A Stochastic Optimization Model for the Placement of Road Site Units

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Abstract. In this paper, we propose a simple and scalable optimization model for the deployment of road site units (RSUs). The model takes advantage of the inherent stochasticity provided by the vehicles' movements by using mobility traces to determine which are the best positions to place RSUs to maximize connectivity in a multi-hop VANET scenario and keep the number of RSU as low as possible. Our simulations results validate that the solutions offered by our model are accurate.

Keywords: Stochastic optimization · Vehicular ad-hoc networks (VANETs) · Road site unit (RSU) · RSU deployment

1 Introduction

One of the characteristics that make the study of vehicular ad-hoc networks (VANETs) challenging is the stochasticity introduced by the mobility of the vehicles. In this work, we propose a stochastic optimization model (SOM) [1] for the optimal placement of Road Side Units (RSU) over a geographical area. The aim of our mixed integer linear model is to choose the minimum number of RSU to be deployed in a specific area such that moving vehicles can reach some fixed infrastructure point in a multi-hop fashion regardless their position. To do that, our model does not rely in any deterministic (particular) vehicle distribution to compute the connectivity information between vehicles and RSUs. Instead, our model considers a representative set of different positions of vehicles that can be extracted from real vehicle movements traces as [7], which are more trustful and are becoming more popular among the research community to test their proposals. Therefore, our model provides a solution that is the best for the whole set of movements. Taking uncertainty into account by means of different vehicles positions to compute the connectivity information, gives a solution to the model that is more reliable than only using a deterministic connectivity matrix.

The rest of the paper is organized as follows: Sect. 2 explains the proposed model in detail. Then, the process to obtain the multi-hop connectivity information is described in Sect. 3. After that, Sect. 4 presents results obtained with

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a solution provided by our model in a realistic scenario. Finally, conclusions and future work are drawn in Sect. 5

2 The Problem Formulation

We propose a two-stages stochastic optimization model with recourse [1] to deploy in an optimal way the RSUs over an area. In our problem, the first stage is represented by the subset of RSU that has to be selected prior to know the distribution of vehicles in the area. On the other hand, the best association between vehicles and the chosen RSUs is done in the second stage after the distribution of vehicles is known (when the stochasticity is disclosed). The results of our model are based on the multi-hop connectivity information. In addition, the model considers an approximation of the effective capacity of the wireless channel due to the multi-hop transmission and takes into account the maximum demand that an RSU can serve.

2.1 Parameters of the Model

Our proposal uses connectivity information between vehicles and RSU as input parameter. Let R be the set of candidate RSUs among which our model chooses the most valuable to maximize the packet delivery ratio from vehicles to the RSU deployed. The set R includes an RSU named r_∞ to which every node can connect. If in the solution of the model a vehicle connects to this RSU, it means that this vehicle is disconnected. The use of this artificial RSU simplifies the model. Each RSU $r \in R$ has associated a traffic load capacity C_r and an installation cost $Cost_r$ in the sets C and $Cost$, respectively.

As we anticipated, the model uses a set of observations of vehicles' positions S in order to consider the randomness of this factor. Each observation $s \in S$ is a snapshot of vehicles located at different positions obtained from movement traces. Let V be the set of vehicles considered in the model. In particular V_s is the subset of vehicles which appear in the scenario s. Each vehicle $v \in V_s$ has associated average traffic load $L_{s,v}$. This data set is useful to test different traffic loads among nodes, for instance, the fleet of buses in the city. H represents the set of path lengths allowed by the model to connect nodes with an RSU. In the model, the maximum route length is denoted by $h_{\max} = |H|$, that is the path length from all the vehicles to the artificial RSU. No other RSU is connected to a vehicle by a path of length $h_{\max}$. Related to the set H is the set P, that are the penalty factors since it uses different path lengths. In this work, these factors are the mean numbers of times that a message should be sent to get one successful reception as a function of the number of hops, according to the results obtained in [8]. $P_{h_{\max}}$ is big enough to penalize the fact that a vehicle is not connected to a real RSU.

CVR is the set of tuples $\langle s, h, v, r\rangle$ that provides the information about the connectivity between vehicles V and the set of candidate RSU R. The presence of the tuple $\langle s, h, v, r\rangle$ in the set CVR means that vehicle v can reach RSU r in the scenario s through h hops. Notice that $\langle s, h_{\max}, v, r_\infty\rangle$ for all $v \in V_s$

are always present in the set because we consider that all nodes can reach the artificial RSU.

2.2 Variables of the Model

Our model uses the following variables to determine which gateways should be selected. S is a boolean variable that indicates if an RSU $r \in R$ is chosen for the solution ($S_r = 1$) of the model. The set S is the first stage decision variables in the structure of our stochastic problem.

