When Vehicular Networks meet Artificial Intelligence

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***Abstract*—In Vehicular Networks, some applications require a fast and reliable warning data transmission to the Emergency Services and Traffic Authorities. Nevertheless, communication is not always possible in vehicular environments due to the lack of connectivity. To overcome these issues (i.e., signal propagation problem and delayed warning notification time), an effective, smart, cost-effective, and all-purpose RSU deployment policy should be put into place. In this paper, we propose GARSUD, a system which uses a genetic algorithm that is capable to automatically provide a Roadside Unit deployment suitable for any given road map layout. Simulation results show that our proposal is able to reduce the warning notification time –the time required to inform emergency authorities in traffic danger situations– and to improve vehicular communication capabilities in different flows of traffic at different times during the day.**

***Index Terms*—Genetic algorithms, Vehicular ad hoc networks, RSU deployment.**

I. Introduction

Vehicular Networks enable communication among vehicles themselves, and also among vehicles and traffic management authorities. Despite the wide variety of applications for Intelligent Transport Systems (ITS) that lie under the umbrella of vehicular networks, traffic safety applications have been undoubtedly one of the most studied in the last years, due to the benefits that they clearly offer to drivers and passengers.

Vehicular Networks include vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications. Roadside Units (RSUs) are infrastructure communication nodes within vehicular networks, playing an important role in vehicular communications since they can: (i) deliver important information to vehicles, (ii) forward received messages to final recipients, or (iii) provide Internet access to vehicles. To sum up, RSUs are deployed to extend vehicle coverage and to improve network performance in vehicular networks [1].

RSUs are usually expensive to install and to maintain, thus there is a trade-off between full coverage (in terms of connectivity) through RSUs and their deployment cost. Hence, authorities tend to limit the number of RSUs, especially in suburbs and areas of less population, making RSUs a scarce resource in vehicular environments. We consider that it is important to optimally deploy a limited number of RSUs in the most appropriate locations (i.e., those that clearly extend coverage and improve the overall network performance). In fact, it would be necessary to find an automatized method to obtain the best locations for the RSU to be deployed in each scenario, due to the great variation of urban street layouts.

In this work, we propose GARSUD, a Genetic Algorithm for Roadside Unit Deployment in VANETs, and compare it against other deployment policies. We compare it with both Geographic-based (i.e., the Uniform Mesh Deployment Policy) [2] and the Density-based Road Side Unit deployment policy (D-RSU) [2] approaches. Our goal is threefold: (i) to reduce the deployment cost, (ii) to automate the deployment decision, as well as (iii) to increase the communication capabilities of the vehicles in the scenario, in terms of reduced warning notification time, i.e., the time required to send warning messages to the emergency authorities.

II. Related Work

Several works related to RSU deployment policies have been proposed so far, including different approaches to determine the number of RSUs required to provide a functional RSU deployment in terms of connectivity within a given scenario [3]. This sort of approaches are focused on reducing the number of RSUs required [4], improving the overall network performance [5], or guarantying the Quality-of-service (QoS) in vehicular networks when delivering data [6].

The work presented in [7] used an evolutionary-based approach to solve the RSU deployment problem but surprisingly, authors neither provided details about how they modeled communications between vehicles and RSUs, or the improvement achieved in terms of vehicles' connectivity.

To the best of our knowledge, the majority of proposals are focused on very specific scenarios (i.e., roadmap layouts and vehicle densities) and consider too simplified assumptions.

III. GARSUD: AUTOMATIC RSU DEPLOYMENT

RSU deployment approaches, based on fixed placement using geometrical rules, present bold limitations such as areas without coverage, or unbalanced load (i.e., some RSUs exhibiting extremely high network activity while others do not). In order to overcome such limitations, we propose GARSUD, a *Genetic Algorithm for Roadside Unit Deployment*.

Genetic Algorithms (GAs) are so called because they are inspired by biological evolution and its genetic-molecular base. Genetic algorithms need to establish a relation between the set of solutions to a problem, called *phenotype*, and the set of individuals in a natural population. This is achieved by encoding information of each solution in a string, usually binary, called chromosome or *genotype*. The symbols that form the string are called *genes*. The populations of possible solutions encoded as genotypes evolve through iterations called generations, and thereby obtaining for each genotype the corresponding phenotypes which are evaluated by using some measure of fitness. The next generations are generated by applying the following genetic operators repeatedly: Parent selection, Crossover, Mutation, and Replacement. The selected values for the different configuration parameters were obtained through extensive testing in order to provide the best results in terms of optimization time and optimality of the solutions found.

