Roadside Unit Deployment for Information Dissemination in a VANET: An Evolutionary Approach

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ABSTRACT

A Vehicular Ad Hoc Network (VANET) is a network where each node represents a vehicle equipped with wireless communication technology. This type of network can improve road safety, traffic efficiency, and many other traffic-related applications, minimizing their environmental impact and maximizing the benefits of road users. This paper studies a relevant problem in VANETs, known as the deployment of Roadside Units (RSUs). A RSU is an access points, used together with the vehicles, to allow information dissemination in the roads. Knowing where to place these RSUs so that a maximum number of vehicles circulating is covered is a challenge. We model the problem as a Maximum Coverage with Time Threshold Problem (MCTTP), and use a genetic algorithm to solve it. The algorithm is tested in four real-world datasets, and compared to a greedy approach previously proposed in the literature. The results show that our approach finds better results than the greedy in all scenarios, with gains up to 11 percentage points.

Categories and Subject Descriptors

C.2.1 [**Computer-Communication Networks**]: Network Architecture and Design—*Network topology, wireless communication*; I.m [**Computing Methodologies**]: Miscellaneous

Keywords

Vehicular Networks, Genetic Algorithms, Wireless Sensor Networks

1. INTRODUCTION

A Vehicular Ad Hoc Network (VANET) [4, 9, 24] is a network where each node represents a vehicle equipped with wireless communication technology. Communication in these networks can be Vehicle-to-Vehicle (V2V), when vehicles communicate directly, or V2I (Vehicle-to-Infrastructure), when vehicles exchange information with access points, called Roadside Units (RSUs), and any other network infrastructure, such as 3G and 3GPP Long Term Evolution (LTE). VANETs are able to collect real-time data on road conditions and make them useful for a wide range of applications, including safety warning systems, drivers assistance and traffic routing [20]. This last information, for instance, could be used to create vehicle routes according to carbon emission levels, avoiding to route certain types of vehicles to polluted areas. Moreover, these data can be used to create intelligent traffic management systems, which can automatically update traffic light cycles, indicate probable urban tolling zones, study the daily population of vehicles in the road, etc.

Some scenarios where VANETs can emerge are illustrated in Figure 1 [13]. The first scenario represents areas with low node density, such as highways, where communication employs opportunistic forwarding, i.e., information is transmitted when two nodes are within each others transmission range. The second and third scenarios illustrate urban areas, where communication may occur using a mix of Wide Area Network (WAN) and Wireless Local Area Network (WLAN) technologies.

Despite all the advantages VANETs can offer to road transport, there is currently a lack of studies on energy-efficient (green) communication on VANETs [21, 22]. Among others issues, Green Communication involves *information dissemination* [11, 1]. In scenarios such as the ones showed in Figure 1, information dissemination is a crucial aspect. Apart from the vehicles, RSUs are specially important agents of information dissemination, because they deal with VANETs characteristics that can make communication hard, such as high mobility, dynamic topology and latency. Given a specific scenario, defining how many RSUs are necessary and where they will be deployed is a challenge. What we want is to use the minimal number of RSUs with the maximum possible coverage of the region (and consequently, vehicles) being considered. This is the problem tackled in this paper.

The problem of where to deploy RSUs that will participate on a VANET can be modeled using different variations of the set coverage problem. Trullols et al. [23],

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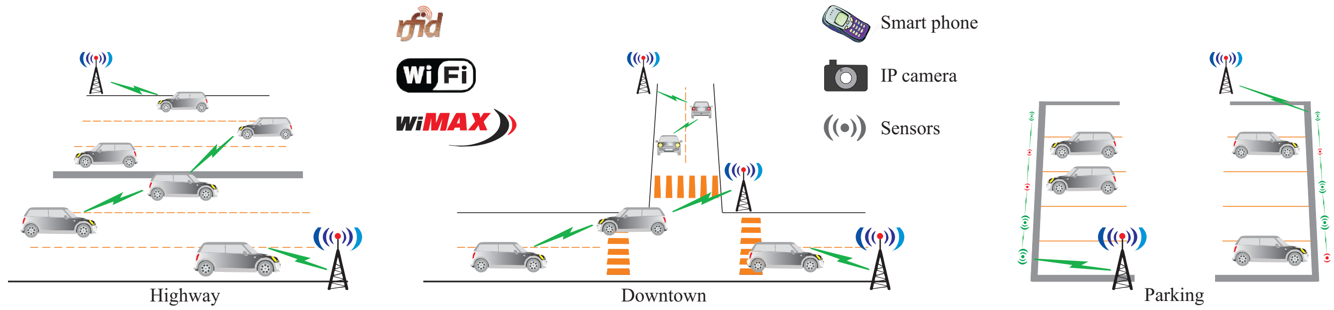


