An Optimized Road-Side Units Distribution Approach for Safe Transport in Vehicular Networks

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Abstract
Road-Side Units (RSUs) are used in vehicular network to enhance connectivity. Due to RSU device and installation costs, a trade-off must be found with other objectives such as connectivity, road safety, etc. In this paper, we propose an extension of the Optimal Road-Side Units Deployment (ORSD) approach. We develop a Pareto-dominance based heuristic to find optimal RSUs placement with minimal deployment cost and maximal connectivity and accident coverage. The proposed algorithm find first RSUs candidate locations based on network density and connectivity probability then apply PGA for Pareto-dominance Genetic Algorithm to find the best solution of our multi-objective problem. The use of a meta-heuristic is justified by the difficulty of the RSU deployment problem classified as NP-complete. For experimentations we use the Simulator of Urban MObility (SUMO) for generating different traffic scenarios. We show that our Pareto-dominance meta-heuristic lead to high quality solutions with best compromise between connectivity, RSU cost and accident cover.

Keywords: *Vehicular network, Road-Side unit, Genetic algorithm, Pareto-dominance*

1. Introduction

VANETs for vehicular ad-hoc networks are widely used in intelligent transportation systems and consist of using smart vehicles which move in a dynamic topology. The establishment of stable routes is a challenge particularly in a Vehicle-to-Vehicle (VtoV) communication. It is why, wireless access points called Road-Side Units (RSUs) are used to enhance connectivity in a Vehicle-to-Infrastructure (VtoI) communication [1].

One of the important applications of VANETs is road safety which has become a priority in most developed countries [2]. This priority is motivated by the increasing number of accidents on roads associated with a growing fleet of vehicles. The objective is therefore to improve travel safety and deal with road accidents.

The main goal of this work is to provide an optimized RSUs position to enhance network connectivity and coverage accident area. In this paper, we propose an extension of ORSD approach recently introduced in [3]. ORSD is an Optimal Road-Side Units Deployment solution that improves the accident coverage in route sections with low connectivity. ORSD find first candidate locations of RSUs based on topology real data (arrival rate of vehicles, density and speed) then uses a heuristic approach to find optimal RSU locations. A multi-objective function is used to maximize both network connectivity and accident area while minimizing the deployment cost. The algorithm developed in this work called PGA for Pareto-dominance Genetic Algorithm is based on Pareto-dominance principle to find the best compromise between the three objectives of ORSD, and use genetic algorithm to explore in a smart way the wide solution space.

The rest of the paper is organized as follows. Section 2 presents recent related works on Road-Side Units deployment. A detailed mathematical model is given in section 3 followed in section 4 by the description of our Pareto-dominance based algorithm. Finally, section 5 presents experimentation results based on various simulations before concluding in section 6.

2. Related works

The optimized deployment of Road-Side Units in vehicular ad-hoc networks is a relevant issue and numerous works have been developed. These works differ in several aspects, including the optimization techniques used, the location of candidate RSU positions (at intersections or along road sections), the traffic scenario (urban, highway, or both) as well as the objectives to be optimized.

The optimization techniques used are essentially metaheuristics such as Genetic Algorithm (GA) [4, 5, 6], Balloon Expansion Heuristic (BEH) [7], or recently Grey Wolf Optimization (GWO) [3]. The authors in [4, 5, 7] consider road intersections as potential places to install RSUs, but other studies [8, 9, 10] have shown that putting RSUs in intersections does not improve the connectivity and propose to distribute the RSUs along the route, equidistantly.

Regarding the objective(s) to be optimized, the authors in [4, 8] consider the optimization of the connectivity and the delay and transmission of messages in the case of urban scenarios. In [11] the objective is to improve the collection and delivery of data on highway. The authors in [5] take into consideration both urban and highway scenarios in order to minimize the transmission delay of safety messages based on information of traffic as speed and density. In a landmark contribution, the authors in [3] consider a multi-objective problem: connectivity, RSU cost and accident coverage, in a new approach called ORSD for Optimal Road-Side Units Deployment in both urban and highway scenarios and use V2I and V2V (V2X) communications to reduce unnecessary infrastructures.