Rts is a set of variables in the $[0, 1]$ domain that associates a portion of the traffic load of a vehicle to an RSU with which it has connectivity. For instance, $Rts_{s,h,v,r} = 0.8$ indicates that the 80 % of the traffic load that belongs to vehicle v can be received by RSU r through a route of h hops in the scenario s. Consequently, Rts plays the role of second-stage variables in the stochastic problem, which are decided for each scenario and after that the RSU has been selected.

2.3 The Stochastic Model

The goal of the proposed model is to select the minimum number of RSUs to maximize the multi-hop connectivity between nodes and fixed infrastructure points. The objective function is shown in Eq. (1). The first term of the objective function adds the installation costs of the chosen RSUs, so the model will try to use the minimum number of them. On the other hand, the second term adds the whole traffic generated in the network. The model tries to connect vehicles with RSUs by employing short paths because we are imposing increasing penalty factors as a function of path lengths. Hence, the solution of the model will select RSUs easily reachable from a high number of nodes using the minimum number of hops in the different scenarios. It is worth to mention that if the penalty factor for disconnected ($P_{h_{max}}$) nodes is greater than the maximum installation cost of a gateway, then the model will not leave disconnected nodes to avoid activating RSUs. Moreover, if the specific interest of user's model is to detect the best positions to install the RSUs, regardless the installation cost, then this value must be the same for the whole set of candidate RSUs.

$$\min_{S,Rts} \quad \sum_{r \in R} S_r Cost_r + \sum_{\langle s,h,v,r \rangle \in CVR} Rts_{s,h,v,r} P_h L_{s,v} \tag{1}$$

$$\text{s.t.} \quad \sum_{\substack{h \in H, r \in R: \\ \langle s,h,v,r \rangle \in CVR}} Rts_{s,h,v,r} = 1, \qquad \forall v \in V_s, s \in S \tag{2}$$

$$Rts_{s,h,v,r} \leq S_r, \qquad \langle s,h,v,r \rangle \in CVR \tag{3}$$

$$\sum_{\substack{v \in V, h \in H: \\ \langle s,h,v,r \rangle \in CVR}} Rts_{s,h,v,r} P_h L_{s,v} \leq C_r, \qquad \forall s \in S, \forall r \in R \backslash \{r_\infty\} \tag{4}$$

$$\sum_{r \in R \backslash \{r_\infty\}} S_r \leq \text{Max}_R \tag{5}$$

Constraints from Eqs. (2) to (5) guarantee a proper solution of the problem. The first condition in Eq. (2) states that the traffic load of every vehicle v of the scenarios in S has to be served by some subset of candidate RSUs reachable from the vehicle through multi-hop routing. Notice that in this subset the artificial RSU r_∞ can be included, which is reachable for all vehicles at the maximum number of hops $h_{\max}$. In this case, only the portion of the traffic served by r_∞ will be highly penalized. Also, notice that any $Rts_{s,h,v,r} = 1$ means that the whole traffic of v can be served by a unique RSU r, and this is the closest solution to the real behavior of a VANET, in which balance of traffic loads (fractional values of $Rts_{s,h,v,r}$) is unlikely. The constraint of Eq. (3) is related to the previous constraint and it basically establishes that if a portion of the traffic load of vehicle v is served by the RSU r (i.e., $Rts_{s,h,v,r} > 0$) then the RSU r must be included in the solution $S_r = 1$. This is the condition that forces the model to activate RSUs in the solution and search from the best ones. Best RSUs are those that can receive as much traffic load as possible.

An important constraint of the proposed model provided the realism that it adds to the solution, is written in Eq. (4). This condition imposes that the maximum capacity load of each candidate RSU $r \in R$ can serve, will not be exceeded by the connected vehicles to them. This constraint does not apply to the artificial RSU used by the unserved traffic loads. The last restriction, Eq. (5) sets the maximum number of RSUs (Max_R) that the solution can have. If such limitation is not at stake, it can be removed of the model.

3 Connectivity Information

In this section, we describe how to obtain the input information about multi-hop connectivity through the boolean matrix multiplication of the adjacency matrix among vehicles A_s and the adjacency matrix between vehicles and candidate RSU notated as B_s. Theses matrices represent the connectivity at 1 hop in the network. A non-zero position in this kind of matrices represents that the nodes involved can communicate between them. In particular B_s stores the information on which vehicles can communicate with RSUs directly. The same information for h hops, called $B_{s,h}$, is computed as follows:

$$B_{s,h} = A_s^{h-1} B_s \tag{6}$$

Notice that, $B_{s,h}$ contains information about vehicles that can connect to RSUs using from 1 to h hops. $B_{s,h}$ is the most expensive step in the process with a complexity of $O(n^3 + n^2 m)$ for each hop in each of the scenario, where n is the number of vehicles and m the number of RSUs. The connectivity matrix $C_{s,h}$, which tells us which are the vehicles that are been connected to a RSU using h hops, is obtained as:

$$C_{s,h} = B_{s,h} - B_{s,h-1} \tag{7}$$

Therefore, the position $C_{s,h,v,r}$ of this matrix, which indicates if the vehicle v can reach RSU r will be 1 only the first time that it can communicate with that

RSU and 0 otherwise. The set of tuples of the CVR parameter are constructed from the non-zero positions of $C_{s,h}$ matrices. Notice that $C_{s,1} = B_s$ for each scenario $s \in S$.

