# An Analytical Model for Energy Harvest Road Side Units Deployment With Dynamic Service Radius in Vehicular Ad-Hoc Networks

**FAN YANG** [1], **(Student Member, IEEE), CHONG ZHAO** [1], **(Member, IEEE),**
**XU DING** [2,3], **(Member, IEEE), AND JIANGHONG HAN** [1]

[1] School of Computer and Information, Hefei University of Technology, Hefei 230009, China
[2] Institute of Industry and Equipment Technology, Hefei University of Technology, Hefei 230009, China
[3] School of Computer and Information, Hefei University of Technology, Hefei 230009, China

Corresponding author: Xu Ding (dingxu@hfut.edu.cn)

**ABSTRACT** Due to the advantage of high data rate, low transmission delay and high reliability, the application of Long Term Evolution for Vehicle (LTE-V) has got more attention on Vehicular Ad-hoc Networks (VANETs). However, the fixed Road Side Units (RSUs), like Base Stations (BSs), in LTE-V have a small coverage, which need consume a large amount of energy to achieve long-distance communication. This could limit the LTE-V application in some practical situations. In this paper, we introduce Energy Harvest Road Side Units (EH-RSUs) in some low frequency service area instead of fixed-point RSUs (BSs) to reduce the cost of deployment and maintenance. Different from fixed-point RSUs with the wired electricity sources, EH-RSUs are powered by themselves and the service time is affected by battery capacity, charging speed, service radius and communication load, which need to be considered comprehensively. To solve these problems, we construct an EH-RSUs deployment model framework based on communication load conditions. Then, on the basis of this framework, we propose an optimization problem to minimize the deployment and operation cost of EH-RSUs and fixed-point RSUs, where the service radius of the EH-RSUs are taken as an optimization variable. Finally, a pre-deployment algorithm is proposed to solve the optimization problem. Simulations evaluate the validity of our proposed method. The results show that the energy consumption with the proposed method could be reduced to 60% compared with only fixed-point RSUs deployed.

**INDEX TERMS** VANETs, energy harvest RSUs, dynamic service radius, modeling and optimization.

## I. INTRODUCTION

With the explosion of mobile communications in 5G, studies have shown that the LTE-V with low latency can effectively improve the safety of road traffic among vehicles [1]–[6]. However, with the data transmission rate increasing, the coverage radius of Road Side Units (RSUs) in 5G is significantly smaller than that in 4G. In this case, more RSUs should be deployed to expand the coverage radius, which can achieve better transmission effect. It will not only increase the cost of materials for deployment and maintenance, but also consume a lot of network energy [7], [8]. All of these could affect the LTE-V application in Vehicular Ad-hoc Networks (VANETs) [9]. Therefore, it is the critical factor to

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design and manage the energy-efficient network, which can be used to achieve energy saving and cost reduction.

In order to achieve this energy-saving target effectively, several techniques have been addressed, such as resource allocation [10], [11], cell zooming [12], Base Stations switching [13], [14] and so on. As a new type of RSUs, Energy Harvest Road Side Units (EH-RSUs) have been attracting attention on the research field and are expected to play important roles in reducing energy consumption, especially in the power-constrained VANETs [15]. In the energy harvesting VANETs, EH-RSUs prolong the service lifetime by utilizing their energy efficiently. Moreover, they provide V2V assisted communication as relays and broadcast services information in non-high load areas to improve the overall network performance. Although deploying EH-RSUs is an effective method that strives to reduce the operational and maintenance costs

in VANETs, its utilization is still limited by energy storage and power collection capabilities, as well as by location and service radius [16], [17]. It is therefore important to deploy EH-RSUs reasonably and adjust the coverage effectively, according to the road traffic load [18]–[21].

In the existing research literatures, most of them focused on fixed-point RSUs deployment problems to optimize communication delay, limit deployment consumption and enhance network performance. Wu *et al.* [22] studied the RSUs placement problem on the highway-like scenario. They accounted for direct transmission or multi-hop relays with RSUs to maximize the aggregate throughput in VANETs and formulated this placement problem via an integer linear programming model. Developing VANET-based services and applications were hindered due primarily to limited and often fluctuating communication capacity of VANETs that stem from the wireless and mobile nature of vehicle-to-vehicle (V2V) communications. To address this limitation, Patil and Gokhale [23] proposed a novel Voronoi network-based algorithm for the effective placement of RSUs when deployed Voronoi networks in terms of the amount of delay incurred by data packets sent over the RSUs. Javier *et al.* [24] proposed a Density-based Road Side Unit deployment policy (D-RSU), specially designed to obtain an efficient system with the lowest possible cost to alert emergency services in case of an accident. Gao *et al.* [25] studied the one-dimensional RSU Deployment (D1RD) problem with n RSUs of different coverage radii and proposed two greedy-based algorithms (named as Greedy2P3 and Greedy2P3E) to solve this problem. Ni *et al.* [26] investigated a RSU deployment problem for 2-D Internet of Vehicles networks considering the expected delivery delay requirements and task assignment. They formulated a novel utility-based maximization problem to solve the RSU deployment problem, where the utility function indicated the total benefit from the RSU deployment.