We propose to extend this approach by overcoming its main drawback which is the difficulty to obtain a compromise between the objectives by using a metaheuristic approach based on Pareto-dominance.

3. System model

We consider a set of road segments in the studied area $S = \{S_1, S_2, \ldots, S_n\}$ where each segment S_i is characterized by density D_i , speed v_i and number of accidents AC_i. Each segment has a length L at least equal to $2 \times r$ where r represents the radio range of vehicles. Also, Pz represents the population size (number of vehicles) in the studied area. Let $CP = \{1, \ldots, m\}$ be the set of candidate positions to install RSUs. We summarized in table 1 the notations used in our model.

Table 1. Model Notations

Designation	Notation
Segment i	S_i
Density in segment i	D_i
Speed in segment i	v_i
Number of accidents in segment i	AC_i
Segment length	L
Radio range of vehicles	r
Population size	Pz
Decision variable to open or not RSU in candidate position j	y_j
RSU deployment cost in candidate position j	c_j
Number of RSU candidate positions	m
Number of road segments	n
Maximum number of RSUs that are authorized by planners	NRSU

The aim of our work is to find the best RSU locations in urban and highway scenarios. The challenge consists to ensure maximum accidents coverage in segments with low connectivity. In fact, our objective is to find the best RSUs placement and to enhance the connectivity of the system while minimizing the number of RSUs and therefore the deployment cost.

We model our problem by a multi-objective function. We use equations (1) to (5) to represent our problem modelling. Equations (1) to (3) represent the objective function components F_1, F_2, F_3:

F_1 represents the system connectivity.

$$F_1 = \max \frac{1}{m} \sum_{j=1}^{m} p_j y_j \qquad (1)$$

where p_j is the connectivity probability in segment containing candidate position j. If $y_j = 1$, the corresponding connectivity probability is set to 1. Computing connectivity probability will be detailed in section 4.1.

F_2 represents the accidents coverage.

$$F_2 = \max \sum_{j=1}^{m} AC_j y_j \qquad (2)$$

and F_3 represents the deployment cost.

$$F_3 = \min \sum_{j=1}^{m} c_j y_j \qquad (3)$$

The solution feasibility must respect the constraints given by:

$$\sum_{j=1}^{m} y_j \leq NRSU \qquad (4)$$

$$y_j \in \{0,1\} \quad \forall j = 1, \dots, m \qquad (5)$$

We can either consider each objective separately and use Pareto-dominance to eliminate dominated solutions, or combine the objective functions into one, considered as a fitness function of a metaheuristic as represented in equation (6):

$$F = \max\left(\hat{F}_1 + \hat{F}_2\right) / \hat{F}_3 \qquad (6)$$

F is a global objective function composed of the three sub-functions, where $\hat{F}_1$, $\hat{F}_2$ and $\hat{F}_3$ are the normalized values of objective functions F_1, F_2, F_3 respectively.

4. ORSD approach and Pareto-dominance optimization

In our work, the objective is to find the optimal positions of RSUs. To do that, we propose two processing steps as depicted in figure 1 [3]. In the first step, we calculate the connectivity probability p_i of each segment. The second step permit to find best solutions. We make use of a meta-heuristic due to NP-completeness of RSU placement problem. Indeed an exhaustive solution algorithm is of $O(2^m)$ complexity.

