Multi-objective Optimization Technique for RSU Deployment

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Abstract. Due to its short latency, low transmission cost, and benefit in data security, the vehicle to roadside-units (V2R) technology is growing in importance in the VANET. Roadside unit (RSU) complicated location, however, has an impact on the RSU network in terms of time delay, transmission efficiency, etc., making it challenging to use large-scale RSU networks. In view of this, a cooperative transmission framework is devised for data transmission in VANET. The number of RSU and the time delay are used as the metrics for measuring the economy and network transmission performance, respectively, in order to create the RSU deployment optimization model in this article, which addresses the issue. A multi-objective evolutionary algorithm is then used to carry out the RSU deployment's optimization. The results of experiments are based on taxi data from ShenZhen. The findings show that the suggested technique can reduce the number of RSU while enhancing the RSU network's transmission capabilities.

Keywords: V2R · RSU deployment · Multi-objective optimization · Network performance · Economy

1 Introduction

In response to the rapid development of the transportation infrastructure and the problems raised by the increasing number of vehicles, the Internet of Vehicles technology has been proposed and iteratively developed for traffic control, vehicle safety, information services, and smart city construction, et al. [1–3].

Intelligent Vehicle Infrastructure Cooperative Systems(IVICS) is a hot topic in the field of Internet of Vehicles, where vehicle to roadside unit (V2R) is a key technique and road side unit (RSU) network is the intermediate medium

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between vehicles and cloud servers. Furthermore, RSU can also be adopted as a part of the cloud-edge collaboration system for special tasks [4–6]. In comparison to the traditional cellular networks, first, the transmission data of RSU are featured with low communication cost, better message transmission capability, lower end-to-end delay and flexible deployment et al. [7]. Second, transmitting the vehicle data with RSU can reduce the data traffic load of the 4G/5G cellular networks. Third, edge computing can be adopted based on RSU to provide real-time services for vehicles [8].

When it comes to RSU deployment, data transmission delay and RSU deployment cost are two optimization factors that are often considered, and there have been a lot of studies to optimize based on one or both of these indicators. It is well known that most research work focuses on reducing the transmission delay to optimize the location of RSU deployment because time delay is an important indicator to measure network performance. In order to overcome the time delay problem of signal propagation, Fogue et al. propose a genetic algorithm for RSU deployment [9]. Ahmed et al. formulate the RSU deployment problem as an integer linear programming model and propose an RSU placement strategy called the Delay Minimization Problem (DMP) [10]. Anbalagan et al. propose a meme-based RSU (M-RSU) placement algorithm to minimize communication latency and increase coverage area between IoV devices by optimizing RSU deployment [11]. Shi et al. propose a V2X network-based RSUD message propagation model and a central-rule-based neighborhood search algorithm (CNSA) [12].

Most deployment optimization algorithms only evaluate vehicle density and intersection attractiveness, ignoring the impact of map obstructions like buildings on RSU deployment. Ghorai et al. suggest a CDT-based algorithm [13]. Wang et al. deduce a connectivity analysis model considering the RSU deployment problem in one-way road scenarios, and analyzed the relationship between the number of RSUs and network connectivity [14]. Liu et al. establish a network model containing vehicle clusters for mathematical analysis [15]. Ni et al. investigate the deployment problem of minimizing the number of RSUs for two-dimensional IoV networks, using a utility-based maximization problem to solve the RSU deployment problem [16]. Ma et al. propose a multi-objective artificial bee colony optimizer (H-MOABC) to optimize a two-level Radio frequency identification networks planning (RNP) model based on hierarchical decoupling [17,20]. Yeferny et al. propose Minimum Mobile Mode Coverage (MPC) as a spatiotemporal coverage method to optimize RSU deployments. MPC mines vehicle trajectory data to describe its travel pattern, then extracts minimal transversals of a hypergraph to calculate the optimal RSU position [18]. Some researchers consider both factors when deploying RSU. Cao et al. construct a six-objective RSU deployment optimization model, including time delay and number of RSU deployments. This paper proposes a clustering method in which the cluster radius varies according to the number of RSUs in the cluster [19]. At the same time, an improved algorithm based on PCMLIA-ADE (PCMaLIA) is proposed to optimize the ES deployment model and achieve the tradeoff between conflicting objectives.