Figure 1: Intelligent vehicular sensor system [13]

for instance, presented three different models and many solutions for the problem, including Maximum Coverage Problem (MCP), Knapsack Problem (KP), and Maximum Coverage with Time Threshold Problem (MCTTP). Their results showed MCTTP as an effective approach, and hence this is the model used in this paper. However, instead of using local search methods, we take advantage of the global search of a Genetic Algorithm (GA) to find the positions of the RSUs, and compare the results with the ones obtained by a greedy approach, which achieved the best results in [23].

The proposed method was tested in four real road topology scenarios from Switzerland, with realistic vehicular mobility traces [16] monitored for one and a half hours. The four scenarios are within a 100 km^2 area, and present different traffic characteristics: Zurich downtown and Winterthur are used to represent heavy traffic; the rural areas of Baden and Baar to characterize lightweight traffic.

Results showed that the GA with an intelligent initialization method, which explores some of the solutions found by the greedy approach, presents results up to 11 percentage points better than the greedy approach. In this particular case, the vehicle percentage coverage increased from 76.2% to 87.77% over a simulation of 1 h and 30 min. Results varying the number of placed RSUs also showed the GA always outperforms the greedy search.

The remainder of this paper is organized as follows. Section 2 presents the state of the art in RSU deployment in VANETs. Section 3 discusses the MCTTP, while Section 4 shows the evolutionary algorithm proposed. Section 5 presents the simulation results, and conclusions and future work are in Section 6.

2. RELATED WORK

The deployment of sensors in wireless networks to improve communication is a classic issue in Wireless Sensor Networks (WSNs), and many authors have proposed solutions based on a variety of methods to tackled it [14, 10, 17, 12, 2]. However, different studies measure quality of communication in different ways. Some of them look at minimizing overhead, while others worry about assuring security and privacy. In our case, we want to maximize the coverage of vehicles within the monitored area.

Here we will first focus on cases where coverage is considered as a metric of communication quality. Huang and Tseng [5] formulated the coverage problem as a decision problem where, given a number k, the goal was to determine whether the area served by the sensor network was covered by at least k sensors. They proposed polynomial-time algorithms, in terms of the number of sensors, which can be translated to distributed protocols.

Habib and Safar [3], in turn, modeled the node placement problem to improve coverage in WSNs as two sub-problems: floorplan and placement, analogous to the solution of constructing circuit boards. In this case, the considered area was first divided into well-defined geometric cells (floorplan problem), and the sensors devices had to be assigned into a set of cells (placement problem). The authors solved these two sub-problems as a single optimization problem, using an evolutionary approach to solve it.

Still in this direction, the objective in [6] was to activate only the necessary number of nodes in a particularly time to have full coverage of the area in a large-scale WSN deployed randomly, saving energy and increasing the network lifetime. The authors proposed to solve this problem as a cover set selection, and used a searching algorithm based on improved elitist nondominated sorting genetic algorithm (NSGA).

Focusing on VANETs, Kchiche and Kamoun [7] proposed a greedy approach based on group centrality to select the best organization of RSUs able to provide the most stable and regular communication between vehicles. They wanted to achieve the best possible performance in terms of communication delay and overhead. Further in [8], the authors showed in simulations that the use of RSUs can optimize the performance of a VANET, specially in low dense areas and in cases of long-distance communication. Moreover, [8] proposed strategies for RSU deployment based on centrality and equidistant, and showed that they are important factors for improving service quality.

Sou [18], in contrast, studied a power-saving model of RSUs deployment to reduce unnecessary power consumption. He considered that RSUs were deployed within the same distance on a road section, and could dynamically alternate between active and inactive modes. The objective was to choose which and how many RSUs should be in active mode so that the power saved was maximized, and the criterion on connectivity constraint satisfied.