4 Results of the Model

We use a synthetic movement trace to determinate which is the best position to locate one RSU among the five candidate positions shown in Fig. 1 within an urban area of Barcelona. Once the model provides a solution, we remove the chosen RSU's position and solve the model again with the remaining set of candidate RSUs until this set is empty. The optimization solver that we use is CPLEX [4]. To test how well the solutions of our model behave, we compare them to simulation results from ten simulations for each one of the candidate RSUs. We use Estinet [2] and C4R [3] to perform this task. The settings of the model and the simulations are depicted in Table 1.

The locations suggested by our stochastic model to install one RSU among the candidate set depicted in Fig. 1 in decreasing order are: *RSU 1, RSU 5,* ***RSU 2***, ***RSU 4***, *RSU 3.* In fact, our model gives a draw between RSU 2 and RSU 4 (the value of the objective function is the same activating these RSUs). However, the best order revealed by the simulation results showed in Fig. 2 is *RSU 1, RSU 5, RSU 2, RSU 4, RSU 3.* The real order is clearly manifest in both vehicle densities if we look at the performance of the packet delivery ratio (PDR) in Fig. 2a and the average delay in Fig. 2b. On the other hand, the performance difference in the average number of hops, in which our model relies, is not so clear, especially between the results provided by RSU 2 and RSU 4.

The results presented in this section validate the reliability of the solutions of our stochastic model to detect the most suitable locations to install RSUs in a city. Additionally, the results show that badly chosen positions could lead to a very poor PDR and high delays.

Table 1. Simulation settings.

Parameter	Value
Area	1.5 km × 1 km
N° of nodes/RSUs	100 and 150/5
N° hops in model	5 Hops
Simulation time	300 s
N° scenarios in model	20 scn, every 15 s
Transmission range	∼400 m (LOS)
Mobility generator	C4R [3]
MAC specification	IEEE 802.11p
Bandwidth	6 Mbps
Packet generation time	$T \sim$ U(2,6) s E(T) = 4 s
Packet size	1000 bytes
Routing protocol	MMMR [6]

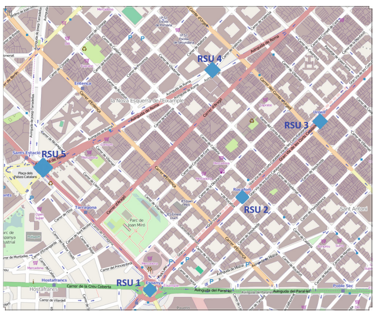
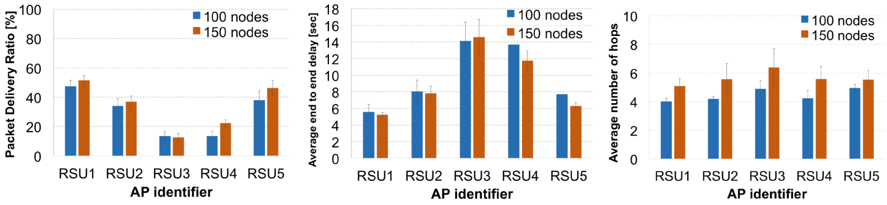


Fig. 1. Considered scenario. Barcelona from OpenStreetMap. 5 candidate *RSUs.*



(a) Packet Delivery Ratio (PDR) (b) Average end-to-end packet delay. (c) Average number of hops.

Fig. 2. Performance metrics results.

5 Conclusions and Future Work

In this paper, we have presented a stochastic optimization model for the optimal placement of Road Site Units. The proposed model is fed by the multi-hop connectivity information provided by different vehicles distribution, which can be obtained from different realistic movement traces. Our tests suggest that our model detects correctly the most important positions to locate RSUs.

Our model could be used as a second stage in the deployment process of RSUs to select the most important RSU to be installed in the geographical area. A first step is to select the candidate positions of the gateways to cover the area.

Our model can be solved for large-scale data sets, which in turns means big geographical areas through the Benders decomposition method [5]. Future work includes the formulation and solution of our stochastic model using this well-known optimization technique and employs real vehicle movement traces.

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