Despite the success of the existing work, few studies can be found for RSU deployment to simultaneously investigate the optimal delay and number of RSUs. First, the communication performance of the RSU networks is affected by the distribution of RSUs, since the traffic flow characteristics are different across areas [21]. Generally, the RSU network's performance should be good if enough RSUs are deployed. For instance, dense traffic commonly brings heavy data transmission load. Consequently, the data packets are crowded in the channel and need to be queued to enter the route for processing, resulting in increasing data transmission delay [22,23]. To this end, it is necessary to adopt more RSUs to reduce the delay and improve the network's performance. However, increasing costs are needed to deploy large-scale RSUs, which results in unexpected budgets and difficulties in implementation [24]. In places with sparse traffic, only small-scale data needs to be processed. Therefore, the density of RSUs can be curtailed to reduce the cost of building the RSU networks [25].

In order to balance the budget and performance of the RSU network, this article proposes a framework for cooperative transmission, based on which a multi-objective system model is built by considering the transmission delay time and the number of RSUs. In the proposed model, the transmission delay and the RSU deployments reflect the performance of the network and the economy of the system, respectively. In comparison to the single-objective based system model, the proposed model can get rid of the prior knowledge of weighting the importance for different objectives.

In summary, this paper makes the following contributions:

1. This paper proposes a hybrid framework for data transmission in the Internet of Vehicles. Vehicles can choose one of the channels for data transmission, so that resources can be fully integrated, and vehicles can be adjusted to select an appropriate channel for data transmission.
2. This paper introduces a multi-objective optimization model based on the time delay and the number of RSUs to optimize the deployment location of RSUs from the perspective of economics and network performance for the first time. We divided the area into grids and selected appropriate grids to deploy RSUs. This simplifies calculations and converges faster for better results.
3. In order to realize the model, we select a suitable multi-objective joint optimization algorithm, conducted experimental analysis, and obtained ideal results on the indicators we set.

The rest of this paper is organized as follows. Section 2 describes the proposed RSU deployment model. Section 3 provides a brief overview of the adopted optimization algorithm. Section 4 presents the experimental results and discussions. Finally, we conclude this paper and provide several future study directions in Sect. 5.

Table 1. Key terms in the model.

Key terms	Descriptions
D	Length of a data frame
R	RSU transmission radius
K	The number of RSUs
A	RSU set, A = $\{A_1, A_2,\ldots,A_K\}$
B	Transmission bandwidth
x	Distance from vehicle to RSU
$RI(x)$	Data transfer rate
D_c	Critical data packet size
n_p	Number of packet received by RSU
T_Q	Queuing delay of packet
μ	Service rate
D_{en}	Packet arrival rate
η	Single RSU computing power
T_{ij}	Communication delay between RSU and vehiclex
$Gi(x)$	Channel gain
N_0	Noise power spectral density
β_1	Communication path loss constant
β_2	Communication path loss index
n_v	Vehicles number in a certain range
RS	Road resource (area)
T_c	Critical delay of transmission

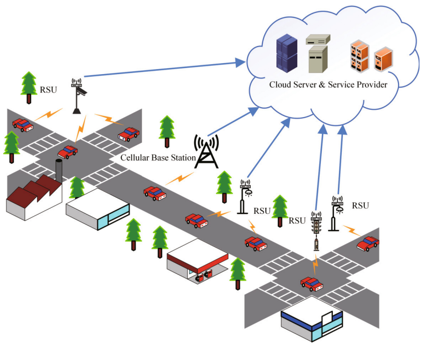


Fig. 1. Transmission network framework of RSU.

2 Problem Description and System Model

For better understanding, the key terms involved in the proposed model are listed in Table 1.

2.1 Multi-RSU Cooperative Data Transmission Network Framework

In current data transmission systems, RSUs are adopted to assist data transmission and relieve the transmission burden of cellular networks. Strong support for intelligent transportation can be furnished by the RSU data transmission paradigm with low latency and low communication cost.

