Smart placement of RSU for vehicular networks using multiobjective evolutionary algorithms

Renzo Massobrio, Santiago Bertinat, Sergio Nesmachnow
Universidad de la República, Uruguay
Email: {renzom,sbertinat,sergion}@fing.edu.uy

Jamal Toutouh, Enrique Alba
Universidad de Málaga, Spain
Email: {jamal,eat}@lcc.uma.es

***Abstract*—This article describes the application of a computational intelligence technique for locating roadside infrastructure for vehicular networks over realistic urban areas. A multiobjective formulation of the problem is introduced, considering the deployment cost, and a new model for quality-of-service is defined, accounting for both the traffic (number of vehicles and speed) and the coverage of street segments in the city. The related optimization problem is solved using a multiobjective evolutionary algorithm. The experimental analysis considers real scenarios in the city of Málaga, using realistic traffic information and real antennas. The reported results indicate that the proposed multiobjective evolutionary algorithm is able to compute accurate trade-off solutions for the problem, significantly outperforming a greedy approach based on the ideas previously applied in the related literature.**

I. Introduction

Vehicular ad hoc networks (VANETs) comprise a set of communicating nodes which are: vehicles equipped with onboard units and road side infrastructure elements known as roadside units (RSUs). Depending on the type of the nodes involved in the communication, we distinguish between: vehicle-to-vehicle (V2V), when the vehicles communicate directly, and vehicle-to-infrastructure (V2I), when the vehicles exchanges data with RSUs (see Fig. 1). RSUs act as network access points with higher communication capabilities than the vehicles. Thus, if two mobile nodes cannot directly exchange information because they are out of range, they can use RSUs to relay information between each other via vehicle-to-infrastructure communications. The deployment of a fixed infrastructure of RSUs has been promoted to improve the communication capabilities of VANETs.

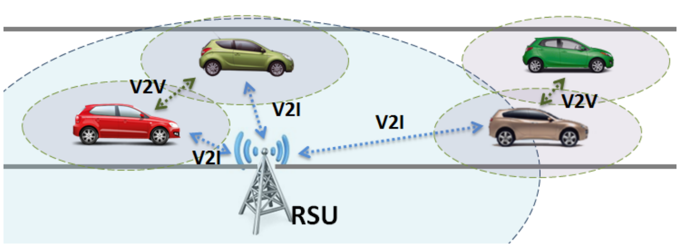

Fig. 1. Global VANET architecture using a RSU.

The work of R. Massobrio and S. Nesmachnow is partly supported by ANII and Pedeciba Uruguay. J. Toutouh is supported by Grant AP2010-3108 of the Spanish Ministry of Education. This research has been partially funded by project UMA/FEDER FC14-TIC36, and the Spanish MINECO project TIN2014-57341-R (http://moveon.lcc.uma.es). University of Malaga, International Campus of Excellence Andalucia Tech.

Deploying such an infrastructure is a challenge in modern cities, because designers must decide about the number, the type, and the location of the RSUs in order to maximize quality-of-service (QoS) of the vehicular network, while satisfying and/or minimizing the deployment cost requirements.

The RSU Deployment Problem (RSU-DP) consists in placing a set of RSU terminals (antennas) along the roads of a given area, maximizing the network capabilities and minimizing the deployment costs.

The RSU-DP is a hard-to-solve optimization problem when dealing with scenarios on city-scaled areas, as the number of possible solutions (i.e. antenna locations) is very large [1]. Therefore, traditional exact methods are not able to find accurate solutions in reasonable times. Computational intelligence methods, including heuristics and metaheuristics [2] are promising methods to deal with the RSU-DP, because they allow computing *good* infrastructure designs—with satisfactory QoS and reduced cost—in reduced execution times [3][4].

Evolutionary algorithms (EAs) are one of such computational intelligence tools, which have emerged to successfully deal with complex optimization problems. In this study, we propose using a multiobjective approach to solve the problem, applying the Non-dominated Sorting Genetic Algorithm, version II (NSGA-II) [5] to optimally design the RSU infrastructure within a city-scaled road network in Málaga (Spain). In order to obtain realistic results, the studied scenarios consider real information about road traffic (traffic flows and road map) and hardware (network capabilities and costs).