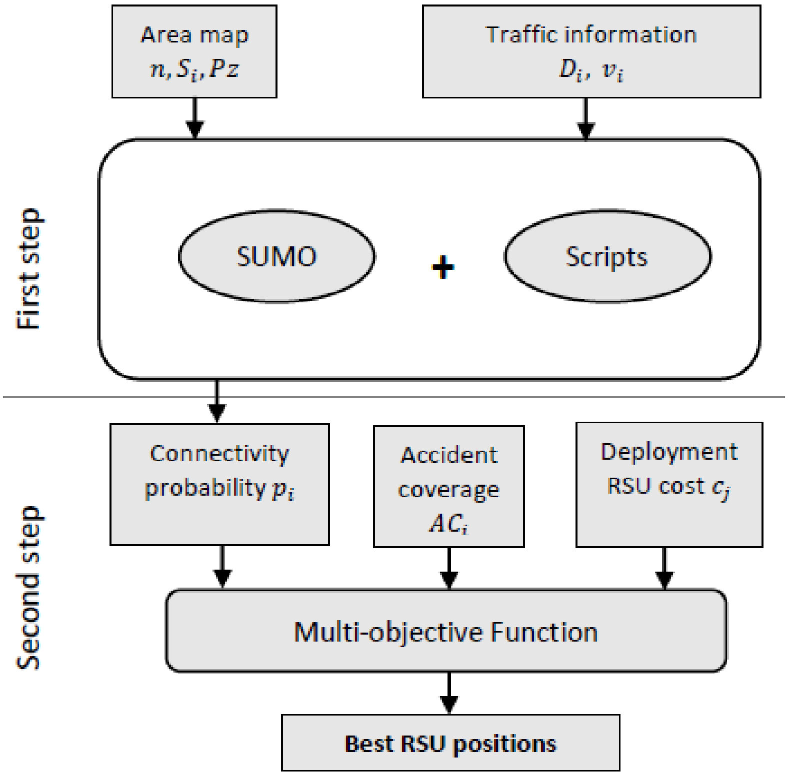

Figure 1. ORSD General Framework

4.1. Calculation of connectivity probability

To apply ORSD, we need to calculate the connectivity probability p_i used in equation (1). p_i is the probability that there is a sequence of connected nodes in the road segment. So, we use the Simulation of Urban Mobility (SUMO) [12] for extracting information about density and speed in each segment to calculate vehicle arrival rate named λ_i according to equation (7). Vehicle arrivals can locally be seen as a Poisson process of intensity D_i.

$$\lambda_i = \frac{2D_i}{\overline{v_i}} \tag{7}$$

where $\overline{v_i}$ represents the average speed in segment i and the factor 2 due to the number of lanes in the segment. So we can compute connectivity probability from theorem 1 in [13].

$$p_i = \sum_{j=0}^{\left[\frac{L}{r}\right]} \frac{\left(-\lambda_i e^{-\lambda_i r}(L-jr)\right)^j}{j!} - e^{-\lambda_i r} \sum_{j=0}^{\left[\frac{L}{r}\right]-1} \frac{\left(-\lambda_i e^{-\lambda_i r}(L-(j+1)r)\right)^j}{j!} \tag{8}$$

p_i represents the connectivity probability of segment i and is simply equal to 1 if every pair of vehicle in segment i are connected. We assume that segment length L is greater than $2r$, otherwise the connectivity probability is obviously equal to 1. Thus we can define system connectivity probability as follows:

$$PS = \frac{1}{n}\sum_{i=1}^{n} p_i \tag{9}$$

4.2. Pareto-dominance optimization

To explain the different steps of our algorithm, we use a scenario of 12 segments and 9 intersections using SUMO (figure 2).

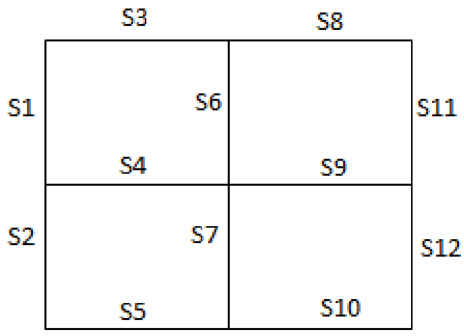

Figure 2. Scenario with 12 Segments and 9 Intersections

4.2.1. Selection of RSUs candidate positions based on connectivity probability: First, we choose the candidate positions based on information of connectivity probability. After computing connectivity probability p_i of each segment using equations (7) and (8), we set a threshold T from which a position is candidate for the installation of an RSU, that is if $p_i \leq threshold$ then $CP = CP \cup \{S_i\}$. Figure 3 shows the values obtained for each segment such as $p_1 = 0.2885$, $p_2 = 0.1035$, $p_3 = 0.3795$, $p_4 = 0.4917$, $p_5 = 0.2301$, $p_6 = 0.4829$, $p_7 = 0.4723$, $p_8 = 0.2949$, $p_9 = 0.4906$, $p_{10} = 0.1123$, $p_{11} = 0.1944$ and $p_{12} = 0.1626$. So the system connectivity probability is $PS = 0.3086$. Then we set the threshold of connectivity probability to determine the candidate positions.