This paper considers a vehicular network with multi-RSU and cellular base stations, which helps to connect vehicles to the cloud servers and transmit data with Internet. Figure 1 illustrates a RSU cooperative data transmission framework, where RSU and cellular networks receive data packets from vehicles and upload them to the cloud servers. Each vehicle has two communication interfaces of RSU and cellular base station. Vehicles can independently choose which interface to connect to. Compared with the cellular base station, vehicles prefer to transmit data with RSU due to its low communication cost, low time delay, and high data security. However, if a vehicle is out of communication range of the RSU or the RSU that a vehicle connects with is overloaded, the vehicle will upload data through the cellular base station. This strategy is capable of reducing the overall communication delay and cost. The RSUs, which are denoted as $A = \{A_1, A_2, ..., A_K\}$, are utilized to receive data packets from vehicles and forward them to the cloud servers, where K represents the number of RSU. Communication base stations are arranged to divert a part of vehicle's data and relieve RSU data transmission pressure to enhance the service efficiency. Suppose that N vehicles, which are denoted as $V = \{V_1, V_2, ..., V_N\}$, are required to upload the collected data to the edge nodes; each vehicle is of the same rate of producing and collecting data, and the collected data will be integrated (Referred as a data packet) and transmitted out when the data stored in the vehicle cache reach a critical value D_C. Here, the set of packets transmitted from vehicles is denoted as $M = \{M_1, M_2, ..., M_N\}$. For the data transmission, vehicles need to select what kind of edge node to connect with, since each vehicle has two choices as mentioned above. First, check whether a vehicle is in the range of RSUs. If the vehicle is in the range of RSUs, it will select the nearest RSU for data transmission. If the distance between the vehicle and the RSU exceeds the communication range of the RSU, the vehicle will transmit data with the cellular base station. The transmission range of the cellular base station is larger than that of the RSU. It is assumed that the cellular base stations fully cover the map and can transmit data successfully for the first time. If the transmission delay with RSU is less than the critical delay, the transmission is considered successful. However, vehicles are constantly moving, or huge amounts of data packets are crowded into one RSU, which will result in the time delay exceeding the critical delay T_c. Therefore, the vehicle will choose the cellular base station for the second time. Here, denote x as the distance between the vehicle V_n and the corresponding selected RSU; R is the transmission cover radius of RSU.

2.2 Transmission Delay Model

As shown in the Fig. 2, transmission delay commonly consists of four parts, i.e., the propagation delay of data packets between different nodes, the transmission delay of devices for pushing out data packets, the processing delay of routers for data checking, and the delay of data packets entering the queue.

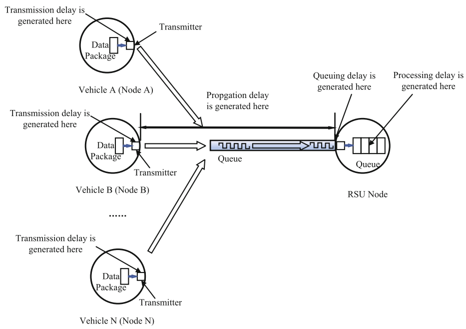


Fig. 2. Time delay model.

In this model, the distance between the roadside unit node and the vehicle is less than 1,000 m, and the speed of data propagation corresponds to the speed of electromagnetic wave propagation through the air. Consequently, the theoretical propagation speed is within 0.003 milliseconds, which is significantly less than the queueing delay and transmission delay of over 100 milliseconds. Therefore, the propagation delay can be disregarded in this model. Additionally, the processing delay is generally considered negligible [26].