A specific QoS model is proposed in this article, considering the number of vehicles, speed, and the coverage of street segments in the city, and a Monte-Carlo simulation approach is used to compute the corresponding QoS metric.

The main contributions of our research are: *i*) introducing a fully multiobjective evolutionary approach to solve the RSU-DP; *ii*) considering realistic scenarios, larger than those solved in the related literature and accounting for real traffic data; and *iii*) reporting accurate results for cost and QoS for the problem instances considered. The proposed NSGA-II is able to significanlty improve over the results computed by randomized greedy heuristics, based on intuitive ideas, to solve the problem. Overall, NSGA-II improves up to **37.1%** in cost and **6.0%** in QoS.

The article is organized as follows. Section II introduces the multiobjective version of the RSU-DP. A review of previous related work on the topic is presented in Section III. Section IV introduces evolutionary computation and the proposed multi-objective evolutionary algorithm (MOEA) to solve the problem. Section V reports the experimental evaluation, including a comparison against two intuitive greedy heuristics to solve the problem. Finally, Section VI formulates the conclusions and the main lines for future work.

II. The RSU Deployment Problem

The mathematical formulation of the RSU-DP considers the following elements:

- A set of *road segments* $S = \{s_1, \ldots, s_n\}$, which are potential locations for placing a set of RSUs $R = \{R_1, \ldots, R_q\}$ along the city streets. Each segment s_i is defined by a pair of points (p_j, p_k), with $p_j, p_k \in P = \{p_1, \ldots, p_m\}$. Each point p_j is identified by its geographical coordinates (latitude, longitude). The length of a given segment s_i is given by the function *len*: $S \rightarrow \mathbb{R}^+$. RSUs can be placed at any location within each segment s_i.
- An estimation of the number of vehicles per time period across each segment s_i, given by function NV: $S \rightarrow \mathbb{N}^+$, and the average vehicle speed for each segment, given by function *sp*: $S \rightarrow \mathbb{R}^+$.
- A set of RSU types $T = \{t_1, \ldots, t_k\}$. Each RSU type is characterized by a given deployment cost and a coverage determined by the transmission power and the antenna gain. The type of a RSU is given by the function *type*: $R \rightarrow T$.
- A cost function C: $T \rightarrow \mathbb{R}^+$, where $C(t_h)$ indicates the monetary cost of placing a RSU of type t_h in the deployed infrastructure.

Solutions of the problem are defined by a set of RSUs placed over the road segments of the city, i.e., $sol = \{R_1, \ldots, R_l\}$, where $l = \#RSU$ in sol. The segments covered by a RSU are given by the function *cov*: $R \rightarrow S$, and the portion of segment s_i covered by RSU R_j is given by the function *cp*: $R \times S \rightarrow [0, 1]$.

The multiobjective version of the problem proposes to find a set of locations and the type of RSU to deploy in each location, with the goal of maximizing the *service time* given by the whole RSU infrastructure, while simultaneously minimizing the *total cost* of deployment. The service time is given by the number of vehicles attended by RSUs and the time they are served (considering the coverage and average speed per each road segment).

Formally, the problem is defined as the simultaneous optimization of the following two objective functions:

$$\max \sum_{R_j}^{R_j \in\, sol} \sum_{s_i \in cov(R_j)} NV(s_i) \times \frac{cp(R_j, s_i) \times len(s_i)}{sp(s_i)} \quad (1)$$

$$\min \sum_{R_j}^{R_j \in\, sol} C(type(R_j)) \quad (2)$$

III. Related Work

Including roadside units in the vehicular networks loop improves the global VANET performance in terms of connectivity, transmission delays, and communication ranges [6]. Thus, in the current literature different studies address the RSU-DP. Most of these works analyze RSU-DP as a version of the Radio Network Design (RND) problem [7]. However, as most nodes in VANETs are vehicles, the design of the roadside platform prioritizes locations taking into account road traffic information as speed of the vehicles, traffic density, etc.

Both exact methods and heuristics have been utilized to solve the RSU-DP and related problems in the literature.