Due to the power supply requirements, these researches are limited to localize the RSUs nearer to the wired electricity sources. However, such deployment limits the area covered by the RSUs and, thus, the offered services. In order to overcome this restriction, self-powered RSUs are required to harvest the energy needed for their work from the surrounding environment, like solar energy [27], [28]. Moumita and Siva Ram [29] proposed joint placement and sleep scheduling of RSUs in a VANET environment to achieve that optimal RSU placement helped to reduce cost and efficient sleep scheduling helped to reduce energy consumption at RSUs. They formulated an optimization problem which captured the behavior of a realistic scenario and proposed an energy efficient candidate location selection algorithm to jointly perform placement and sleep scheduling of grid-connected solar powered RSUs. Chamola and Sikdar [30] conducted researches on mobile RSUs, which mainly performed short distance assistance transmission in downloading tasks. Sellil Atoui *et al.* [31] investigated the problem of scheduling the downlink communication from renewable energy-powered RSUs

toward vehicles, with the objective of maximizing the number of served vehicles. They considered the situations occurred when the EH-RSUs did not harvest enough energy or take full advantage of the one available. The EH-RSUs must be able to efficiently manage their available energy by adapting to both the energy harvesting process and the communication requirements. Kim *et al.* [32] investigated a new strategy of how to best deploy RSUs so that their spatiotemporal coverage was maximized under a limited budget. There were three types of devices: deploying RSUs on static locations, public mobile transportation, and fully controllable vehicles owned by the local government. In this situation, the RSUs were still deployed as fixed-point. Although other two types were as mobile RSUs, they were much worse than EH-RSUs in terms of processing speed and coverage.

In these researches, the EH-RSUs were fixed service radius, which introduced limitations on the modeling of an energy limited RSUs. And the EH-RSUs were fixed in a given position, used only as transmission relays and ignored the application of their flexibility. Little progress has been made about the collaborative deployment of fixed-point base stations with EH-RSUs according to the rechargeable characteristic. In this paper, we construct a novel RSUs deployment framework with adjustable service radius depending on communication load conditions, which would prolong the service time for EH-RSUs while taking advantages of flexibility. The main contributions are as follows:

- We develop an analytical EH-RSUs deployment framework taking EH-RSUs' battery capacity, charging speed, service radius, communication load into account.
- We use the service radius of EH-RSUs as an optimization variable, which is adjusted to adapt the communication load of the road and extend their service duration. In addition, we propose an optimization problem that minimizes the cost of deploying EH-RSUs and BSs.
- Since there are quadratic constraints in the optimization problem, we propose a heuristic deployment algorithm that narrow down the solution search range and preset approximate optimal solution for the optimization problem.

The remainder of this paper is organized as follows. In Section II, we develop a system model of scenario with multiple BSs and EH-RSUs in VANETs. In Section III, we propose an optimization problem about RSUs deployment. In Section IV, we design a pre-deployment algorithm to solve the problem. And on this basis, Section V presents the results of our simulation and the conclusion of this paper is given in Section VI.

## II. SYSTEM MODEL

In this section, we display a scenario of vehicles communications including multiple crossroads and roads, as shown in Fig. 1. The relevant models used in this work are described as follows. Here, there are two types of devices to provide Vehicle-to-Infrastructure (V2I) service, one is the Base Stations (BSs), the other is EH-RSUs.
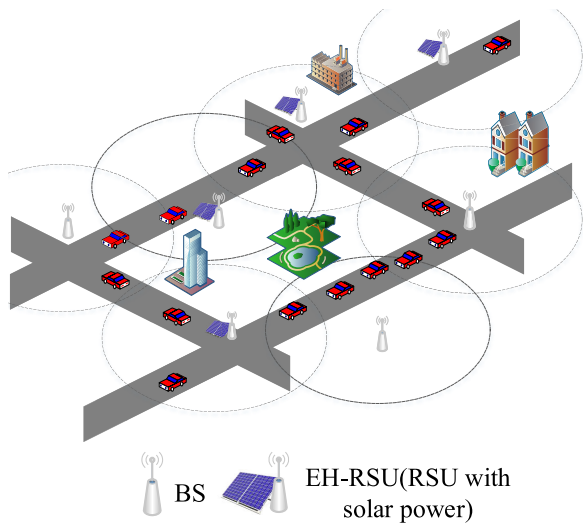
BS  EH-RSU(RSU with solar power)

**FIGURE 1.** Scenario of VANETs with multiple BSs and EH-RSUs.

As stationary roadside devices, BSs are powered by wired grid, which can provide continuous network services for vehicles within the coverage. Each EH-RSU is equipped with an energy storage battery, which is recharged by solar power. For follow-up studies, we suppose the standard capacity of every EH-RSU battery is the same, denoted as $E_e$. For each battery, the charging speed is also the same, defined as $C_s$.

We divide the road into several cells. Symbol $C = \{c_1, c_2, \cdots, c_m\}$ represents the set of cells. In VANETs, the road should be covered by BSs or EH-RSUs to ensure data reliable transmission. Thus, the service radius of BSs or EH-RSUs with minimum service power is exactly enough to cover such one cell. Symbol $r_{min}$ represents the minimum service radius of EH-RSUs and BSs. Denote $R_B^i$ as the service radius factor of BSs deployed in the cell $c_i$, the symbol $B$ is used in the subscript to denote the BSs. $R_E^i$ is service radius factor of EH-RSUs deployed in the cell $c_i$, the symbol $E$ is used in the subscript to denote the EH-RSUs. Here, we use $\omega$ and $\mu$ to represent the maximum service radius factor that can be provided by the BSs and the EH-RSUs, respectively. The example of cells map is shown in Fig. 2.
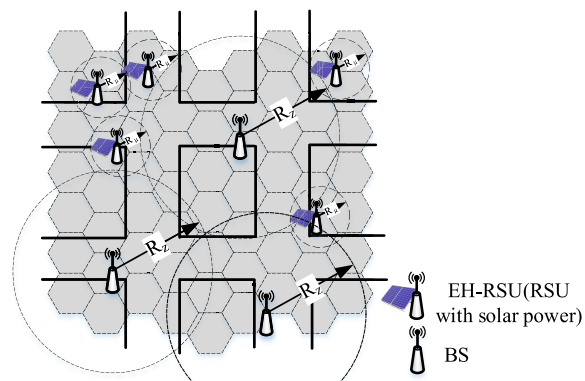


EH-RSU(RSU with solar power)

BS

**FIGURE 2.** Example of Road Cells Map.

In this situation, we suppose the service time is divided into $T$ time frames and each frame is with the same length.