The sending delay T_{ij} is calculated by (1):

$$T_S = \frac{D}{RI(x)} \tag{1}$$

where T_S represents the data transmission time of the ith vehicle in the jth time slot, $RI(x)$ is the transmission rate of the current location, and $RI(x)$ is calculated according to

$$RI(x) = B \cdot \log_2 \left(1 + \frac{\mathrm{Gi}(x) \cdot P_N}{B \cdot N_0} \right) \tag{2}$$

$$Gi(x) = \beta_1 \cdot x^{\beta_2} \tag{3}$$

where $Gi(x)$ and x are the channel gain and distance between vehicle V_N and the RSU, respectively; β_1 and β_2 represent the path loss constant and path loss exponent in the communication, respectively; P_N is the RSU's transmission power; B is the bandwidth and N_0 represents the noise power spectral density [8]. In order to calculate the waiting time of a packet to be received by the RSUs, the queuing theory of M/M/1 model is adopted in this paper with assuming that the arrival rate is λ and the service rate of the RSU is μ. λ can be calculated according to

$$\lambda = \frac{D_{en}^k}{m \cdot k!} e^{-D_{en}} \tag{4}$$

where D_{en} represents the vehicles' density and D_{en} can be obtained by

$$D_{en} = \frac{n_v}{RS} \tag{5}$$

where n_v is the number of the vehicles in specific regions and RS represents the road resources. μ is calculated according to

$$\mu = \frac{\eta}{S} \tag{6}$$

where η is the computing power of a single RSU and S is the average length of packets. Afterwards, the average waiting time can be obtained according to (7) to (8).

$$n_v = \frac{\rho}{1-\rho} = \frac{\lambda}{\mu - \lambda} \tag{7}$$

$$T_Q = \frac{n_v}{\lambda} = \frac{\rho}{(1-\rho)\lambda} = \frac{1}{\mu - \lambda} \tag{8}$$

where T_Q is the waiting time. Then, the total transmission delay of one packet is calculated by

$$T_{ij} = T_S + T_Q \tag{9}$$

where T_{ij} is the total delay of the ith vehicle in the jth time slot. Note that the RSU-based transmission of the ith vehicle in the jth time slot is successful only if $T_{ij} \leq T_c$, or the ith vehicle will transmit data with cellular stations in the jth time slot. When sending data packets with the cellular base station, since the cellular base station has a longer delay and higher communication cost, we set a larger delay time for the data packets transmitted with the cellular base station as punishment.

2.3 RSU Number Model

All the RSUs in the model share the same characteristics, such as performance and deployment costs. Therefore, the cost of building the RSU network depends on the number of RSUs. In this paper, the map is divided into multiple refined grid areas G_R and each grid only includes one RSU or not. Accordingly, the number of RSUs deployed in the entire model can be calculated by

$$G_R(n) = \begin{cases} 1, & \text{if } RSU \text{ depolyed in this area } n \\ 0, & \text{none } RSU \text{ depolyed in this area } n \end{cases} \tag{10}$$

$$K_{RSU} = \sum_{1}^{n} G_R \tag{11}$$

In order to reduce the overall deployment cost, the number of RSUs in the model should be reduced. Note that this objective is conflict to minimize the overall delay mentioned above.

2.4 Problem Formulation

This paper aims at minimizing the average time delay of RSU data transmission and reducing the number of deployed RSUs by optimizing the location distribution of the RSUs. These two objectives can be formulated as

$$minf_1 = \left\{ \sum_{n=1}^{K} T_{ij} \right\} \tag{12}$$

$$minf_2 = \{K_{RSU}\} \tag{13}$$

3 Algorithm Background

The goal of this work is to minimize the transmission delay and the number of RSUs to achieve an efficient RSU network. NSGA-II is a powerful tool in solving multi-objective optimization problems [28], which are briefed as follows.