Sun et al. [19], in turn, considered security and privacy issues when placing RSUs. Their objective was to find critical points along the roads in order to preserve security and privacy in VANET. They proved that the RSUs deployment problem is equivalent to the Set Covering

Algorithm 1 The MCTTP greedy approach

Require: k, T, τ, $\mathbf{S}$
Ensure: $\mathbf{S}'$
1: $\mathbf{S}' \leftarrow \varnothing$
2: $t_j \leftarrow 0$, $j = \{1, \ldots, v\}$
3: **repeat**
4: $\quad W_i \leftarrow \sum_{j=1}^{v} \min(\tau - t_j, T_{ij})$, $i = \{1, \ldots, n\}$
5: $\quad$ Select $S_i \in \mathbf{S}$ that maximizes W_i
6: $\quad t_j \leftarrow \min(\tau, t_j + T_{ij})$, $j = \{1, \ldots, v\}$
7: $\quad \mathbf{S}' \leftarrow \mathbf{S}' \cup S_i$
8: $\quad \mathbf{S} \leftarrow \mathbf{S} \setminus S_i$
9: $\quad k \leftarrow k - 1$
10: **until** $k = 0$ or $\mathbf{S} = \varnothing$

Problem (SCP), and presented a cost-efficient greedy solution for it.

Trullols et al. [23] presented three different ways for modeling the problem of deploying RSU: as a KP, MCP, or a MCTTP. For each model, they provide a subzone and a greedy solution, and the MCTTP approach solved with a greedy algorithm achieved the best results. Based on an analysis of [23], in this paper we use the MCTTP to model the problem, and compare the proposed method with the greedy one (described in Section 3).

3. MAXIMUM COVERAGE WITH TIME THRESHOLD PROBLEM

As previously mentioned, in this paper we use the MCTTP to model the RSUs deployment problem. We are particularly interested in deploying k RSUs with transmission range R on a urban road topology of area equals to A and n intersections. In this case, i represents an intersection between two roads, and each element $v_j \in S_i$ is a vehicle crossing intersection i. An intersection is limited by the transmission range R of the RSU (assuming it is placed in the center of two crossroads). The weight of v_j represents the time the vehicle remains in the intersection. In our case, there are v vehicles going around during the observation period, and τ is the minimum time required for a vehicle to contact a RSU and successfully transmit information. Note that the transmission does not need to be done by a single RSUs. One of them can start transmission and another one finish it, as long as the sum of the times the vehicle remains in both intersection reaches the minimum time required for information dissemination.

Formally, let $V = \{v_1, \ldots, v_v\}$ denote a set of vehicles, and $S_i \subseteq V$ represent a subset of vehicles that enters intersection i. We want to choose at most k sets in order to maximize the cardinality of $S_1 \cup S_2 \cup \cdots \cup S_k$. Consider $T_{n,v}$ the matrix of vehicle intersection, where $T_{i,j} \geq 0$ represents the total time vehicle j spends in intersection i. The maximum coverage problem with time threshold can be formulated as [23]:

$$\max \sum_{j=1}^{v} \min\left(\tau, \sum_{i=1}^{n} T_{i,j}\, y_i\right), \tag{1}$$

Algorithm 2 GA for MCTTP

Require: k, T, τ, $\mathbf{S}$
Ensure: $\mathbf{S}'$
$\mathbf{P}_{1,p/2} \leftarrow$ random individuals
$\mathbf{P}_{p/2,p} \leftarrow$ individuals generated by a modification of Algorithm 1
repeat
$\quad$ Evaluate individuals according to the fitness function
$\quad$ Perform tournament selection
$\quad$ Execute one-point crossover with probability p_{cross}
$\quad$ Execute one-point mutation with probability p_{mut}
$\quad$ Insert elitists in the next population P'
$\quad$ Insert new individuals to P'
$\quad$ $best \leftarrow \max(best, f_{\mathbf{I}_i})$, $i = \{1, \ldots, p\}$
until max number of generations not reached
$\mathbf{S}' \leftarrow \mathbf{I}_i$

subject to:

$$\sum_{i=1}^{n} y_i \leq k \tag{2}$$

$$y_i \in \{0, 1\}, \forall i, \tag{3}$$

where y_i indicates whether there is a RSU in intersection i. The objective function (Eq. 1) represents the MCTTP problem, while the restriction described in Eq. 2 ensures that at most k intersections are selected.