For each time frame, we consider it is a relatively short period of time [33], in which the relative position of vehicles does not change. Symbol $D_{i,j}(t)$ represents the distance between vehicle $i$ and vehicle $j$ in the $t^{th}$ time frame. As a main part of the communication content, it is particularly important for vehicles to interact with safety-related information, which is affected by safety distance among vehicles. Therefore, symbol $R_s$ represents the safe distance between vehicles to consider the safe driving in reality.

## III. RSU DEPLOYMENT AND COST OPTIMIZATION PROBLEM

The deployment cost of BSs is higher than that of EH-RSUs, which have a large service radius and sufficient power supply. On the contrary, EH-RSUs own a low deployment cost, which have a small service radius and limited power supply. Therefore, it is necessary to consider the balance of power and service, when BSs and EH-RSUs are deployed in the road. To this end, the model is divided into the following steps to achieve our targets.

- Step 1: A road load estimation model is established to measure BSs and EH-RSUs service capabilities.
- Step 2: An energy consumption and service radius model is developed for EH-RSUs to constrain service time.
- Step 3: On the base of multi-BSs and multi-EH-RSUs collaborative deployment, an optimization problem to minimize deployment cost is established.

### A. SERVICE CAPABILITIES MODEL OF BS AND EH-RSU
In this section, a connectivity map $G = (C, E)$ is constructed to represent the relationship of each cell. $C$ is the set of divided cells, which is defined in Section II. $E = \{e_{1,2}, e_{1,3}, \cdots, e_{i,j}, \cdots\}(i \neq j)$ is the relationship of each cell. For cell $c_i$ and $c_j$, $e_{i,j}$ is the distance between them. If $e_{i,j} \leq R_B^i$, the BS can be deployed in $c_i$ with service radius $R_B^i$, which could provide service for $c_j$ as well. Denote $\alpha_{ij}(t)$ as the boolean variable to indicate whether a request for information exchanging between $c_i$ and $c_j$ at $t^{th}$ time frame is initiate. Specially, $\alpha_{ij}(t) = 1$ if the distance between $c_i$ and $c_j$ is less than $R_s$ and 0 otherwise. The constraint can be written as:

$$\alpha_{i,j}(t) = \begin{cases} 1, & D_{i,j}(t) \leq R_s \\ 0, & D_{i,j}(t) > R_s \end{cases} \qquad (1)$$

For all network, each vehicle could communicate with others about safety related information. The sum number of requests for safety related information is used to describe the network load for every cell. Denote $f_i(t)$ as the sum number of requests for safety related information in cell $c_i$. Then, the constraint can be written as:

$$f_i(t) = \sum_{k \in V_i(t)} \sum_{j \in N(t)} \alpha_{k,j}(t) \qquad (2)$$

where $N(t)$ is the number of vehicles at $t^{th}$ time frame in the network and $V_i(t)$ is the number of vehicles in $c_i$ at $t^{th}$ time frame.

In each cell, only one type device could be deployed, the BSs or the EH-RSUs. Denote $L_b$ and $L_e$ as the set to describe the deployment points of BSs and EH-RSUs, respectively, which can be expressed as $L_b = \{l_b^1, l_b^2, \cdots, l_b^m\}$ and $L_e = \{l_e^1, l_e^2, \cdots, l_e^m\}$. If $l_b^i = 1$, the BS is deployed in $c_i$. Or $l_e^i = 1$, the EH-RSU is deployed in $c_i$. The constraint can be written as:

$$l_b^i + l_e^i \leq 1, \quad (c_i \in C) \qquad (3)$$

Due to limited by transmission power of devices, the service range of devices deployed in $c_i$ is relying on the type of devices, then the maximal service radius can be written as:

$$\begin{cases} R_B^i \leq l_b^i \cdot \omega \\ R_E^i \leq l_e^i \cdot \mu \end{cases} \qquad (4)$$

Denote $P_i$ as the number of devices that could provide service for $c_i$. As for system requirements, every cell should be covered by only one device, which means

$$P_i \geq 1, \quad (c_i \in C) \qquad (5)$$

According to the system model, $P_i$ is affected by the number of devices that could provide service for $c_i$, which can be yielded through:

$$P_i = \sum_{c_j \in C}^{e_{i,j} \leq R_B^j} l_b^j + \sum_{c_j \in C}^{e_{i,j} \leq R_E^j} l_e^j, \quad (c_i \in C, i \neq j) \qquad (6)$$

$\Phi_i$ is the network load that the appropriate device is deployed in $c_i$ to realize information interaction, which should take into account. The constraint of network load about the $f(t)$ in $c_i$ can be expressed by

$$\Phi_i = \begin{cases} \displaystyle\sum_{c_j \in C}^{e_{i,j} \leq R_B^j} f_j(t), & (l_b^i = 1) \\ \displaystyle\sum_{c_j \in C}^{e_{i,j} \leq R_E^j} f_j(t), & (l_e^i = 1), \end{cases} \quad (c_i \in C, i \neq j) \qquad (7)$$