Aslam et al. [8] applied the Balloon Expansion Heuristic (BEH) and Binary Integer Programming (BIP) to minimize the reporting time installing a fix number of RSUs in Miami, USA. They utilized information relative to the speed, traffic density, and likelihood of incidents for the computations. BEH performed better than BIP in the reported experiments.

A Voronoi-based algorithm was applied to optimize packet loss, communications delays, and network coverage, while minimizing the number of RSUs required in a deployed vehicular network in an area of Nashville, USA [9]. The algorithm used information about the speed of vehicles and the traffic density to evaluate the solutions.

Trullols et al. [10] defined the Maximum Coverage with Time Threshold Problem (MCTTP) to maximize the number of vehicles that get in contact with the RSUs for a giving amount of time over the considered area given a number of RSUs. Three different greedy algorithms with different knowledge of the road topology and identity of the vehicles are proposed. These approaches were applied taking into account real road and mobility data from Zurich, Switzerland. The results showed that knowledge of vehicular mobility is the main factor in achieving an optimal roadside deployment.

Finally, some studies have applied genetic algorithms (GA) for solving the RSU-DP. An early approach studied applying a GA that uses a VANET simulator to evaluate the QoS of the computed solutions in a given area of Brunswick, Germany [11]. Other two studies applied the same metaheuristic to optimize the coverage. Cavalcante et al. [3] compared GA against the greedy approach proposed in [10], showing that the GA solutions obtained better vehicle coverage than those given by the greedy approach. Another GA proposal is by Cheng et al. [12], who used just geometric information about the roads (without vehicles mobility related data) of Yukon Territory, Canada, for the computations. The GA outperformed the α–*coverage* algorithm executed under the same constraints.

The first study that applied an explicit multiobjective formulation to solve the RSU-DP is our previous work [13]. That proposal was oriented to maximize the coverage, in terms of the time that vehicles are connected to the RSUs, and minimize the deployment cost. We consider real information concerning both traffic (speed, traffic density, and road map) and hardware (costs and capabilities) for the case of urban locations in Málaga, Spain. The proposed MOEA obtained significantly better results than ad-hoc greedy approaches, but the computed solutions did not cover properly the map, focusing on streets with high number of vehicles instead.

In this article, we extend our previous work [13] by considering a more comprehensive QoS model that accounts for enhanced diversity on the RSU locations, trying to avoid the concentration of RSUs on streets with high number of vehicles (a specific drawback of our previous approach). In addition, a Monte Carlo approach is proposed to evaluate the coverage and number of vehicles for each RSU (see details in the next section).

IV. A MULTIOBJECTIVE EVOLUTIONARY ALGORITHM FOR THE RSU-DP

This section introduces evolutionary algorithms and describes the main features of the proposed MOEA for RSU placement.

A. Evolutionary algorithms and NSGA-II

Metaheuristics are high-level strategies for designing computational methods to solve complex problems [2]. Evolutionary algorithms are non-deterministic metaheuristic methods that emulate the evolution of species in nature to solve optimization, search, and learning problems [14]. In the past thirty years, evolutionary algorithms have been applied to solve many highly complex optimization problems.

Multiobjective evolutionary algorithms (MOEAs) [5] have obtained accurate results when used to solve difficult real-life optimization problems in many research areas. Unlike many traditional methods for multiobjective optimization, MOEAs find a set with several solutions in a single execution, since they work with a *population* of tentative solutions in each generation. MOEAs are designed taking into account two goals: *i*) approximate the Pareto front, and *ii*) maintain diversity instead of converging to a reduced section of the Pareto front. A Pareto-based evolutionary search leads to the first goal, while the second is accomplished using specific techniques that are also used in multi-modal function optimization (e.g. sharing, crowding, etc.).

In this work, we apply the non-dominated sorting genetic algorithm, version II (NSGA-II) [15], a state-of-the-art MOEA that has been successfully applied in many areas. NSGA-II has an improved evolutionary search function compared with the previous version (NSGA), based on three features: *i*) a non-dominated, elitist ordering that diminishes the complexity of the dominance check; *ii*) a crowding technique for diversity preservation; and *iii*) a fitness assignment method that considers crowding distance values.