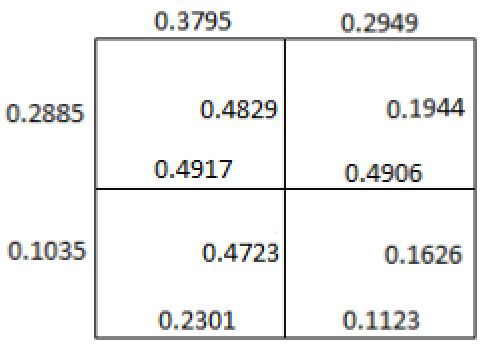

Figure 3. Connectivity Probability of each Segment

If we set the threshold to 0.20, there are four candidate positions to deploy RSUs as depicted in figure 4 (red points represent candidate positions). So, the result is the set of candidate positions CP of cardinality m. If we install RSUs on all candidate positions the system connectivity probability becomes $PS = 0.5942$ because connectivity probability on segments containing an RSU is 1.

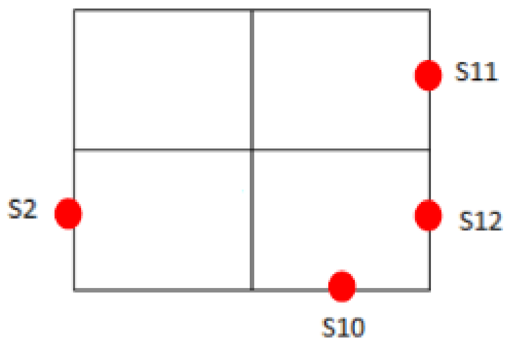

Figure 4. RSU Candidate Positions

Of course, it is not always possible to install RSUs in all candidate positions due to constraint (4) which represents the maximum number of RSUs that are authorized by planners. Also, if we increase the threshold, the system connectivity probability should increase. In our example, if we set the threshold to 0.4, still considering that RSUs are installed in all candidate positions, the system connectivity PS becomes 0.8281.

4.2.2. Finding best RSUs position by Pareto-dominance based meta-heuristic: The combination of the three objectives (Connectivity, Accident Cover and RSU Cost) in a single model could inhibit interesting solutions (those with a better compromise from the manager point of view). It's why we propose to consider the three objectives separately. We apply a population-based heuristic where Pareto dominated solutions are discarded. The proposed algorithm called PGA for Pareto-dominance Genetic Algorithm is described by addressing the main components of the algorithm: Chromosome structure, Pareto-dominance and Genetic algorithm operators.

Chromosome representation. A chromosome is simply a solution of our problem. It's represented by a binary vector Y where y_j represents decision variable to open or not RSU in candidate position j. The initial population of solutions is randomly generated in such a way that all solutions are feasible; that is $\sum_{j=1}^{m} y_j \leq NRSU$. We evaluate each chromosome of the population by the tuple (Connectivity, Accident Cover, RSU Cost). In the previous example, the following feasible chromosome $\mathfrak{s}$ can be generated randomly (figure 5).

Candidate positions

S2	S10	S11	S12
1	**0**	**1**	**0**

Figure 5. Example of a Chromosome

If we consider for the evaluation of chromosomes, the data given in table 2 (Accident cover and RSU costs) including connectivity probabilities and threshold T used previously, the corresponding value of chromosome $\mathfrak{s}$ is given by the tuple (0.4504, 110, 60).