Even if genetic algorithms may take a considerable amount of time to compute, the longer the evolution lasts, the better solutions are found (reaching the global optima if the parameters of the algorithm are adequately tuned). Notice that in real scenarios and prototypes, RSU deployment is not done on the fly or dynamically in real time. A RSU deployment is a well thought process design, therefore, the computational process time that an algorithm takes will not impact the design. GARSUD algorithm is executed before the RSU installation and deployment to decide the most suitable places for them. Our tests showed an execution time up to 4 hours in single Core i5 machine, which is a very reasonable time for a deployment policy lasting several weeks.

- **Representation of individuals**

Each possible solution of the problem needs to be codified in a genotype before applying the genetic operators. Possible solutions of the RSU deployment problem would include the location for all the available RSUs, which constitutes the phenotype. GARSUD assigns a unique number to each possible location for the RSUs, and the genotype of each solution contains a sequence of numbers representing the location selected for each RSU, as depicted in Figure 1.

- **Parent selection**

The parent selection phase compares the individuals in the current population to select the fittest of them to transmit their genetic information to the next generation. In GARSUD, this stage is performed by using tournament selection [8] in which k random individuals in the population are compared, and the one presenting the highest fitness value becomes a potential father of new individuals.

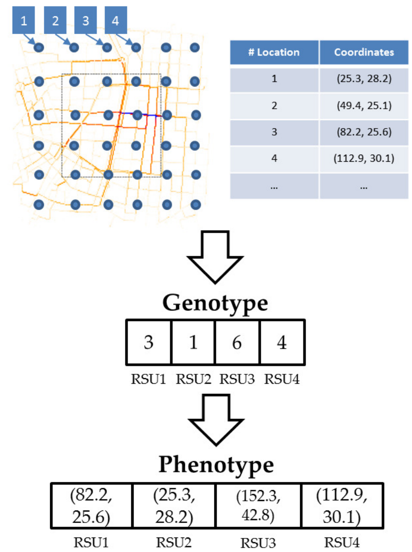


Fig. 1. Representation of individuals in GARSUD.

- **Crossover**

The recombination or crossover operator combines two parents to generate a new individual. GARSUD uses the default recombination operator in Genetic Algorithms, i.e., the 1-point crossover [9].

- **Mutation**

The mutation operator is used to introduce diversity in the population, thereby avoiding local minima solutions [10]. GARSUD specifically adapts the mutation probability to the size of the genotype, making one change in each individual on average.

- **Replacement**

The replacement, also known as selection of survivors or environmental selection, is usually implemented by means of generational replacement, where the new offspring completely replaces the individuals from the last generation. GARSUD assures that the best values stay alive in future generations. In particular, it uses a steady-state scheme [11] where only a fraction of the individuals are replaced (those with the lowest fitness values) to ensure that the best values obtained so far survive in future generations. In our approach, the fraction of individuals replaced in each generation is set to 50%.

- **Fitness function**

The target function to maximize, also known as fitness function, summarizes in a single numerical figure how close the given design solution is to meet the overall specification requirements. The RSU deployment problem we are targeting aims to achieve low notification time for warning messages to the emergency authorities.

Since the RSU deployment is fixed, the fitness function should reflect the results obtained for the different traffic flows that could be found during a single day in a particular city. The approach followed calculates the average warning notification time in each scenario tested to assign a uniform importance to every possible vehicle density. The fitness function that guides GARSUD is indicated in 1, where $wnt(i)$ represents the average warning notification time measured in scenario i, and N is the number of tested scenarios.

$$GARSUD\_Fitness(s) = \frac{100}{\frac{\sum_{i=1}^{N} wnt(i)}{N} + 1.0} \qquad (1)$$

The GARSUD fitness function provides values between 0 and 100, whereas 0 represents the worst possible result where the warning notification time is maximum, and 100, when the warning notification time is low, close to 0.