The NSGA-II algorithm proposed in this work has been engineered to compute accurate solutions for the RSU-DP; the main implementation details are presented next.

B. Implementation details

Solution encoding. Solutions are represented as vectors of real numbers, having $n = \#S$ elements (the number of road segments in S). Each position on the vector defines the RSU information for the corresponding segment. The RSU type is given by the integer part of the real number (0 stands for no RSU placed on the segment, and integers $1 \dots k$ represent RSUs of types $t_1 \dots t_k$, respectively). The position within the segment is given by the fractional part of the real number, mapping the interval $[0, 1)$ to points in the segment $[p_j, p_i)$. Fig. 2 presents an example of solution encoding for a scenario with four segments and three RSUs. The value 1.50 in position 2 of the array means that a RSU of type t_1 is placed at the middle ($0.50 \times len(s_2)$) of the segment $s_2 = (p_2, p_3)$.

Evolutionary operators. The evolutionary search in the proposed NSGA-II for RSU-DP is defined by the operators described next:

1. *Initialization*. The population is initialized by considering the solutions computed by two randomized greedy heuristics for the problem (see a description of the greedy heuristics in Section V-B). A total number of 20 % of the individuals in the population are seeded using the greedy solutions. Given that one of the extremes of the ideal Pareto front is known (i.e., the solution that places no RSU has cost 0), we add that solution to the initial population as well. The remaining individuals of the population are randomly initialized, using reals from the interval [0, k+r] being k the number of different RSU types in T, and $r \in [0, 1)$.

2. *Selection*. A tournament selection is applied (tournament size: two individuals), as originally proposed in the NSGA-II algorithm [5].

3. *Recombination*. The crossover operator is *Intermediate Recombination*; two parents $\vec{x} = \{x_i\}$ and $\vec{y} = \{y_i\}$ are combined to generate two offspring O1 and O2; they satisfy $\text{O1}_i = \alpha_i x_i + (1 - \alpha_i) y_i$ and $\text{O2}_i = \beta_i y_i + (1 - \beta_i) x_i$ with α_i, β_i randomly chosen from the interval $[-\mu, 1+\mu]$ for a given value of parameter $\mu \in [0, 1]$. The recombination operator is applied with a probability p_C.

4. *Mutation*. An ad-hoc mutation operator is designed to provide diversity to the search, which works as follows. Mutation is applied over solutions with probability p_M. When applied, the mutation operator selects a number of segments to modify (s_i) according to a uniform probability in [1, 5]; then, with probability π_A the mutation removes the RSU (if any) from each segment s_i to modify, with probability π_B the mutation changes the type of the RSU (if any) to a random type picked uniformly from set T, and with probability $1 - \pi_A - \pi_B$ a Gaussian mutation on the value for segment s_i is applied with a standard deviation given by parameter σ.

5. *Parallel model*. A master-slave parallel model for metaheuristics [16] is applied to reduce the execution time demanded to evaluate the objective functions (especially, the Monte Carlo simulations for QoS calculation) for each individual in the population.

Computing the objective functions. The calculation of the total cost is straightforward, by adding the cost (according to the corresesponding type) of each RSU placed in the scenario. For computing the QoS metric (number of vehicles attended), we consider the distances and values depicted in Figure 3: the RSU placed in the point "$\times$" in segment $s_1 = (p_1, p_2)$ covers the subsegments c_1 (in s_1), c_2 (in s_2), both in street A, and c_3 (in s_3), and c_4 (in s_4) in street B, according to the coverage defined by the RSU type. The number of effective vehicles attended is given by $\sum_{i=1}^{i=4} NV(s_i) \times \frac{c_i}{sp(s_i)}$. This operation requires computing the intersections between the road segments and the circle representing the coverage of the RSU. Coverage is computed using a Monte-Carlo simulation approach: each segment is divided in 10 points and the length of the subsegment c_i is computed by simulation, considering the coverage radius of the corresponding RSU.