Table 2. Example of Data Used in Chromosome Evaluation

Candidate Position	S2	S10	S11	S12
Accident Cover	45	105	65	85
RSU Cost	35	70	30	50

Pareto-Dominance. An important aspect of the solution process is that throughout application of Genetic Algorithm, some solutions can be discarded. One reason to discard a solution is that it violates maximal number of RSUs (NRSU) constraint. Another relevant reason to discard a solution candidate is that it is not better than some other candidate. For example, the random solution depicted previously $\mathfrak{s}$(0.4504, 110, 60) dominates another random solution evaluated by (0.3826, 105, 70), because it has an equal or higher connectivity probability and accident cover values combined with same or lower RSU cost value compared to dominated solution. Such dominated solutions are not of interest. Removing dominated elements from a set is referred to as Pareto minimization [14]. The result of Pareto minimization is the set of so-called Pareto points, i.e., the points (solutions, in our case) that are not dominated by any of the other solutions in the population. Finally, a set of feasible non dominated solution candidates is obtained.

***Genetic Algorithm*.** The Pareto-dominance is used for the design of an efficient GA-heuristic since exact solution cannot be practical. The number of solutions grows exponentially even with eliminating dominated and infeasible solutions. Furthermore, the amount of dominated and infeasible solutions remains relatively low to envisage any exact solution to our problem. The parameters that we have to configure for Genetic Algorithm are:

- Maximum population size
- Fitness function
- Selection operator
- Cross-over operator
- Mutation operator

The Genetic Algorithm starts with a randomly-generated population, then infeasible and dominated solutions are discarded. At each iteration, cross-over and mutation operators are applied to build new populations. We choose to keep all non-dominated solutions of previous populations in the current population as long as the maximum population size has not been exceeded. Otherwise, an elitist selection operator based on a fitness function described in equation (6) is applied. For each new population, infeasible and dominated solutions are discarded. We obtain after a fixed number of iterations, a set of non-dominated high quality feasible solutions.

5. Computational experiments

In this section, we present simulation results of PGA-ORSD with different scenarios. We use the Simulator of Urban MObility (SUMO) for generating different traffic scenarios. We develop scripts to extract different information as density, speed and travel time in each segment. Then, we develop PGA-ORSD algorithm to calculate connectivity probability for each segment and selects best RSUs position. Experiments are done on a workstation Xeon W3550 3.07GHZ CPU and 9 GB of RAM and all algorithms are implemented using python language.

Table 3 gives the simulation parameters. The size of problem instances is determined by number of segments and population size Pz ranging from 100 segments and 20000 vehicles for medium size instances, up to 1000 segments and 100000 vehicles for large size instances.

Table 3. Simulation Parameters

Parameter	Value
Number of segments	100-1000
Segment density (vehicle/km)	1-25
Average speed (km/h)	15-70
Segment length (m)	500
Radio range of vehicle (m)	250
Population size Pz	20000-100000
Number of accidents in segment	1-20
Threshold of connectivity probability T	0.1-0.9

The experiments carried out deal with medium to large instances representing regions consisting of 100 sections up to 1000 sections. As table 4 shows, the coverage AC rate could reach 100% if RSUs deployed is close to RSU candidates as scenarios 3, 6 and 9 show. By cons, the rate of coverage AC is low when we use less RSUs as scenarios 4, 7 and 10 show.

Table 4. Simulation Results

Scenarios	Section Number	NRSU	Threshold	RSUs candidate	Accident number	Coverage AC number	Coverage AC rate	PS	RSU Cost
1	100	60	0.2	34	644	355	55.10%	0.606	823
2	100	60	0.4	36	444	437	98.42%	0.712	899
3	100	60	0.7	40	560	560	99.10%	0.770	921
4	200	100	0.2	57	813	308	37.88%	0.594	1307
5	200	100	0.4	58	1176	897	76.27%	0.674	1445
6	200	100	0.7	59	1234	1132	91.73%	0.736	1387
7	400	200	0.2	128	2086	370	17.73%	0.597	2840
8	400	200	0.4	128	1917	1246	64.50%	0.684	2770
9	400	200	0.7	129	1879	1681	89.45%	0.714	2769
10	1000	500	0.2	427	5324	1535	28.83%	0.583	5784
11	1000	500	0.4	430	5221	2895	55.45%	0.637	5283
12	1000	500	0.7	435	5834	4505	77.22%	0.697	5559

Then we compare the contribution of our PGA algorithm compared to a deterministic approach which consists to install RSUs in all candidate positions according to the threshold T. Figure 6 shows for a given instance, that the PGA algorithm is better in terms of overall objective for several threshold values except for very low thresholds (≤ 0.1) or high thresholds (≥ 0.9).