GARSUD makes use of Evolutionary Computation, more specifically Genetic Algorithms, to test different configurations and guide the search process to maximize the value of the objective function. Testing all the possible configurations is unfeasible time- and resources-wise, due to the high amount of possible combinations of locations for the RSUs, even when considering small map layouts. For instance, deploying only 5 RSUs in a map with 200 possible locations for each RSU could produce $\binom{200}{5} = 2.53565004e+9$ different deployments. Considering, for example, that our well-equipped computation power allowed us to evaluate 1000 deployments per second (which requires a high computing performance), it would require more than 29 days of computing time to determine the optimal deployment for only one small specific scenario.

GARSUD requires a map of the target area including the street and junctions layout, the possible obstacles interfering with the wireless radio signal, mobility traces representing the behavior of the traffic using realistic vehicle densities, and the number of RSUs to be deployed in the area. Using this information as input, our proposal computes a location for every RSU increasing the coverage provided and reducing the notification time of warning messages in the given scenario.

GARSUD performs the following steps to obtain a suitable RSU deployment: First of all, it makes an initial random RSU deployment, secondly, it simulates this specific scenario by using a modified version of ns-2 simulator, which allows us to calculate the solution fitness. After that, it performs the parent selection, the crossover, and the mutation operations. Finally, it evaluates the fitness of the new solution, makes the partial replacement, and checks whether the termination condition is fulfilled. If not, it performs again the parent selection process and repeats the subsequent operations. Table I summarizes the parameters defined in GARSUD.

TABLE I
PARAMETERS USED IN GARSUD

Representation	Integer strings [1..#RSUs]
Recombination	1-point crossover
Recombination probability	95%
Mutation probability	1 gene/individual (avg.)
Parent selection	Tournament k = 2
Survival selection	Steady-state
Generational Gap	50%
Population size	8
Initialization	Random
Termination condition	20 generations
Number of executions	5

IV. SIMULATION ENVIRONMENT

In this section, we present the simulation environment that we have set and used to assess the performance of our proposal. Since deploying and testing crowded Vehicular Networks is not feasible due to economic costs, we used simulation as an alternative to real implementation.

Concerning the simulated map layout, we selected the city of Madrid, located in Spain, as the target location to simulate the RSU deployments. In our previous work [12], we demonstrated that the area around the Gran Via Street in Madrid provides a standard environment for radio message propagation.

The mobility of vehicles, at macroscopic level (i.e., global motion constraints such as streets, roads, junctions, and traffic lights), was obtained with the CityMob for Roadmaps (C4R)[1], a realistic traffic generator software based on SUMO [13].

The mobility at the microscopic level (i.e., movements of each vehicle and its behavior with respect to others) has been modeled following two different mobility patterns, thus evaluating our proposal under different mobility conditions. In particular, we used (i) the Krauss model, including traffic lights and multi-lane behavior [14], and (ii) the Downtown model [15], which additionally considers that urban areas can present different vehicle densities, i.e., vehicles may not be uniformly distributed and there are points of interest that may attract the vehicles. This methodology probes that our approach provides suitable RSU deployments regardless the special characteristics of the traffic distribution in the map.

We have used the ns-2 simulator [16] to perform our simulations, including the IEEE 802.11p [17] standard so as to closely simulate the WAVE standard. In terms of the physical layer, the data rate used for packet broadcasting is of 6 Mbit/s, as it is the maximum rate for broadcasting in the IEEE 802.11p. The simulator was also modified to make use of our Real Attenuation and Visibility (RAV) propagation model [18], which increases the level of realism of the vehicular network simulations by accounting for real urban roadmaps and obstacles that have a strong influence on the wireless impairments, hence the signal propagation. The RAV model is based on real-world measurements and accounts for attenuation and fading due to radio obstacles.