### B. ENERGY CONSUMPTION MODEL OF EH-RSU
For each EH-RSU, its capacity is limited by battery. Symbol $M_i(t)$ represents the residual energy of the device deployed in $c_i$ at the $t^{th}$ time frame, which can be expressed:

$$\begin{cases} M_i(t) = E_e, & (l_b^i = 1) \\ M_i(t) \leq E_e, & (l_e^i = 1) \end{cases} \qquad (8)$$

Because the service radius of the EH-RSUs is variable, the energy consumption is also affected by the network load of the EH-RSUs service cells. There are following cases of the residual energy at the $(t + 1)^{th}$ time frame:

(i) When the EH-RSU is deployed at $c_i$, the residual energy at the $(t + 1)^{th}$ time frame is the sum of $M_i(t)$ with the energy charged and the power consumption during one time frame.

(ii) Due to the limited battery capacity, the residual energy of the EH-RSU cannot exceed the capacity of battery.

(iii) When the power is exhausted, the EH-RSU stops working and the remaining power is 0.

By combining the above analysis, the constraints of the EH-RSU residual energy can be written as:

$$\begin{cases} M_i(t + 1) = M_i(t) + C_s - \varphi(\Phi_i(t)), \\ (M_i(t) + C_s - \varphi(\Phi_i(t)) \leq E_e); \\ M_i(t + 1) = M_i(t), (M_i(t) + C_s \\ \quad - \varphi(\Phi_i(t)) > E_e); \\ M_i(t + 1) = 0, (M_i(t) + C_s \\ \quad - \varphi(\Phi_i(t)) \leq 0); \end{cases} \quad (l_e^i = 1) \qquad (9)$$

where $\varphi(\Phi_i(t))$ is the power output function of EH-RSUs to provide service for $\Phi_i(t)$.

The energy consumption rate of EH-RSUs has a quadratic relationship with the coverage area, which can be expressed $\varphi(\Phi_i(t))$ as:

$$\varphi(\Phi_i(t)) = \begin{cases} \phi \cdot \Phi_i(t) \cdot (R_B^i \cdot r_{min})^2, & (l_b^i = 1) \\ \phi \cdot \Phi_i(t) \cdot (R_E^i \cdot r_{min})^2, & (l_e^i = 1) \end{cases}$$
$$= \phi \cdot \Phi_i(t) \cdot [(R_B^i \cdot r_{min})^2 \cdot l_b^i + (R_E^i \cdot r_{min})^2 \cdot l_e^i] \qquad (10)$$

### C. OPTIMIZATION PROBLEM OF MINIMIZING COST FOR RSUs
The consumption of devices consists of two parts: deployment and operation cost. Symbol $C_D$ represents the deployment cost, which can be written as

$$D_C^i = D_B \cdot l_b^i + D_E \cdot l_e^i \qquad (11)$$

where $D_B$ and $D_E$ are the deployment cost of the BS and EH-RSU, respectively. For the BS, the extra operating cost $\Psi_B^i$ is energy from power grid. $\rho$ is a consumption weight factor of electricity, then we get

$$\Psi_B^i = \rho \cdot \sum_{t=1}^{T} \varphi(\Phi_i(t)), \quad (c_i \in C) \qquad (12)$$

Hypothesize the total number of time frames is $T$ in the VANETs, the optimization objective is to minimize the overall cost. Then the optimization problem OPT-C can be expressed as:

$$\textbf{OPT} - \textbf{C} : \begin{cases} \textbf{Min} \left( \displaystyle\sum_{c_i \in C} D_C^i + \sum_{c_i \in C} \Psi_B^i \right) \\ s.t. (1) - (12) \end{cases}$$

## IV. PRE-DEPLOYMENT METHOD AND ALGORITHM FOR OPTIMIZATION PROBLEM
Based on the above constraints, the optimization problem has been formulated in section III. In this formulation, constraint (10) is a quadratic one, which contains a large number of integer variables. This turns the optimization problem into a Mixed Integer Nonlinear Programming (MINLP), which is difficult to obtain a suitable solution in polynomial time.

Compared with other heuristic algorithms, such as particle swarm optimization (PSO) [34] that tends to fall into the

local optimal solution and Genetic Algorithms (GA) [35] that converges slowly and on high-dimensional problems with difficulty, Differential Evolution (DE) [36] algorithm has better performance. The basic idea of DE algorithm is as follows. 1) Start from a randomly generated initial population. 2) Sum the vector difference of any two individuals in the population with a third individual to generate a new individual. 3) And then compare the new individual with the corresponding individual in the contemporary population. 4) If the fitness of the new individual is better than the fitness of the current individual, the old individual will be replaced by the new individual in the next generation. 5) Otherwise the old individual will still be saved. 6) Through continuous evolution, good individuals are retained, poor ones are eliminated, guiding search to the optimal solution. However, There are still some problems in the DE algorithm, like a) fewer individuals in the population which could lead to that the adaptive value of the new generation of individuals is worse than the original population, making it difficult for individuals to update and eventually fail to converge to the extreme point; b) if the parameters are not set properly, the convergence would be too fast, resulting in the local optimal problem and so on. In this paper, because of more variables and large scale in the scenario, it is very suitable to be solved by DE algorithm.