The greedy approach for this problem [23], described in Algorithm 1, optimizes the RSUs' vehicles coverage time. Given the number of intersections k to be deployed, the set $\mathbf{S}$ of intersections, the matrix T that represents the vehicle times in each intersection and the minimum time required for data transmission (τ), the algorithm works as follows. For each intersection i, W_i ($i = 1, \ldots, n$) denotes the RSUs' vehicles time of coverage (line 4). This number is obtained by summing up the time each vehicle remains in the intersection. However, for a single vehicle, when this time is greater than τ, the extra time of coverage is disregarded, since transmission is completed at time τ. By contrast, if the time the vehicle remains in the intersection is not enough for transmission, it is saved up in vector t_j (line 6), so that in the next iteraction the time required to complete transmission is calculated ($\tau - t_j$, line 4) .

Having the values of W_i, the intersection S_i with maximum coverage is selected and inserted in the subset $\mathbf{S}'$ (line 7), and then removed from the set $\mathbf{S}$ (line 8). This procedure is executed until k intersections are selected or $\mathbf{S}$ is empty.

4. EVOLUTIONARY APPROACH

Considering the characteristics of the MCTTP problem, evolutionary approaches with their global search and noisy tolerance suit very well the problem. This section presents the GA proposed. The first version does not differ a lot from the standard GA, although an intelligent scheme for population initialization is used to speed up the process of finding solutions with acceptable coverage.

Given a road map with n intersections and k RSUs to be deployed, each individual is represented by

$$\mathbf{I} = \{G_1, G_2, \ldots, G_k\},$$

where $G_j \in \mathbb{N}^+$, $0 \leq G_j < n$. For instance, a scenario with $n = 10$ intersections to deploy $k = 4$ RSUs, a valid individual is $\mathbf{I} = \{0, 4, 8, 9\}$, i.e., RSUs are placed in intersections numbered 0, 4, 8 and 9.

Algorithm 2 presents the GA implemented. Lines 1 and 2 represent the population initialization, which will be discussed later. After the population is initialized, individuals are evaluated, and selected using a tournament selection to undergo one-point crossover and one-point mutation operations. An elitist procedure keeps the best individuals in the next population, and the new population is augmented with the individuals produced by crossover and mutation. This procedure is carried out until a maximum number of generations is reached. If crossover produces children with repeated intersections, a correction operation is used to remove the repeated ones.

Besides the individual representation, two components in the proposed algorithm are problem-dependent: the fitness and the population initialization procedure. The fitness of an individual is defined as the percentage of covered vehicles in the considered area

$$f_{\mathbf{I}} = \frac{|\widehat{V}|}{v},$$

where $\widehat{V} \subseteq V$ and $\widehat{v}_i = \sum_{j=1}^{n} T_{i,j} \geq \tau$.

The population initialization procedure was changed after the first results were analysed, as we observed that the algorithm took too many generations to reach solutions similar to the greedy one. In order to make the evolutionary process more efficient, instead of starting evolution from scratch, we gave the GA the chance to work with solutions previously found by the greedy search. At the same time, we also kept half of the population random, in order to avoid the introduction of biases towards the greedy solution.

We could have inserted only the final solution of the greedy search into the random initialized population. However, we modified the greedy algorithm so that, at each iteration, not only the best intersection (the one with maximum coverage) was selected. Instead, we allowed any random intersection among the top 10 ranked ones to be chosen. This modification was introduced by replacing line 5 of Algorithm 1 by the following:

> Select $S_i \in \mathbf{S}$ where $i = rand(1:10)$ is the ith that maximizes W_i.

As explained, the modified algorithm was executed to generate half of the population. The other half was completed with random generated solutions.

5. RESULTS AND DISCUSSION

The proposed GA was evaluated using four datasets extracted from a simulated vehicular mobility trace, collected during 1 h and 30 min, from an urban road network in Switzerland [15]. The datasets comprehend four different regions located within a 100 km^2 area: Zurich downtown and Winterthur, characterizing heavy traffic, and the rural areas of Baden and Baar, characterizing lightweight traffic. Each region has its own topology and vehicular density, as described in Table 1.