With regard to data traffic, vehicles operate in two modes: (a) warning mode, and (b) normal mode. Warning-mode vehicles inform other vehicles about their status by sending warning messages periodically (every T_w seconds). These messages have the highest priority at the MAC layer. Normal-mode vehicles enable the forwarding of the warning packets and, periodically (every T_b seconds), they also send *beacons* with information such as their positions, speed, etc. These periodic beacons are not propagated by other vehicles and

[1] `C4R` is freely available at http://www.grc.upv.es/software/

TABLE II
PARAMETER VALUES FOR THE SIMULATIONS

Parameter	Value
mobility generator	C4R [19]
number of vehicles	$100, 200, 300, 400$
simulated area	$2000m \times 2000m$
simulated layout	Madrid
mobility models	Krauss [14] and Downtown model [15]
maximum acceleration of vehicles	$1.4\ m/s^2$
maximum deceleration of vehicles	$2.0\ m/s^2$
driver reaction time (τ)	$1\ s$
number of warning mode vehicles	3
message size	$512Bytes$
message rate	$1\ per\ second$
MAC/PHY	IEEE 802.11p
maximum transmission range	$400m$
warning message priority	$AC3$
normal message priority	$AC1$

they have a lower priority than warning messages. The desired RSU deployment should be suitable for a wide range of vehicle densities, thus we tested different number of vehicles involved in the simulations: 50, 100, 200, 300, and 400. Table II shows the representative parameter values used in our simulations.

V. SIMULATION RESULTS

In this section we present the results obtained using our proposed GARSUD algorithm. To ensure that results we have obtained are representative, all the results included in this paper represent an average of 3 repetitions.

A. Performance of the Genetic Algorithm used by GARSUD

As aforementioned, we tested GARSUD with the Madrid layout using several vehicle densities, representing different flows of traffic at different times during a day. Existing approaches are able to obtain good results assuming a single vehicle density only. However, GARSUD is capable to find a suitable deployment for a wide range of densities.

Figure 2 presents the evolutionary process in terms of fitness of the best and average individuals (representing possible deployments) using GARSUD in two different scenarios, i.e., deploying 4 RSUs and 9 RSUs, respectively. As shown, the genetic algorithm is able to guide the search process obtaining iteratively better solutions as generations advance. The shape of the function is typical of this kind of algorithms: first generations provide a steep improvement of the target function until the solutions start to converge towards the nearest maximum. Nevertheless, there are some sudden improvements in the best value, as the mutation operator allows searching new areas of the solution space where new maximums can be found. Let's remember that the main objective is to reduce the warning notification time, and a fitness value of 100 represents a warning notification time equal to 0 seconds.

Regarding the obtained fitness values, it is noticeable how increasing the number of RSUs deployed improves the value of the target function of the solutions. As using more RSUs allows us covering a wider area in fewer hops, this result was expected. In addition, since the fitness value is obtained by combining the warning notification time values for the selected vehicle densities, the search process ensures more efficient deployments as it progresses.

Another view of the evolutionary process is presented in Figures 3 and 4. In particular, these figures depict the RSU locations provided by GARSUD when deploying 4 and 9 RSUs, respectively. To better understand the evolutionary process, four intermediate locations selected during the first stages of the algorithm are presented (i.e., from generation 0 to 20, from generation 20 to 40, etc.).

As shown, when only 4 RSUs are available to be deployed, the initial random deployment is widely modified during the first generations, achieving a completely different distribution of RSUs after 20 generations. This corresponds to the major gain in the fitness of the solutions as previously mentioned. After this stage, some RSUs are assigned to their final position. However, noticeable variations in location are shown for the rest of RSUs, even if these location changes are minor as the algorithm advances.

Figure 3(e) presents the average warning notification time when considering different vehicle densities. The warning notification time is greatly reduced with each new generation of solutions for almost all the selected densities, especially in low-density scenarios. More specifically, it is reduced from $30.25s$ to $5s$ when only 100 vehicles are present in the scenario, which represents over 80% of improvement. It is noteworthy how the algorithm slightly worsens the results for 200 vehicles after 20 generations, but it is only due to the overall improvement when the rest of densities are taken into account for the analysis. The final reduction is about 80% for 200 vehicles, and about 60% for 300 vehicles. The improvement when simulating 400 vehicles is very reduced, since increasing the density of vehicles over this threshold increases the probability of finding a connected path of vehicles between the sender vehicle and an RSU even when using random deployments.