Firstly, we design a RSUs pre-deployment method based on network load weights to compress the search space of the feasible solution. Then the quadratic constraint is avoided to translate the problem into an MINLP problem, which can be solved by DE. Limited by network load and charging speed, we could find such cells where EH-RSUs cannot be deployed according to the road load in advance. If the charging capacity cannot satisfy the power output requirements in the current network load, the EH-RSU cannot be deployed in the cell. Then we get

$$l_e^i = 0, \quad (\sum_{t=1}^{T} C_s \leq \sum_{t=1}^{T} \varphi(\Phi_i(t))) \tag{13}$$

For some cells, if the cost of BSs is lower than EH-RSUs, EH-RSUs shouldn't be deployed here. So we obtain

$$\begin{cases} l_b^i = 0, & (D_B + \Psi_B^i \geq D_E) \\ l_e^i = 0, & (D_B + \Psi_B^i < D_E), \end{cases} \tag{14}$$

If a cell is covered by other BS and $P_i \geq 2$, the EH-RSU can be removed, then we get

$$l_e^i = 0, \quad (P_i \geq 2) \tag{15}$$

Combining the above analysis, we turn to the conditions of DE algorithm with limited feasible solution search range in this sequel.

**Step1**: Determine the control parameters and fitness function. Differential evolution algorithm control parameters include: population size $M$, scaling factor $F$ and hybrid probability $CR$, iterations $k = 1$;

**Step2**: Randomly generate initial population;

**Step3**: Evaluate the initial population, namely calculate fitness value of each individual in initial population;

**Step4**: Evaluate whether achieves termination conditions or maximum iterations. If yes, the evolution is terminated and the best individual outputs as the optimal solution; If not, continue;

**Step5**: Carry out mutation and crossover operations to obtain the intermediate population;

**Step6**: Select individuals from the original population and the intermediate population to obtain the new generation population;

**Step7**: $k = k + 1$, then turn to step **Step4**.

The pseudo code is described at the top of page 6. The input variables in the algorithm are $G$ of all cells and historical location of vehicles in this VANETs. During the process, the maximum time $T$ of generations is set and the complexity of algorithm is $O(n^2)$, determined by $M \cdot Z$. $M$ is size of population which is initialized randomly and dimension $Z$ is limited by size of the road (For large size city, it could be divide into several parts and solved separately). After the evolution, policy of deployment is obtained represented by $L = \{L_b, L_e\}$.

## V. PERFORMANCE EVALUATION

In this section, we use the real mobility trace data of a German city, Cologne, as an experimental data to evaluate the validity and feasibility of the proposed algorithm. The map scenario is shown in Fig. 3 [37].



**FIGURE 3.** Map of Cologne City in Simulation.

In this simulation, the safety distance between vehicles is set 100m. The minimum service radius of BSs and EH-RSUs is 50m. Maximum service radius of EH-RSUs is 250m and the BSs' is 500m, respectively. The maximum service radius factors are equal to the maximum service radius over the minimum service radius. The power consumption of BSs is 1000w for $r_{min}$ and power-grid cost is $\phi \cdot \rho = 1.5e - 4$. The value of simulation parameters are listed in Tab. 1.

According to the distribution of city roads in Cologne, the cells are created to obtain $G = (C, E)$ as shown in Fig. 4, which cover road completely. The corresponding network load map is shown in Fig. 5.

**Algorithm 1** DE Algorithm for Optimization Problem of Minimizing RSUs Cost

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**Require:** $G = (C, E)$, $E = \{e_{1,2}, e_{1,3}, \cdots, e_{i,j}, \cdots\}$,
    Population:$M$;Dimension:$Z$; Iterations:$K$

**Ensure:** $L = \{L_b, L_e\}$

1: Initialize $L_b = \{l_b^i\}$, $L_e = \{l_e^i\}^t$ randomly;
2: Initialize $\alpha_{i,j}$ depending on vehicles location and safety distance;
3: $k = 1$;
4: **while** $k \leq K$ or $|f(\Delta)| \geq \varepsilon$ **do**
5:   **for** $m = 1$ to $M$ **do**
6:     **for** $i = 1$ to $Z$ **do**
7:       $m_e = Mutation(l_e^i)$;
8:       $m_b^{t+1} = Mutation(l_b^i)$;
9:       $L_e^{t+1} = Crossover(L_e, l_e^i, m_e)$;
10:      $L_b^{t+1} = Crossover(L_b, l_b^i, m_b)$;
11:     **end for**
12:     **if** $OPT - C(\{L_b^{t+1}, L_e^{t+1}\}) \leq OPT - C(\{L_b^t, l_e^t\})$ **then**
13:       $L_e = L_e^{t+1}; L_b = L_b^{t+1}$;
14:       **if** $OPT - C(\{L_e, L_b\}) \leq OPT - C(\Delta)$ **then**
15:         $\Delta = \{L_b, L_e\}$;
16:       **end if**
17:     **else**
18:       $L_e = L_e; L_b = L_b$;
19:     **end if**
20:     $k = k + 1$;
21:   **end for**
22: **end while**
23: return $L = \{L_b, L_e\}$;

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**TABLE 1.** Simulation parameters.

| Parameter | Value |
|---|---|
| $\rho$ | 1 |
| $\phi$ | 0.01 |
| Safety Distance | 100m |
| Minimum service radius of BS and EH-RSU | 50m |
| Maximum service radius of EH-RSU | 250m |
| Maximum service radius of BS | 500m |

Different colors correspond to different network loads. As the color gradient increases, the network load increases, which means communication times increase. The closer the color to yellow is, the greater the communication load increases. It means that the current area is a heavy traffic area.