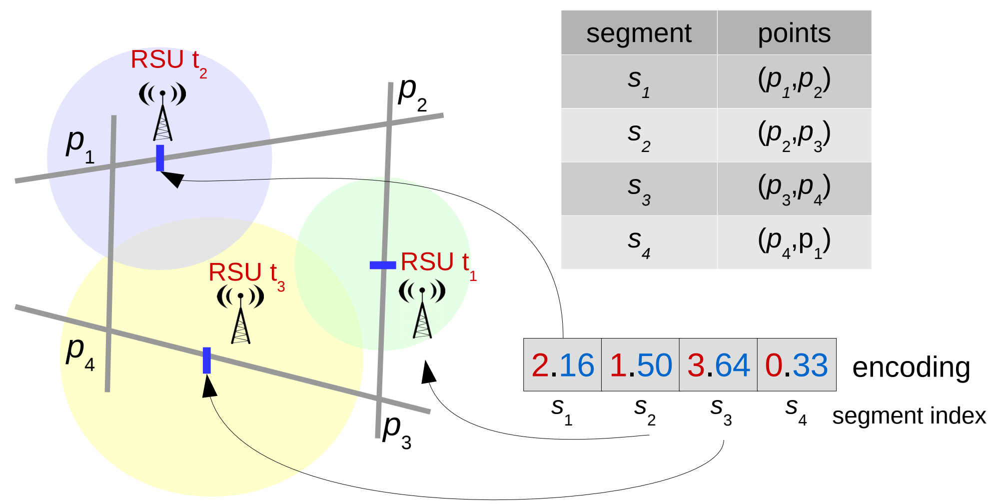

Fig. 2. Encoding for RSU-DP solutions.

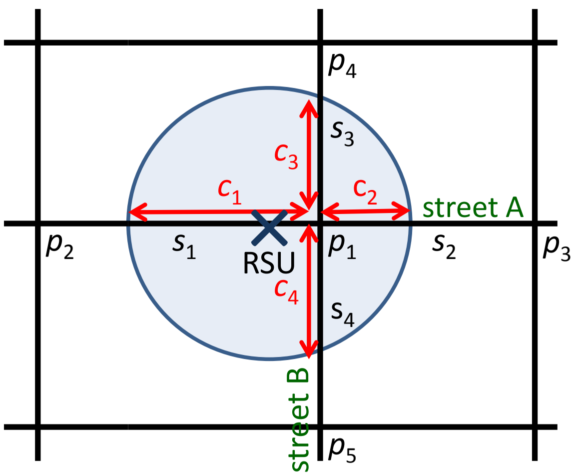

Fig. 3. Calculation of the vehicles attended by a RSU.

Given that the distances involved in the problem are relatively small, we use the Euclidean distance in the latitude-longitude space as an estimation, with negligigle error. This approximation makes the problem significantly faster to compute, thus improving the overall performance of the algorithm. Since the distance of a degree of longitude depends on the latitude, it is necessary to adjust for that by multiplying the longitude by the cosine of the latitude.

Parametric configuration. We performed an analysis to find the best values for NSGA-II parameters. In the parameter setting experiments, the best results were obtained using the configuration: *population size* = 72, $p_C = 0.95$, $p_M = 0.01$, $\pi_A = 0.5$, $\pi_B = 0.25$. The value of μ in the *Intermediate Recombination* operator was set to 0.25. In the Gaussian mutation the value of parameter σ is 0.25.

V. Experimental analysis

This section reports the experimental analysis of the proposed MOEA for smart RSU placement.

A. Problem instances

We defined a real world problem instance based on a real map of Málaga, real road traffic data, and real RSU network interfaces/antennas.

The map covers an area of 42.557 km^2 in the city, including a number of 106 points, which define 121 segments with lengths between 55 and 1556 m. All major traffic ways, including avenues and important streets in Málaga are sampled. Some important avenues with large traffic volume define multiple segments in the map (e.g., *Avenida de Andalucía*, *Avenida de Velázquez*, *Avenida de Valle Inclán* and *Paseo Marítimo Pablo Ruiz Picasso*, all of them with more than 6 segments defined in the map).