Table 1: Scenario characteristics

	Zurich	Winterthur	Baden	Baar
Intersections	83	43	38	46
Vehicles	70,537	13,578	11,632	9,876

Table 2: Algorithm Settings

	# RSUs	Pop Size	Crossover	Mutation
Zurich	25	400	0.95	0.10
Winterthur	13	200	0.95	0.01
Baden	11	200	0.90	0.10
Baar	14	200	0.80	0.10

Crossroads in the selected region and vehicles that transit in the region for at least 60 s during the observation period are identified by an integer. This information is used to generated the matrix T, with $n \times v$ dimensions. Each element $T_{i,j}$ in T is the difference between the initial and final times when vehicle i entered and left intersection j boundaries, i.e., the area in the transmission range R.

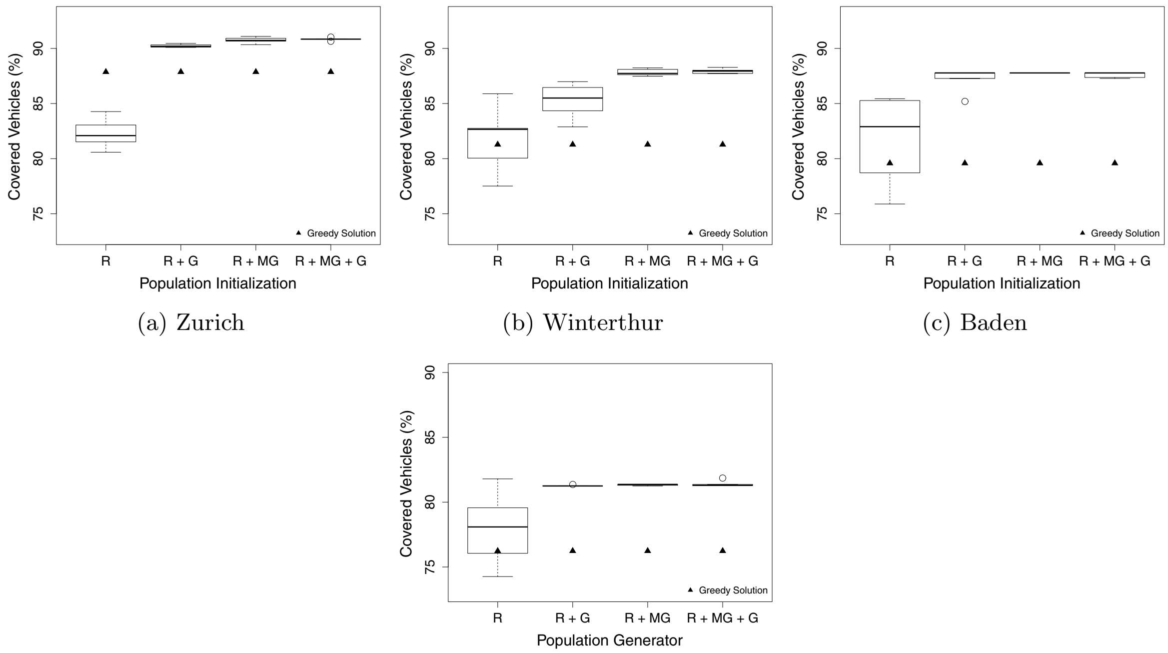
The performance of the GA is compared with the one proposed in Trullols et al. [23], where a greedy solution is discussed to model the RSU deployment problem as a MCTTP. In order to make the comparisons among the two approaches as fair as possible, the k (number of RSU) value was fixed to be 30% of the number of intersections in the considered scenario, and the transmission information time threshold τ was defined as 30 s.

The GA parameters, such as population size, number of generations, mutation and crossover rates, and tournament size were set in preliminary experiments, where the evolution time, convergence and best fitness of the algorithms were analyzed. Hence, the values of these parameters are not optimal, but presented the best results when compared to other parameter configurations tested during the algorithm tuning phase. Tournament size 2 showed the best results in all scenarios, as well as 100 generations. Table 2 shows the final values obtained for number of RSUs, population size, and crossover and mutation probabilities in each scenario. Note that the population size varied from the Zurich configuration to the others, as Zurich presented a higher number of intersections and vehicles than the other scenarios. Hence, Zurich needed more evaluations to explore the bigger search space.