Figure 4 shows how increasing the number of RSUs to 9 presents a slightly different trend in the behavior of the algorithm. The number of possible deployments grows drastically when more RSUs are considered, and thus more generations are needed until convergence (as previously evidenced by Figure 2). The search space is bigger and the random nature of the process makes it possible to find new optima during longer stages of the algorithm. As shown, the locations of several RSUs are modified during the first 60 generations, and after that, 8 RSUs are placed in their final location; only one of them is moved. Finally, Figure 4(e) shows that the biggest improvement in terms of warning notification time is obtained during the first 40 generations. The last 20 generations only provide a slight reduction when 100 vehicles are simulated. These results prove that random RSU deployments are highly inefficient for low vehicle densities, and the effect of traffic distribution should be taken into account to obtain efficient RSU deployment policies. Our proposal, as it relies on a genetic algorithm, requires relatively high computational resources and

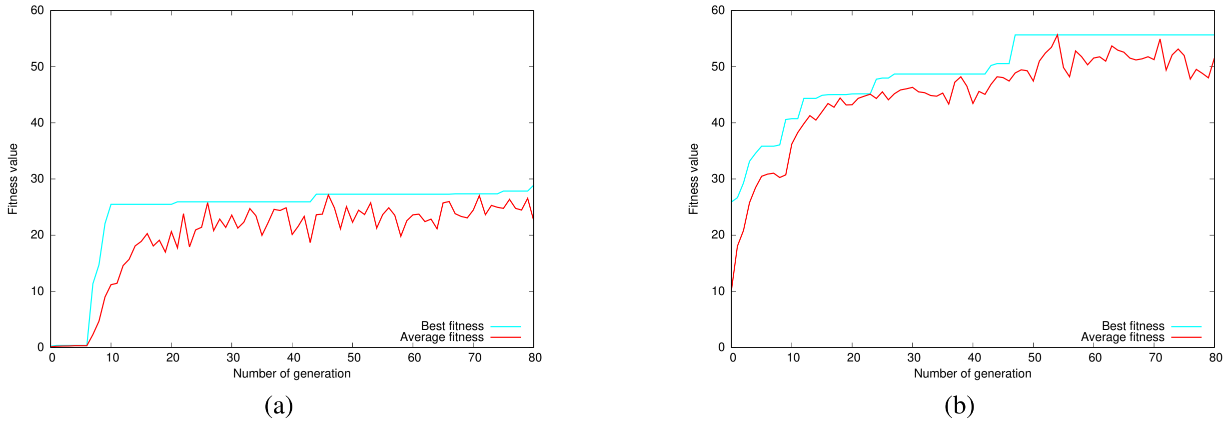


Fig. 2. Fitness evolution of the individuals in the populations using GARSUD in the Madrid scenario when deploying (a) 4 RSUs and (b) 9 RSUs.

it can be slower than other different approaches. However, these requirements are negligible, especially compared to the time and efforts required to make the real deployment of communication infrastructure in the urban environments.

B. Performance comparison between GARSUD and other existing approaches

So far, several schemes have been proposed to achieve an efficient RSU deployment in a given scenario. For example, the Geographic approach [2] tries to provide a balanced coverage of an area by maximizing the distance between RSUs. We slightly modified the Geographic approach to place each RSU in main crosses making it easier the communication with vehicles. On the contrary, the D-RSU scheme [2] requires a previous knowledge of the distribution of traffic to perform an asymmetric deployment, assigning less RSUs to the areas with higher vehicle densities (where the wireless multi-hop communication is easier), while increasing the number of RSUs to cover areas with fewer vehicles where communication is often blocked by buildings and other obstacles. Other approaches proposed by different authors do not provide enough implementation details in order to implement them and perform a fair comparison. Therefore, we selected our own well proven algorithms as a comparison basis.

