algorithms 2 RSUs site selection optimization

1: **RSUs location** (D, N, r_s, d_r, $P_{t\_\max}$, $\delta_{\min}{}^2$, p_c, p_m, s_p, M)
2: Initialize the particle population $X^0 = \{X_1^0, X_2^0, \cdots X_N^0\}$ and the velocity $V^0 = (V_1^0, V_2^0, \cdots, V_N^0)$, $P_i = P_g = X_i$, initialize the external file $A^{(0)} = X_1{}^0$, at this time, the number of iterations $t = 0$;
3: Calculate the $C(x_{t,i}, A)$ of each particle ; According to the $C(x_{t,i}, A)$, the inertia weight w and the learning factor c_1 c_2 of each particle were calculated;
4: Update V^t and X^t
5: Calculate the $f_{ij}{}^t$ of each particle;
6: Maintain the $A^{(k)}$ and update the global optimal g_i;
7: If the algorithm termination condition is not met, return to Step3 to continue the iteration, otherwise end the search and output the non-dominated solution in $A^{(k)}$;
8: Use the information entropy method to calculate the weights of the *n* targets of the $A^{(k)}$ *m* schemes, and standardize them;
9: Calculate the relative distance and find the maximum value as the location decision scheme of RSU in complex environments

4. Experiments and results

The parameters of the IMOPSO algorithm are shown in Table II in the current scenario. TOPSIS merit-based results in different circumstances are in Table III. f1 is network deployment coverage, f2 means total transmit power, f3 is communication system quality index.

Table II Algorithm related parameters

No.	Parameters	Value
1	population size N	100
2	external file capacity np	200
3	particles dimension D	-
4	iterations times M	100
5	variation rate p_m	0.1
6	crossover rate p_c	0.2
7	memory interval length s_p	5
8	variance threshold $\delta_{\min}{}^2$	0.1

Table III TOPSIS merit-based results in different circumstances

Case	f_1	f_2	f_3	Site point
a	100%	-	-1.82e-5	44, 426, 599
b	97.83%	9.89 dBm	-4.37e-5	77, 264, 642
c	100%	-	-5.12e-5	56, 134, 155
d	88.51%	7.19 dBm	-5.20e-5	3, 79, 314

Figure 4 shows the distribution of the PS optimal solution set searched using the algorithm in this paper, where the number of stations is 3, the transmit power constraint uses a typical value of 5dBm and the road constraint threshold is 20m, and the corresponding TOPSIS decision solution is given in Table III. As can be seen in Table IV, 100% coverage may be achieved at three site selection points without power constraints, namely cases (a) and (c). In addition, for cases (b) and (d), under the same power constraints, after adding road constraints, f_1 decreased by 9.52%, but f_2 increased by 18.99% compared to case (a). It is clear that after the RSU was constrained, the coverage decreased, but total transmit power and the performance of communication quality targets improved.

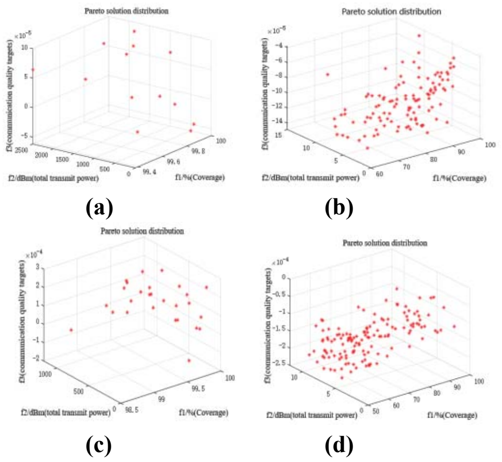

Figure 4. PS optimal solution distribution in different cases

Table IV Comparison of objective function values of empirical site selection and IMOPSO optimization

Algorithm	f_1		f_3	
	unconstraint	constrained	unconstraint	constrained
Empirical	79.52%	73.59%	-6.4465e-5	-6.3884e-5
IMOPSO	97.82%	96.89%	-9.7483e-5	-9.4690e-5

From Table V that the S-index performance of the improved algorithm IMOPSO, i.e., the uniformity, is improved by 39.99% compared with CMOPSO. And from Figure 5, the external DE convergence characteristics corresponding to the three objective functions of IMOPSO are better than those of the CMOPSO algorithm.Figure 6 shows a schematic diagram of empirical site selection.

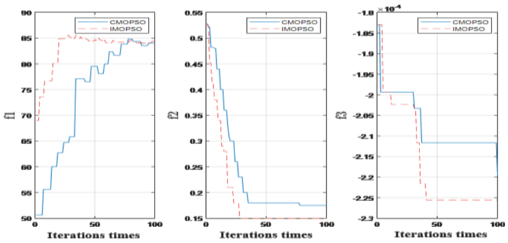

Figure 5. External un-convergence curves for different targets

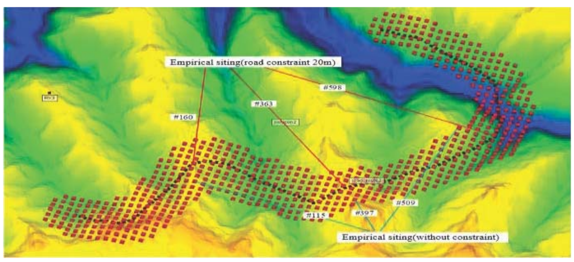

Figure 6. Schematic diagram of empirical site selection

Table V The performance comparison of the algorithm

Algorithm	f_1	f_2	f_3	S Index
CMOPSO	76.0829	1.9482	-2.21e-4	22.73
IMOPSO	78.3756	2.1237	-2.35e-4	13.64

5. Conclusion

In this work, the slow site selection speed and low positioning accuracy of RSU in C-ITS complex mountain environment were studied, and the wireless channel environment was modeled and simulated by radio tracing method, which was used as an empirical data source for the optimization algorithm. In the solution process, an improved multi-objective particle swarm algorithm was adopted, and the TOPSIS method based on information entropy was used to make decisions on the optimal deployment scheme.

6. Acknowledgements

This work was supported in part by National Science Foundation grant 62261051 and Southwest University of Science and Technology PhD Fund grant 21ZX7128.
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