The next sections report the experiments performed to evaluate the GA in the four aforementioned scenarios. They were divided in two phases: first we show the differences when initializing the population randomly or adding information about the problem through the greedy approach. Next we show the effect a variation in the number of RSUs deployed has in the coverage of the vehicles.

5.1 Population Initialization

The first tests with the GA showed it was taking a long computational time to find good solutions for the problem. In order to reduce this exploration time, we modified the random initialization of the population by a more intelligent one. However, as half of the population is still generated randomly, the risk of biasing solutions towards the greedy one is low. Four different variations of the



(a) Zurich (b) Winterthur (c) Baden

(d) Baar

Figure 2: Population initialization for each scenario: R stands for random population, G for population generated by a greedy algorithm and MG for individuals generated by a modified version of the greedy algorithm.

population initialization procedure were tested, as showed in Figure 2. In the first case (labeled **R** in the graph), the initialization is purely random. In the second case (labeled **R+G**), the greedy solution was inserted to the initial random population. In the third case (labeled **R+MG**), the population is half random and half initialized by the modified version of Algorithm 1 described in Section 4. Finally, in the last case (labeled **R+G+MG**), the three previous variations are combined.

It is important to note that, for all experiments reported in this paper, five replication of the GA were run, with different initialization seeds. This number was set to 5 because the variance of the results of each experiment is low and, furthermore, the computational cost of the evaluations is high. Hence, the graphs in Figure 2 show the average fitness of the best individual returned for each of the 5 repetitions, and its associated standard deviation. Complementary to Figure 2, Table 3 shows the values associated with the percentage of covered vehicles for the four scenarios, and compares the results obtained with the greedy approach.

Figure 2 shows that the random population initialization (R) presents the highest standard deviations among all approaches. Besides, an analysis of the evolution of the GA and the average fitness of the individuals in the last generations show that there is still a lot of diversity. Modifications in the way the genetic algorithms and its operators work might alleviate this problem. However, as showed by the results obtained using the more intelligent approaches (and corroborated by the numbers in Table 3), using solutions previously explored by the greedy approach to initialize the population really makes the evolutionary process faster and successful.

For the Zurich scenario, the best results obtained by the GA occur when the population is initialized using any approach but not the random (R+G, R+MG and R+G+MG are not statistically different). In this case, the R+MG algorithm reaches 90.46% of coverage, while the greedy obtains 87.86%. This result is statistically inferior to the one obtained by the GA according to a paired t-test with 99% confidence. The only population initialization method which obtains results statistically worse than those obtained by the greedy algorithm is the random initialization approach. Note that the Zurich dataset presents the bigger area (83 intersections) and the denser traffic patterns (70,537 vehicles) among the four datasets, which makes its search space larger.

When analyzing the results for the other three scenarios, all the four population initialization approaches are statistically better than the results obtained by the greedy algorithm, including the random scenario. This can be easily explained by the characteristics of these scenarios, which present a smaller number of intersection and traffic when compared to the Zurich dataset. However, although all approaches were statistically better than the greedy, the population initialization that uses any information coming from the greedy algorithm is always statistically better than the random initialization approach, as expected.

The best results obtained for each scenario are showed in bold in Table 3 (we show the best absolute value, although in many cases it is not statistically different from other versions of the greedy initialization). Note that we increase coverage in 3, 7, 8 and 11 percentage points for the Zurich,

Table 3: Results of coverage obtained for different population initialization approaches

Scenario	Algorithm	Population Initialization				Gain
		R	R+G	R+MG	R+MG+G	
Zurich	GA Best (%)	84.2688	90.4566	91.0947	**91.0333**	3.1666
	Greedy (%)				87.8667	
Winterthur	GA Best (%)	85.8889	86.9863	88.2383	**88.2825**	7.0040
	Greedy (%)				81.2785	
Baden	GA Best (%)	85.4367	87.7751	87.7751	**87.7751**	8.1929
	Greedy (%)				79.5822	
Baar	GA Best (%)	81.7943	81.3690	81.3690	**81.8651**	5.6298
	Greedy (%)				76.2353	