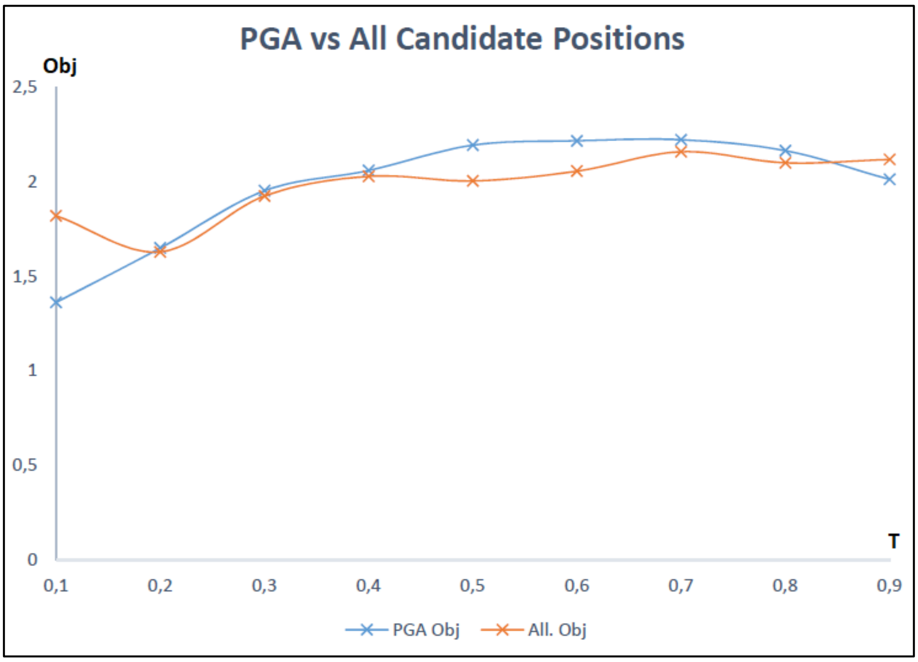

Figure 6. Pareto-dominance Genetic Approach Versus Deterministic Approach

The following figures (7, 8 and 9) refine this comparison by representing each objective separately. We can then notice that PGA-ORSD algorithm can find the best trade-off thanks particularly to the use of Pareto-Dominance in our algorithm.