1. Initialization
   Given that MG is the maximum number of iterations, P_{size} is the population size, P_{size} individuals are randomly generated, according to the characteristics of the problem. f_1 and f_2 are calculated for each individual.
2. Pareto sorting
   Execute the non-dominated sorting according to the fitness [27].
3. Selection
   Select P_{size} individuals to participate the crossover and mutation operations [28].
4. Crossover
   The standard NSGA-II algorithm adopts an analog binary crossover operator, and the new individuals in generation k are generated based on the selected individuals (See Step 2) according to

$$p_{1,k+1} = \frac{1}{2}\left[\left(1-\beta_{qi}\right)p_{1,k} + \left(1+\beta_{qi}\right)p_{2,k}\right] \tag{14}$$

$$p_{2,k+1} = \frac{1}{2}\left[\left(1+\beta_{qi}\right)p_{1,k} + \left(1-\beta_{qi}\right)p_{2,k}\right] \tag{15}$$

   where $p_(1,k+1)$ and $p_(2,k+1)$ are the individuals generated at generation k with the crossover operation; $p_(1,k)$ and $p_(2,k)$ are the selected individuals at k generation; β_{qi} is calculated according to

$$\beta_{qi} = (2\mu_i)^{\frac{1}{\tau+1}} \quad {}^{\mu_i} \leq 0.5 \tag{16}$$

$$\beta_{qi} = \frac{1}{\left[2\left(1-\mu_i\right)\right]\frac{1}{\tau+1}}\mu_i \geq 0.5 \tag{17}$$

   where μ_i is a random number within $[0,1)$; τ is the cross-distribution index, which will affect the distance between the generated individuals and the parent individuals.

5. Mutation
   The mutation operation is to simulate the genetic mutation behavior. This paper adopts the polynomial mutation operator, which is shown as

$$p_{k+1} = p_k + \left(p_k^{\max} + p_k^{\min}\right) \delta_k \tag{18}$$

   where p_k is the individuals to be mutated at generation k; p_k^{max} and p_k^{min} are the upper and lower bounds of the decision variables; δ_k is calculated according to

$$\delta_k = \begin{cases} (2r_k)^{\frac{1}{i_m+1}} - 1 & r_k < 0.5 \\ 1 - [2(1 - r_k)]^{\frac{1}{i_m+1}} & r_k \geq 0.5 \end{cases}, \tag{19}$$

   where r_k is the uniformly distribute random number in $[0, 1]$; i_m is the mutation index.
6. Termination criterion checking
   If the termination criterion has been satisfied, output the individuals; If not, select P_{size} individuals as $P(k+1)$ from $P(k) \cup P_{child}(k)$ and return to Step 2, where $P(k)$ and $P_{child}(k)$ are the populations and the newly generated individuals at generation k, respectively [27].

The NSGA II's time complexity is $O(MN^2)$, where M represents the number of objectives and N represents the size of the population. The NSGA II's space complexity is $O(BTN)$, where B represents the number of blocks in the map and T represents the number of time periods.

4 Experiment and Simulation

4.1 Simulation Set up

In the experimental part, all the simulations are run with Intel i7-11800H; Table 2 lists the key parameters in the experiment.

Where P_N is the RSU transmit power, N_0 is the noise power spectral density, β_1 is the communication path loss constant and β_2 is the communication path loss index, these four parameters are cited from reference [8]. In order to balance the solution quality and computation time, this paper sets the max generation G_{max} and the population size of one generation P_{size} as 200 and 50, respectively. i_m is the mutation index and τ is the cross-distribution index, which are cited from reference [28].

4.2 Experiment Data

The experiments are conducted based on a Shenzhen taxi dataset which records the travel coordinates of 602 taxis in Shenzhen on October 22, 2014, and the coordinate data are updated about every 20–40 s. The following criterion is adopted for data processing: Data interpolation. We divided the whole day into 12 time periods in chronological order. Every time period contains 2 h and the sampling is performed every 30 s in each time period.

Table 2. The value of key terms.

Key terms	Descriptions	Value
D	Length of a data frame	1 Mb
R	RSU transmission radius	1000 m
D_c	Critical data packet size	5 Mb
P_N	RSU transmit power	23 dBm
N_0	Noise power spectral density	−174 dBm/Hz
β_1	Communication path loss constant	0.0007
β_2	Communication path loss index	2
T_c	Critical delay of transmission	5S
G_{max}	Max generation	200
P_{size}	Population size of one generation	50
i_m	The mutation index	20
τ	The cross-distribution index	20