Table 4: Results of coverage obtained for RSU number variations

Scenario	Algorithm	k				
		5	10	15	20	25
Zurich	GA Best (%)	40.0753	59.9603	73.3779	83.9360	91.0947
	Greedy (%)	30.7887	56.1232	68.2419	80.1635	87.8667
Winterthur	GA Best (%)	57.8436	81.2564	91.4052	96.6784	98.0704
	Greedy (%)	40.8602	74.6870	85.9847	93.6441	95.9051
Baden	GA Best (%)	67.9849	85.4367	94.4464	98.7620	99.3982
	Greedy (%)	50.8339	74.5272	92.5808	98.0227	99.2779
Baar	GA Best (%)	48.6533	72.3167	83.8295	92.5375	96.9421
	Greedy (%)	43.1045	62.9101	78.0275	88.7404	93.7019

Winterhur, Baden and Baar scenarios, respectively. In summary, using information from the greedy algorithm can improve significantly the results obtained by the GA. This method is specially useful in larger and denser scenarios, with characteristics such as Zurich.

5.2 RSU Number Variations

In a second set of experiments, we test the variations in coverage the number of RSUs deployed in each scenario can cause. Recall that we initially set this value as 30% of the number of intersections. In this section, we vary this number from 5 to 25 in 5 units intervals. The original number of RSUs in the four scenarios varied from 11 to 25. Figure 3 and Table 4 summarize the results.

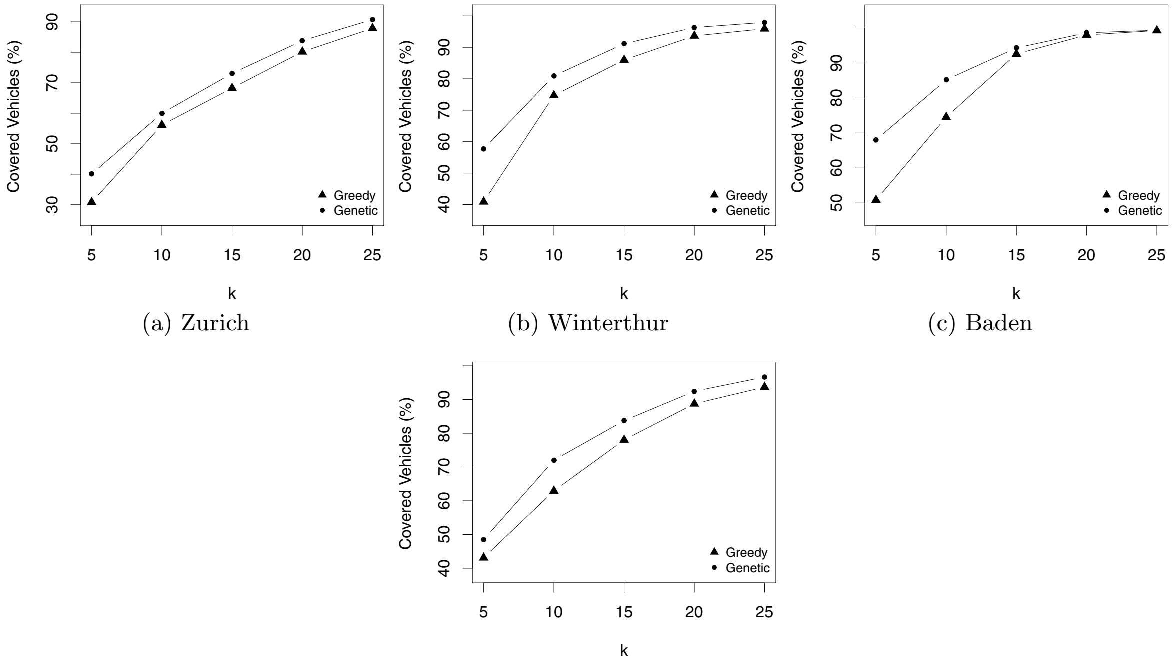
As expected, as the number of RSUs increase, so does the percentage of covered areas. Note that, in all graphs, the R+MG version of the GA always obtains better results than the greedy search. Considering when the maximum number of RSUs is deployed, for the Zurich dataset, in particular, there is no change from the original scenario presented in the previous section (the maximum number of RSUs deployed does not change). However, for the other three datasets, the number of sensor increased considerably. For Winterthur, where 43 intersections were available, 25 RSUs correspond to approximately 60% of the intersections covered. In this case, the number of covered vehicles increased from 88.28% to 98.1%. For Baden, the proportion of intersections covered is even higher, with 65% of intersections having RSUs, and the number of vehicles covered equals to 99.4%. Finally, for Baar, 55% of the intersections were equipped with sensors, leading to 96.7% of vehicle coverage.