The traffic data was collected by the Malaga City Council using a set of sensors located along the roads. These sensors returned the total number of vehicles that circulated during the last three months of 2014. Thus, this information was utilized to define the *normal* pattern for traffic. In addition, two probabilistic multiplicative factors were applied over the *normal* pattern to define two other ones: *low* pattern, reducing the traffic randomly in [0%–20%] and *high* pattern, increasing the traffic randomly in [0%–20%]. These patterns represent situations with low and high road traffic density, respectively.

The RSUs hardware is defined by a processing unit equipped with a IEEE 802.11p network interface. Each network interface is connected to an external antenna to improve the communication range according to a given antenna gain. The gain, measured in decibels (dBi), is a measure of the power of the radio signal radiating from the antenna. Generally, the higher the gain of an antenna, the longer radio range will be obtained. The used antennas have to operate in 5.9 GHz band utilized in IEEE 802.11p standard. Our instance includes three types of RSUs that differ in the antenna gain connected. Three types of IEEE 802.11p antennas are considered, according to three commercial omni-directional antennas that can be found in [17]. Table I summarizes the main features of such antennas.

In order to define the *effective radio range* (ERR) of each RSU we evaluated via simulations the average packet delivery

TABLE I. GENERAL INFORMATION ABOUT THE USED ANTENNAS TO DEFINE DIFFERENT RSU.

type	*commercial model*	*gain*	*ERR*	*cost*
t_1	Echo Series Omni Site Antenna	6 dBi	243.12 m	121.70 $
t_2	Echo Series Omni Site Antenna	9 dBi	338.70 m	139.20 $
t_3	Echo Series Omni Site Antenna	12 dBi	503.93 m	227.50 $

ratio (PDR, the percentage of data packets delivered correctly), at different distances (from 0 to 650 m) for each RSU. The experiments were performed using the ns-2 simulator [18] to simulate vehicular communications using IEEE 802.11p PHY/MAC standard in a urban scenario defined in a one lane road of 1 Km with one RSU and 10 moving cars at 40 Km/h. During the simulations, the RSU sent continuous data streams at 256 Kbps to the cars. The Probabilistic Nakagami radio propagation model [19] was used to represent channel fading characteristics of urban scenarios. In order to ensure a competitive QoS, we defined the ERR of each RSU as the distance at which the average PDR is equal or higher than 66.667%.

B. Comparison against two greedy strategies

In order to compare the results achieved by the proposed MOEA, we developed two randomized greedy heuristics, focused on each one of the probem objectives. These heuristics apply intuitive ideas that simulate the behavior of human-planning strategies, and they are improved versions of the methods defined by Trullols et al. [10] and later used in the comparative study by Cavalcante et al. [3]. The improvements in our heuristics (over the ones in [10]) include: *i*) in our methods, RSUs can be located anywhere within road segments (instead of placing RSUs only at road intersections), *ii*) we consider a variable number of RSUs (instead of using a fixed number of RSUs) and *iii*) a set of RSU types and coverages are considered (instead of a single RSU type).

The two greedy heuristics are described next:

1. *Greedy QoS* (*GQoS*): the set of segments P is sorted according to the QoS they provide (i.e., the ratio between number of vehicles and average speed) in case they are totally covered by a RSU. Iteratively, GQoS adds to the solution the RSUs that provide the best QoS—or cheaper in case of overlapping—, at a random location in the sorted segments (in order), while computing the segments covered by the located infrastructure in each step. Segments that are already covered are not taken into account to be included in the solution.

2. *Greedy cost* (*GCost*): starting from the solution computed by GQoS, the algorithm tries to reduce the cost without significantly affecting the quality of service. Different solutions are explored, by replacing existing RSUs by cheaper ones, or deleted, and the option with the lower QoS degradation is selected. The algorithm stops when all segments are considered or when the QoS of the solution is equal to $\alpha \cdot Q$ where Q is the best QoS value achieved by the greedy algorithm for QoS and $\alpha \in [0, 1]$. For the experimental analysis, GCost was executed using $\alpha \in \{0.70, 0.75, 0.80\}$.