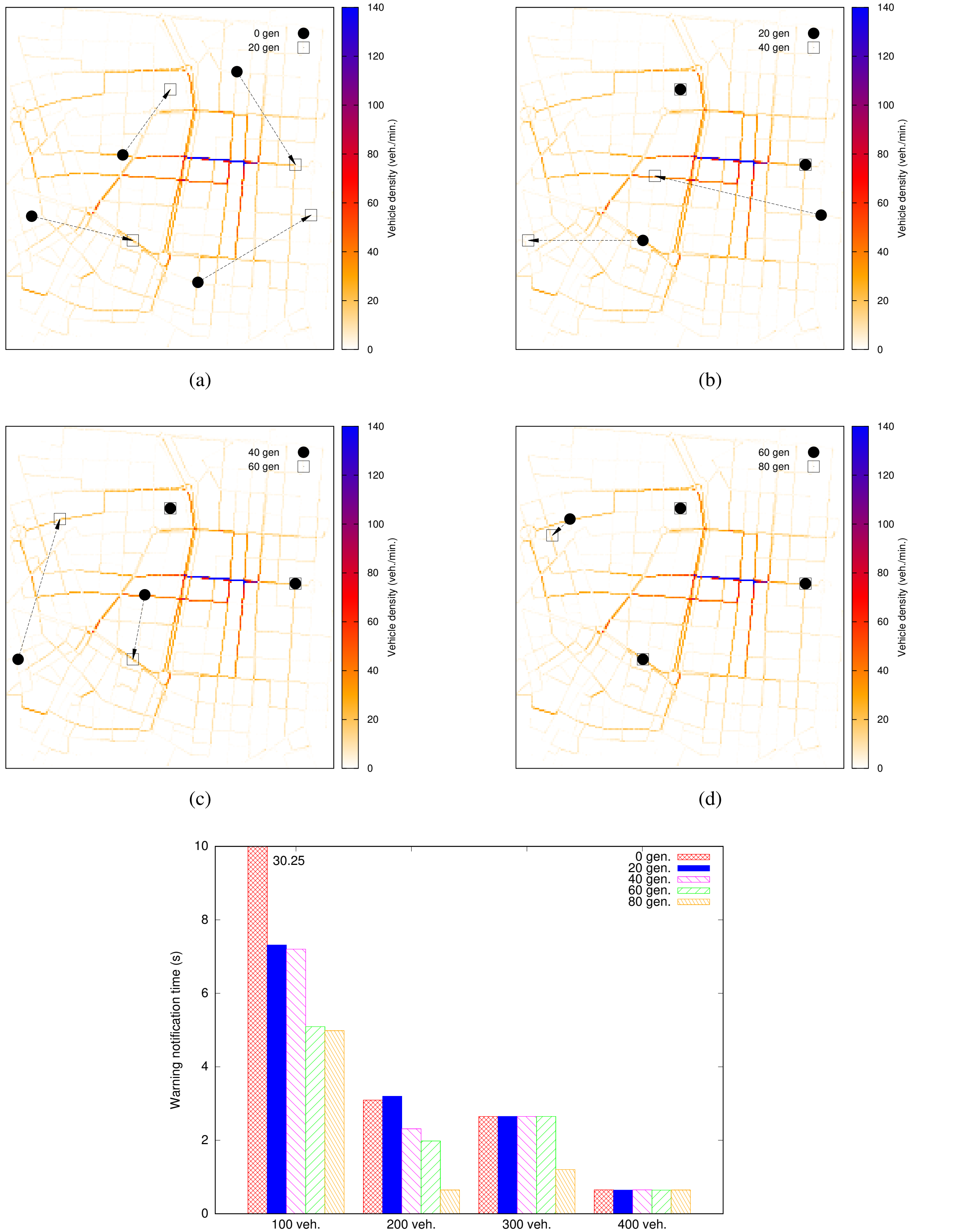
In this section we compare the performance of our proposed GARSUD algorithm against these two existing schemes in terms of warning notification time. In particular, the Geographic distribution does not account for different traffic densities in different areas; it tries to increase the coverage area by regularly deploying the available RSUS. Instead, the D-RSU assigns a fixed number of RSUs to each subarea (i.e., downtown and outskirts) depending on the vehicle densities expected. However, the D-RSU does not consider the street layout to find the most suitable location for the available RSUs, but it applies a geographic mechanism to each individual subarea given the number of RSUs to be deployed.