Among the results presented, Baar shows the lowest vehicle coverage, although 55% of its intersections are equipped with RSUs. This can be explained by the characteristics of this scenario, which has lightweight traffic. Observing the graphs in Figure 4 and data in Table 4, we note that the percentage of vehicles covered is highly correlated to the density of the regions. As expected, is easier to cover vehicles in denser regions than in lightweight. Hence, reaching maximum coverage in Zurich is easier than doing the same thing in Baar, although the Zurich area is bigger. Looking at Figure 4(b), Baar has many vehicles concentrated in a few intersections, while this distribution is smoother in the Zurich scenario (Figura 4(b)).

6. CONCLUSIONS AND FUTURE WORK

This paper studied the problem of deploying RSUs in VANETs, which are important components for helping information dissemination in traffic networks. VANETs can be very useful mechanisms to help proposing solutions to deal with problems of energy costs and global carbon emissions generated by the road transport. Among their applications, we emphasize intelligent traffic management systems, which can indicate probable urban tolling zones or facilitate studies on the daily population of vehicles in specific roads.

The RSUs deployment problem was modeled using a variation of the set coverage problem, namely the MCTTP. A simple GA was proposed to the problem, and its initialization procedure enriched with data coming from a greedy search procedure previously proposed. We showed



(a) Zurich (b) Winterthur (c) Baden

(d) Baar

Figure 3: Results of coverage obtained when varying the number of RSUs in each scenario.

that, by taking advantage of global search, we found RSU positions that lead to better vehicle coverage than those obtained by a greedy approach. The results showed that the GA obtained gains up to 11 percentage points.

As future work, we intend to customize the GA for this particular application, proposing new operators or multi-objective fitness functions and do a qualitative comparison with other techniques used to solve this problem. We also want to test different scenarios, where the number k of RSUs allowed can be minimized. Another interesting aspect to be studied is the parallelism of the solution, which can considerably increase the algorithm performance. In additional, we want to apply the GA to bigger scenarios, such as São Paulo. However, this last experiment depends on generating traces of real traffic.

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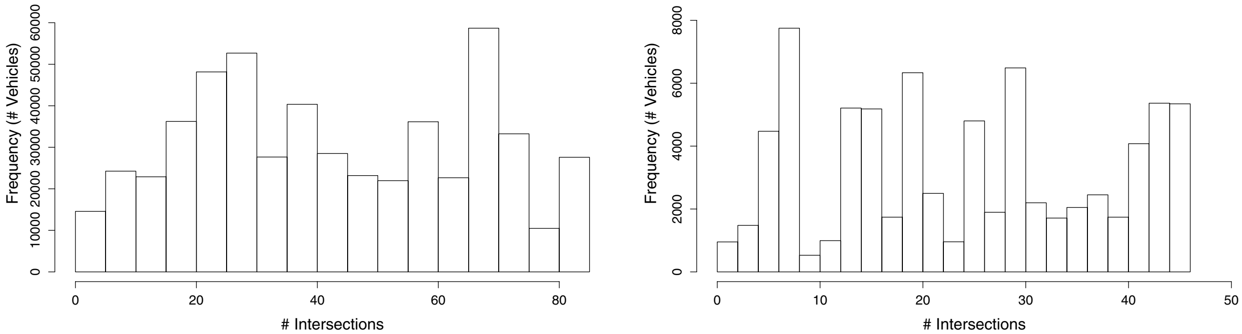

(a) Zurich

(b) Baar

Figure 4: Frequency of vehicle visits in intersections for the Zurich (4(a)) and Baar (4(b)) scenarios

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