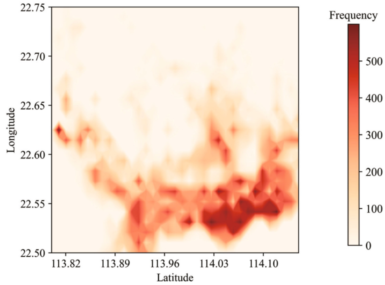
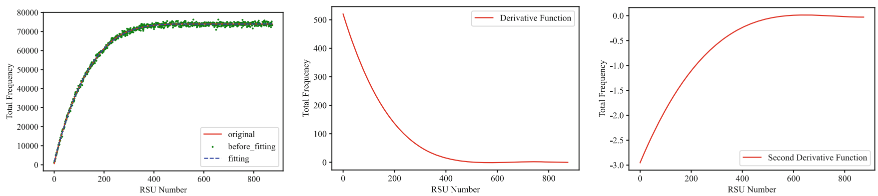


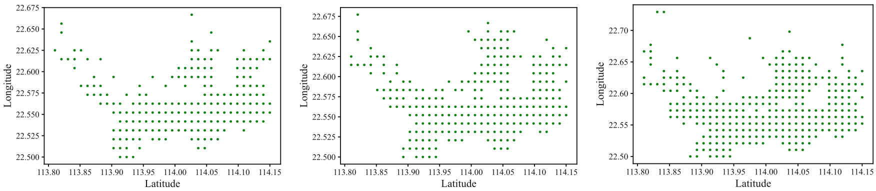
Fig. 3. Frequency of RSU's likely location



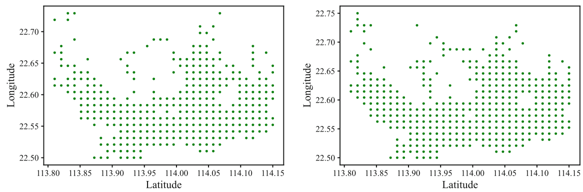
(a) The Fit Function of Statistics Curve
(b) The Derivative Function of Fit Function
(c) The Second Derivative Function of Fit Function

Fig. 4. Fit function of RSU frequency statistics curve and derivative function

In this paper, we apply the multi-objective optimization algorithm to optimize taxi trajectory data for each time period to find the pareto optimal surface of RSU deployment positions and numbers. RSU deployment locations vary each time period due to taxi trajectories. The frequency heat map of RSU possible sites is obtained by stacking RSU likelihood locations over all time periods, as illustrated in Fig. 3. Then we sort and count the frequency of the possible positions of each RSU, accumulate from the high frequency to the low frequency, and obtain the change curve of the frequency and quantity shown in the Fig. 4, and then fit the curve to obtain the fitted continuous function.



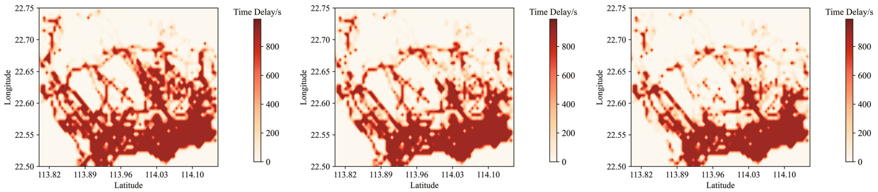
(a) Deployment Scheme with 200 RSUs (b) Deployment Scheme with 250 RSUs (c) Deployment Scheme with 300 RSUs



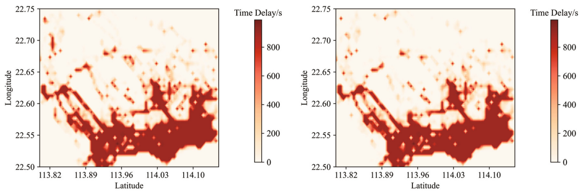
(d) Deployment Scheme with 350 RSUs (e) Deployment Scheme with 400 RSUs