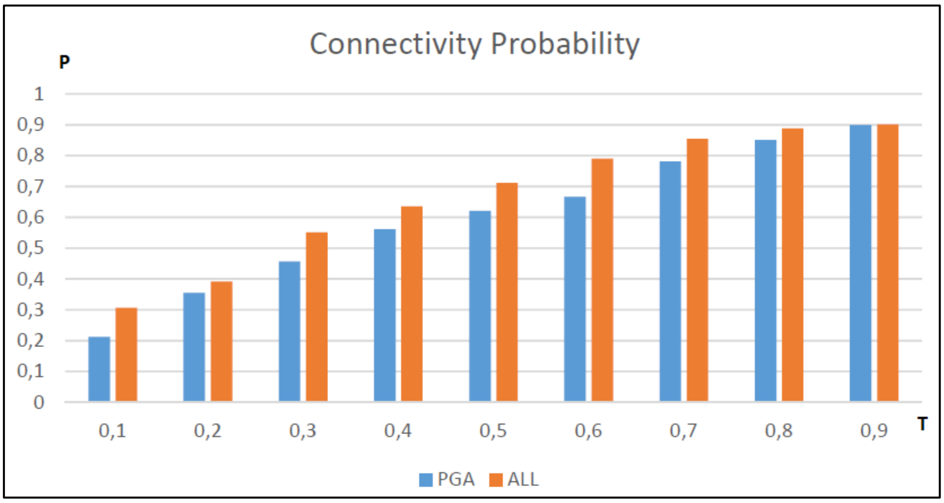

Figure 7. Comparison of Connectivity Probability

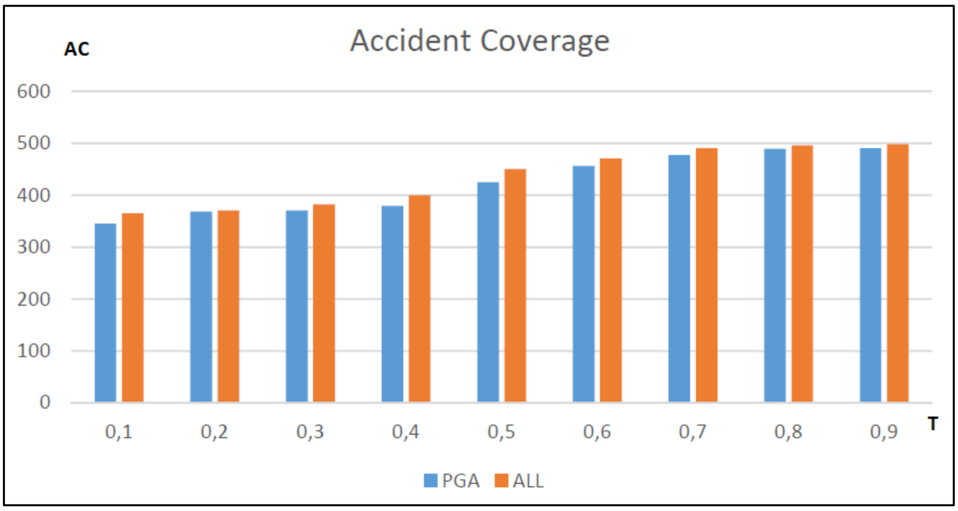

Figure 8. Comparison of Accident Cover

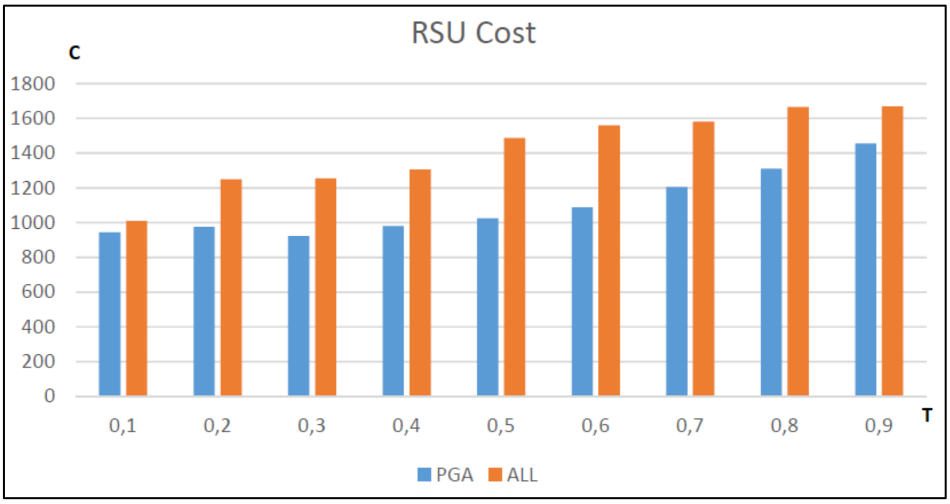

Figure 9. Comparison of RSU Cost

6. Conclusion

This work has proposed an extension of the ORSD approach which uses a method of deploying RSUs to maximize system connectivity and accident coverage and minimize the deployment cost. This approach uses two phases, the first calculates the probability of connectivity of each segment based on vehicle density and speed and other traffic parameters. In the second phase we applied a genetic algorithm based on Pareto-dominance in order to select the optimal locations of RSUs. Pareto-dominance has been successfully used to discard dominated solutions and obtain a set of high quality solutions.

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