Figure 5 presents the average warning notification time in the selected layout for the studied densities, while using a Geographic deployment, the D-RSU, and our GARSUD approach. As demonstrated, GARSUD outperforms all the previous schemes, reducing the time required to notify safety authorities about dangerous situations. This improvement is especially noticeable in low-density situations, where GARSUD only requires 25% and 15% of the time needed when 4 and 9 RSUs are deployed using other RSU placement schemes, respectively. Note that increasing the density of vehicles over 400 vehicles (i.e., 100 vehicles/km^2) reduces the overall performance of the system due to high densities tend to increase the contention and collisions in the shared transmission medium, forcing the packet retransmission and delaying the overall dissemination system. However, this effect is reduced when GARSUD is used by selecting the most adequate location, for example RSUs are placed in the junctions where the average wireless traffic does not exceed the capacity of the channel. As a performance indicator, each solution took about 4 hours to complete running in a single core of an Intel Core i5 processor, a time that could be further reduced implementing parallelization techniques to run in several cores at the same time. However, the algorithm only needs to be executed beforehand the deployment of the RSUs, i.e., it is not necessary to provide real time results and the algorithm could be re-run if noticeable changes in the traffic patters are detected, which are not likely to change in short term, reducing the importance of the optimization time.

VI. Conclusions

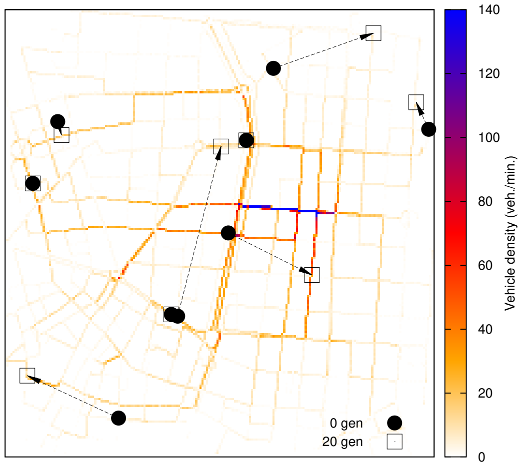
Roadside Units (RSUs) are a key component in Vehicular Networks since they propel the communication capabilities of the vehicles either forwarding important messages or providing connectivity to vehicles, drivers, and passengers.

In this paper, we propose GARSUD, a genetic-algorithm-based RSU deployment scheme that is capable to automatically determine a suitable RSU location for fast warning message delivery in any particular roadmap layout. Simulation results demonstrate that our proposal is able to reduce the warning notification time under different density scenarios, and when a different number of RSU should be deployed. Additionally, GARSUD improves vehicular communication

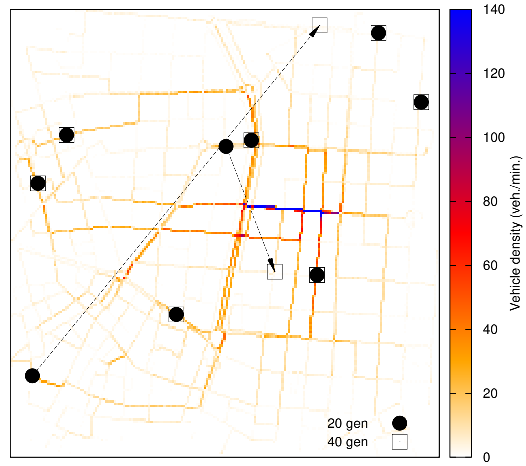


(a) (b) (c) (d) (e)

Fig. 3. Evolution of the deployment of 4 RSUS in the Madrid scenario using GARSUD: (a) after 20 generations, (b) after 40 generations, (c) after 60 generations, and (d) after 80 generations. The evolution of warning notification time for each vehicle density is shown in (e).



(a)



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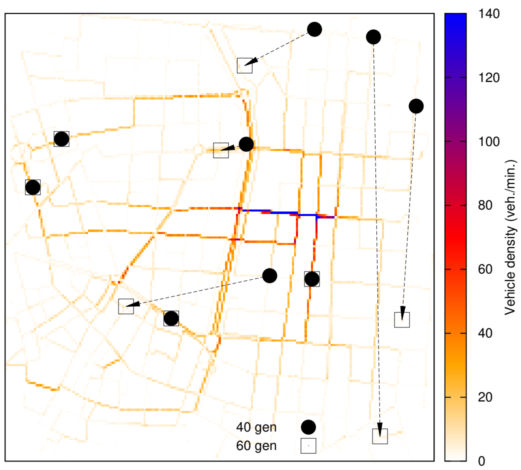