To further illustrate the network load on each cell varies greatly, a number of cells is randomly selected to describe the load variation at the same time. In Fig. 6, seven cells are selected randomly to show the load variations.

Here, the cells circled in the red are middle cells, which are on the traffic artery and communicate heavily. The cells circled in the yellow are common cells, of which traffic is relatively small and just called cells. Cell 2 and Cell 7 are
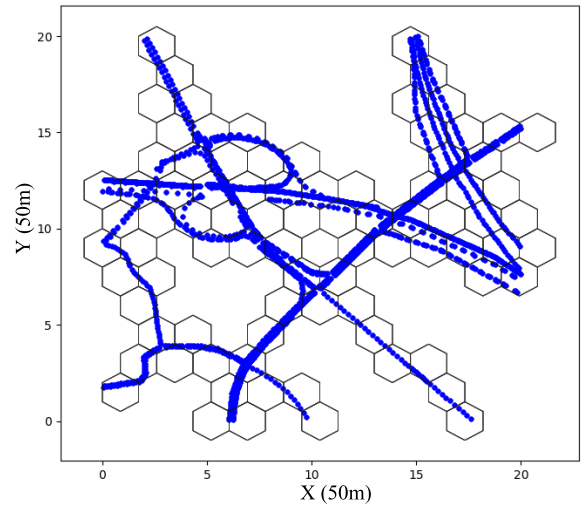


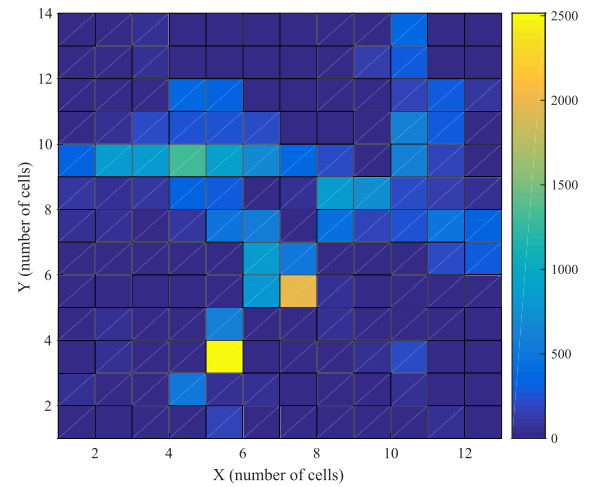**FIGURE 4.** Map of Cells (The blue points are vehicles in VANETs.



**FIGURE 5.** Map of Network Load in Cells (The color of every cell indicates network load).
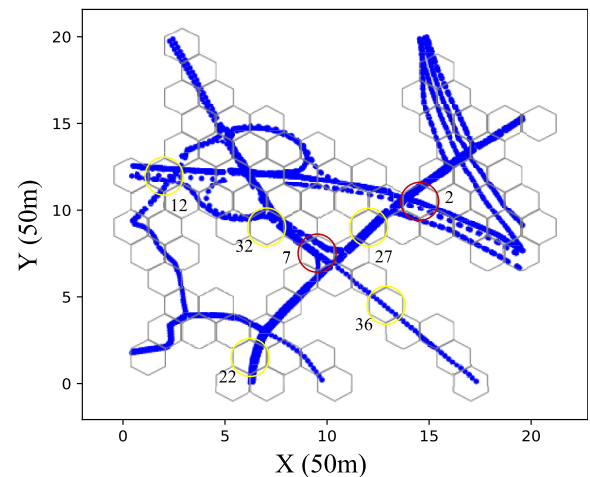


**FIGURE 6.** Randomly Sample Cells.

middle cells, they have a high communication load in a certain period of time. For other cells, because of the small

number of driving vehicles, the communication load is lower. In addition to this, for the same cell, the network load usually varies dramatically at different times. The results are shown in Fig. 7. Therefore, it is indispensable to use EH-RSUs in this situation, which can effectively regulate the use of resources.
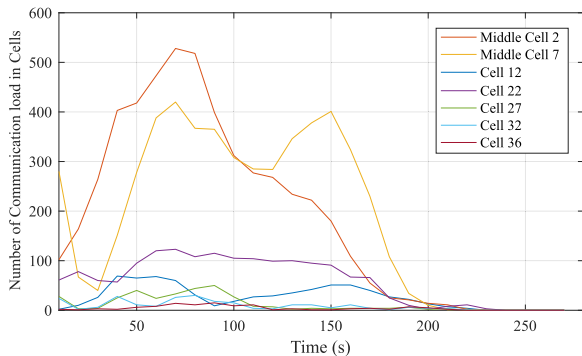


**FIGURE 7.** Dynamic Change Curves of Network Load in Sample Cells.

According to [28], we use three parallel $4 - 4.0 - 100$ solar panels with rated open circuit voltage of 5.0 V and short circuit current of 100 mA. The maximum power point of the panel is 3.0 V and varies slightly depending on the time of day shown in Fig. 8.
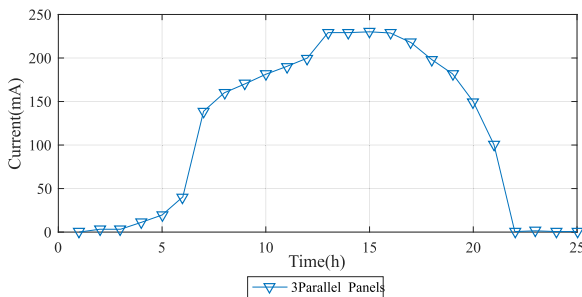


**FIGURE 8.** Characteristics of the $4 - 4.0 - 100$ solar panel.

On the basis of the change of traffic flow in a day, the most frequent communication periods are mainly concentrated on from 8:00am to 10:00am and from 16:00pm to 20:00pm. For the rest of the day, the solar panels are charged to store electric energy. Therefore, the EH-RSUs power consumption can be satisfied by fitting solar panels with appropriate size. By the analysis of the load in Fig. 5, we can find that the heavier load communication is mainly concentrated on a few cells, while the rest cells have no busy communication process. Combined with Fig. 8, we select the moment with a high load, while the charging speed stays largely the same in a corresponding time period. Thus, we assume that the average charging rate of each EH-RSU is 1% in the simulation.