Fig. 5. RSU depolyment scheme with different number of RSUs

Since the derivative of the fitted function is greater than zero and the second derivative is less than zero within the domain of definition (0, 875), it can be seen that the fitted function is a concave function, and because there are no inflection points and stagnation points, we cannot find the only optimal point. According to the derivative function, when the number of RSUs is 200, the value of the derivative is 136.548, when the number of RSUs is 400, it is 16.388, and in this interval, the total frequency of RSUs is close to the maximum point. It can be seen that in this interval, the two indicators of economic activity and delay are balanced. Therefore, we obtain a series of new RSU deployment schemes in the interval of 200–400. The delays of these schemes are shown in Fig. 7, and the deployment position of RSU is shown in Fig. 5. Additionally, the time delay distribution in each block is shown in Fig. 6, one can see that the number of the areas with high time delay decreases with the increasing number of RSU.



(a) Blocks Delay with 200 RSUs (b) Blocks Delay with 250 RSUs (c) Blocks Delay with 300 RSUs



(d) Blocks Delay with 350 RSUs (e) Blocks Delay with 400 RSUs

Fig. 6. Time delay distribution in each block with different number of RSUs

NSGA-II is applied to find the proper solutions to (12) and (13). The performance of the population with respect to these two objectives are shown in Fig. 7, indicating that with the increasing of the system delay (from about 1,148,176s to 1,245,795s), the number of RSUs decreases from 200 to 400. In comparison to the original delay of 4,054,000s and the original RSU number of 450, the delay is reduced by about 69.3% to 71.7% and the number of RSUs is reduced by 11.2% to 55.6%.

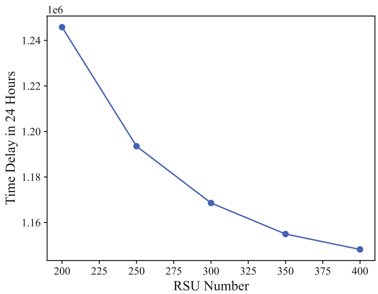


Fig. 7. Total time delay in 24 h of each scheme

By counting the frequency of RSUs' usage positions in different regions in different time periods of the Pareto optimal surface, and selecting the appropriate number and location of RSUs according to the total frequency changing curve, we can obtain 5 highly robust RSU deployment schemes which can adapt to the traffic flow in different time periods. And the number of RSUs is reduced at the same time to decrease the deployment cost.

Furthermore, we compare the proposed deployment strategy with the genetic algorithm-based deployment method [9]. In the genetic algorithm (GA) based deployment strategy, the two objectives are weighted together with the same importance. GA adopts the same parameter settings with NSGA-II, which are shown in Table 2. The fitness function of GA is formulated by the follow equation [11]:

$$Fitness_{GA} = w_1 n_{RSU}^{norm} + w_2 T_{total}^{norm}. \quad (20)$$

Here, w_1 and w_2 range from 0 to 1, which adjust the importance of the normalized objectives: RSU's number n_{RSU}^{norm} and the time delay T_{total}^{norm}, respectively. We set $w_1 = 0.5$ and $w_2 = 0.5$. The results are shown in Table 3. One can observe that NSGA-II achieves better performance in the same traffic-flow environment. Furthermore, the proposed strategy leads to a reduced RSU number in comparison to GA-based strategy with similar delay performance.

Table 3. Comparison results on two algorithm.

Algorithm	Time delay/seconds	RSU's number
GA	1.246×10^6	472
NSGA-II	$1.148 \times 10^6 - 1.245 \times 10^6$	200–400

In summary, the experimental results demonstrate that the adopted algorithm on proposed framework is effective in simultaneously reducing the time delay and RSU number, which is beneficial to the application of the large-scale RSU network.

5 Conclusion and Future Work

This paper proposes a cooperation data transmission framework-based RSU deployment model to minimize data transmission delay and RSU number. These objectives measure network performance and economy. By adopting a multi-objective optimization algorithm, the presented RSU deployment strategy is capable of adapting to the traffic conditions in different regions. Experimental results show that both the delay and the RSU number can be effectively reduced with respect to a real-world dataset.

In our future work, we will investigate more factors in the RSU network, including the RSU work/sleep strategy and the multiple retransmission strategy, to continue improving the performance of the RSU network.

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