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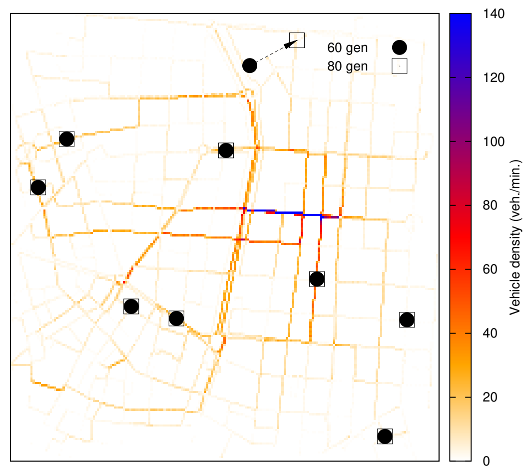
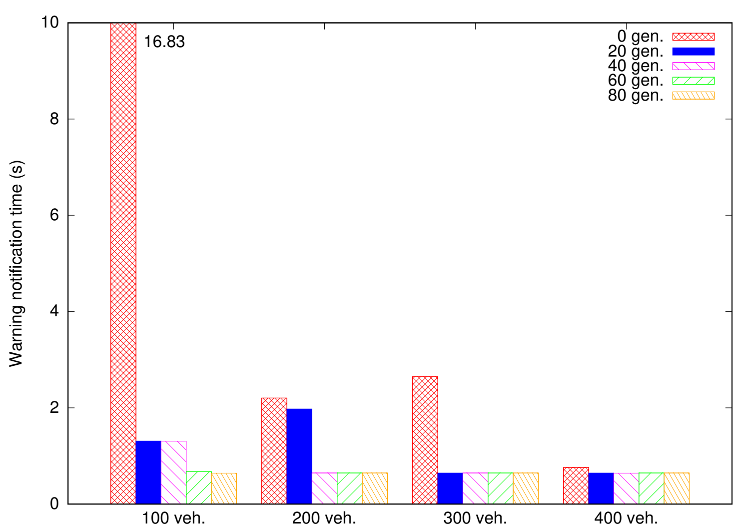
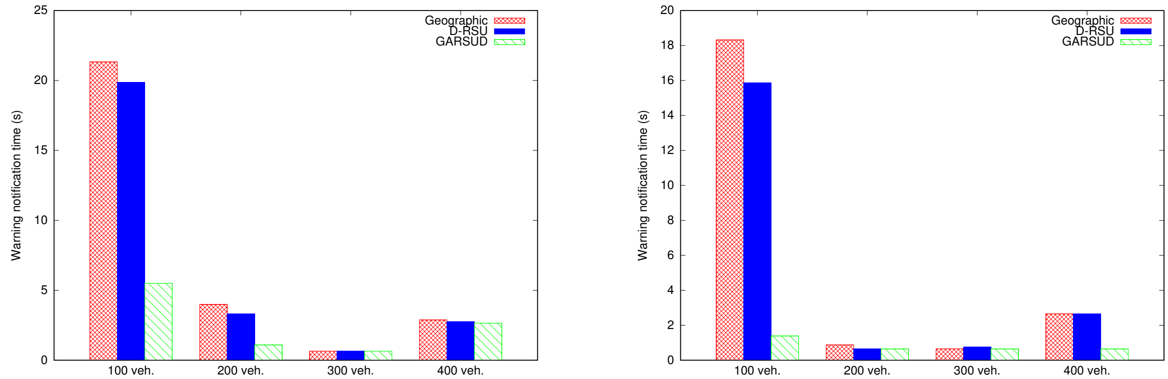


(d)



(e)

Fig. 4. Evolution of the deployment of 9 RSUS in the Madrid scenario using GARSUD: (a) after 20 generations, (b) after 40 generations, (c) after 60 generations, and (d) after 80 generations. The evolution of warning notification time for each vehicle density is shown in (e).



(a) (b)

Fig. 5. Warning notification time in Madrid when varying the density of vehicles and deploying (a) 4 RSUs and (b) 9 RSUs.

capabilities since it increases the probabilities that warning messages can be received by emergency services. To the best of our knowledge, existing approaches are able to obtain good results under a single vehicle density. Our proposal has proved to pinpoint suitable solutions for a wide range of densities, thereby increasing the probability of successful reception of warning messages by emergency services under different conditions.

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