To solve the optimization problem OPT-C by using the proposed DE algorithm, we set different BSs and EH-RSUs deployment cost in each solving process. Here, the ratio of a single BS to EH-RSU, $\frac{D_B}{D_E}$, is used to represent different deployment cost. As a comparison, the other three
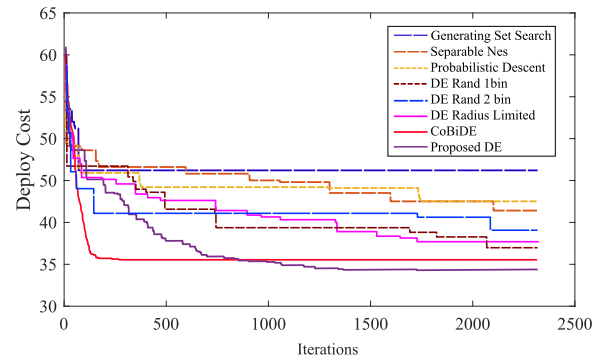
heuristic algorithms, Generating Set Search (GSS), Separable Nes [38] and Probabilistic Descent(PD) are applied to solve the optimization problem OPT-C. Meanwhile, some typical Differential Evolution methods, DE/rand/1/bin [39], DE/rand/2/bin [40], DE/rand/1/Radius Limited [41] and CoBiDE [42], are be adopted to compare the convergence performance and solving ability with the proposed algorithm. In Fig. 9, the results are shown as follows. 1) The differential evolution algorithms are superior to other evolutionary algorithms in solving the optimization problem OPT-C. 2) In the applied differential evolution algorithms, the proposed DE algorithm is better than others in terms of solving for the optimal solution. 3) Although the convergence speed of the proposed DE algorithm is a little slower than CoBiDE, the solution obtained is better than that of CoBiDE within an acceptable time range.
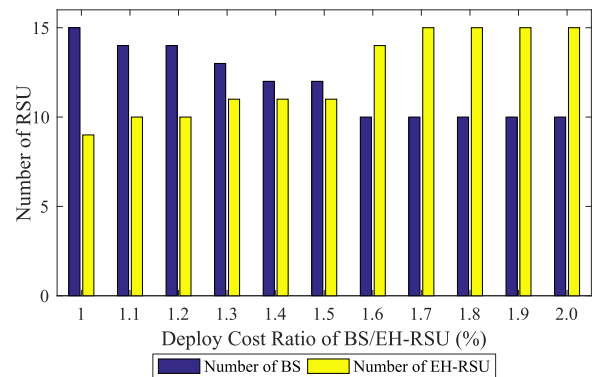


**FIGURE 9.** Convergence speed of different algorithms.



**FIGURE 10.** Number of EH-RSUs and BSs Compared with Deploy Cost Ratio.

According to different settings of deployment cost, the number change of BSs and EH-RSUs is shown in Fig. 10. When deployment cost is the same, $\frac{D_B}{D_E} = 1$, there are 15 BSs and 9 EH-RSUs deployed to provide service for the whole network communication. With the increase of deployment cost ratio, namely the BSs deployment cost increase, they are replaced by EH-RSUs, which have high flexibility and adjustable radius. However, when the ratio falls to a certain degree, the number of BSs and EH-RSUs no longer changes. This is due to some high load areas, the BSs must be used

to provide service for communication in some cells, which cannot be replaced.

Power consumption is also a major problem in this paper. With the cost of power increases, BSs are decreasing in proportion to deployment. Similar to Fig. 10, BSs are irreplaceable in some cells. Thus, when the ratio of BS to EH-RSU deployment drops to a certain extent, it tends to stabilize as shown in Fig. 11.
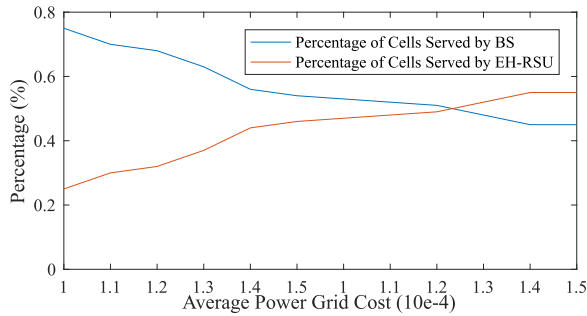
**FIGURE 11.** Percentage of Served Cells of EH-RSUs and BSs.

In Fig. 12, we discuss the deployment cost in two case: one is only the deployment of BSs, which means there is no EH-RSUs; the other is that BSs are deployed at the same time with EH-RSUs. For the sake of description, we standardize the different costs to dimensionless number. These data are added together as a sum of costs in different ratios of BS to EH-RSU, and then compared with others. In addition to this, to ensure the universal X-axis data, we standardize the cost of one EH-RSU is 1 in every ratio case. Then, the ratios of BS to EH-RSU and the cost of one BS can use the same dimensionless number to represent.
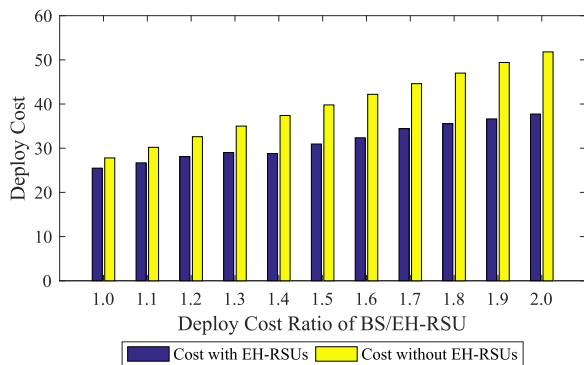
**FIGURE 12.** Cost of EH-RSUs Deployed Compared with No EH-RSUs.

In case one (Cost without EH-RSUs), as the costs of BS increases, the deployment cost increases significantly. In case two (Cost with EH-RSUs), with the increase of $\frac{D_B}{D_E}$, the deployment cost also increases. Compared with no EH-RSUs deployed, the cost with EH-RSUs is much less. Although BSs have larger radius of coverage and longer service times, the deployment cost and power-grid cost also have an impact on overall cost. The results show that the combination deployment of BSs and EH-RSUs outperforms

the deployment of only BSs. Taking into account the operating costs, when the number of BSs decreases, the operating cost decreases as well. As the sum of deployment cost and operating cost, the overall cost of BSs would fall down while BSs and EH-RSUs are deployed simultaneously.
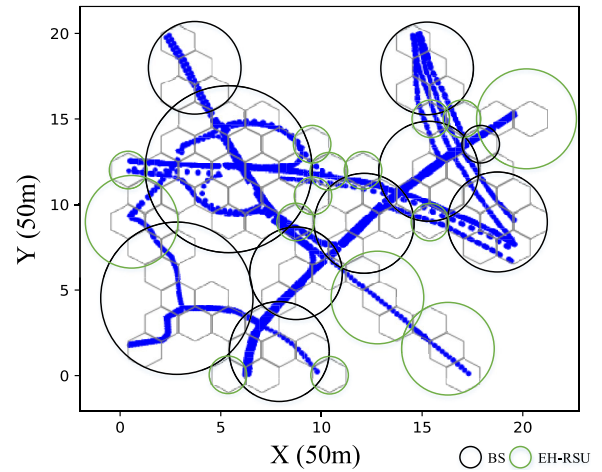
**FIGURE 13.** Deployment Policy for Simulation.

Analyzing all these reasons, the deployment with 10 BSs and 15 EH-RSUs is selected as the solution to achieve communication service in this situation as shown in Fig. 13, which is satisfied with the minimum overall cost. Since the deployment of devices is based on cell model, there are some overlapping areas in VANETs. So, the size of cells should be adjusted according to the actual device service capability for practical application.

## VI. CONCLUSION

In this paper, we develop an analytical deployment framework for deploying BSs and EH-RSUs in VANETs, which consists of two models: service capabilities model and energy consumption model. In these models, the network load, charging speed and battery capacity of EH-RSUs are considered to meet communication requirements in every cells. Combined with these model, an optimization problem is proposed to minimize deployment and operation cost. Because this is a MINLP, we design a limited conditions DE algorithm to solve the optimization problem. The real mobility trace data of a German city, Cologne, as an experimental data to evaluate our method. The simulation results show that by using EH-RSUs could reduce the deployment and operation cost while satisfying the communication requirements of VANETs. Our future research intends to introduce a prediction model, such as long short term memory [43], to achieve dynamic service radius of EH-RSUs in real time to further increase network communication flexibility and improve network overhead.

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**FAN YANG** (Student Member, IEEE) received the B.S. degree in computer science and technology and the M.S. degree in computer application technology from the School of Computers and Information, Hefei University of Technology, Hefei, China, in 2010 and 2013, respectively, where she is currently pursuing the Ph.D. degree with the School of Computer and Information. Her current research interests include reliable communication of VANETs and neural networks.

**XU DING** (Member, IEEE) was born in 1984. He received the B.S. and Ph.D. degrees from the School of Computer and Information, Hefei University of Technology, in 2006 and 2015, respectively. He is currently an Associate Research Fellow with the Institute of Industry and Equipment Technology, Hefei University of Technology. His research interests include wireless communications and wireless sensor networks.
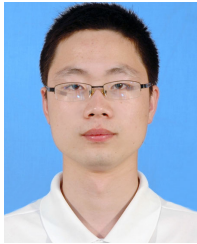
**CHONG ZHAO** (Member, IEEE) received the B.S. degree in mechatronics from the School of Mechanical Engineering, Hefei University of Technology, Hefei, China, in 2011, and the M.S. degree in computer application technology from the School of Computer and Information, Hefei University of Technology, in 2014, where he is currently pursuing the Ph.D. degree. His current research interests include reliable communication of VANETs and neural networks.

**JIANGHONG HAN** received the B.S. and M.S. degrees from the Hefei University of Technology, China, in 1982 and 1987, respectively. He is currently a Professor and a Research Lab Leader with the School of Computer and Information, Hefei University of Technology. His research interests include computer networks, wireless sensor networks, discrete-time control systems, embedded systems, and smart homes.

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