C. Numerical results

The experimental analysis is oriented to evauate the problem solving capabilities of NSGA-II for the RUP. On the one hand, we compare NSGA-II with the greedy heuristics; on the other hand, we evaluate several standard multiobjective optimization metrics [15]: *generational distance* (GD), to evaluate the solution quality; *spacing* and *spread*, to evaluate the distributions of solutions; and the combined metric *relative hypervolume* (RHV), to evaluate both quality and dispersion). We also analyzed the Pareto fronts computed by NSGA-II for each scenario in the experimental evaluation. For each probem instance, we performed 20 independent runs of the MOEA and both greedy algorithms.

In the experimental analysis the proposed MOEA has shown a good solving capability. NSGA-II significantly outperforms the two greedy heuristics while computing accurate Pareto fronts. The solutions computed by the greedy heuristics tend to group in different areas of the solution space, depending on the parameters used for their execution. Therefore, the results obtained by the MOEA are compared against the average results of each group of greedy solutions.

The improvements of NSGA-II over the greedy strategies are reported in Table II. NSGA-II is able to improve the QoS of the greedy heuristics in up to **6.0%** while keeping the same cost, and improve up to **37.1%** the cost of the greedy heuristics while keeping the same QoS (this value represents a $5218.4 saving on a $14079.7 investment). Regarding the cost objective, NSGA-II improves over the greedy results 19.8% in average (for low traffic instance), 20.3% in average (for normal traffic instance), and 17.0% in average (for high traffic instance). Improvements on QoS are smaller but still significative: 4.2% in average (for low and normal traffic instances) and 3.5% in average (for high traffic instance).

TABLE II. NSGA-II IMPROVEMENTS OVER GREEDY HEURISTICS.

instance	*cost improvement*		*QoS improvement*	
	best	*mean±std*	*best*	*mean±std*
normal	36.9	20.3±10.7	6.0	4.2±1.2
low	37.1	19.8±10.3	5.6	4.2±0.9
high	31.0	17.0±8.3	5.5	3.5±1.4

Table III shows the average, standard deviation and best results for the studied standard multiobjective optimization metrics. The ideal Pareto front (which is unknown for the problem instances studied) is approximated by gathering the non-dominated solutions obtained over all executions performed. The small generational distance values indicate a good convergence to an hypothetical ideal Pareto front, and demonstrate the robustness of the NSGA-II approach. Both the spread and spacing values suggest a good distribution of the non-dominated solutions. These results are confirmed by the unitary value of the relative hypervolume metric.

Finally, Figs. 4–5 show the global Pareto fronts achieved by NSGA-II in the 20 executions performed, compared against the results obtained by the greedy heuristics on normal and low traffic scenarios.

VI. CONCLUSIONS AND FUTURE WORK

This article presents a multiobjective evolutionary approach to the problem of locating roadside infrastructure for vehicular networks over realistic urban areas.

TABLE III. NSGA-II RESULTS (MULTIOBJECTIVE OPTIMIZATION METRICS).

instance	*GD*		*spacing*		*spread*		*RHV*	
	best	*mean±std*	*best*	*mean±std*	*best*	*mean±std*	*best*	*mean±std*
normal	1.2	1.5±0.1	203.6	224.2±17.4	0.7	0.7±0.0	1.0	1.0±0.0
low	1.2	1.5±0.3	166.0	204.0±18.3	0.7	0.7±0.0	1.0	1.0±0.0
high	1.0	1.6±0.2	198.2	249.9±26.3	0.7	0.7±0.0	1.0	1.0±0.0

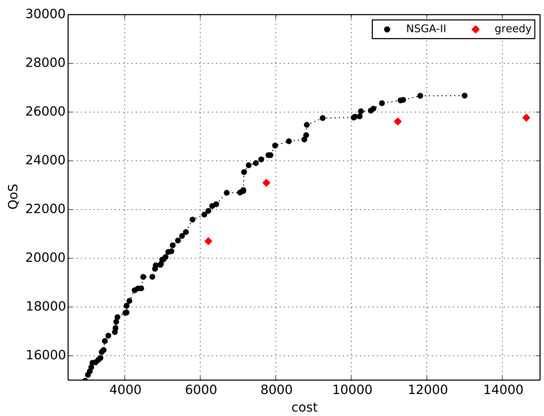

Fig. 4. Global Pareto front and heuristics results (normal traffic instance)

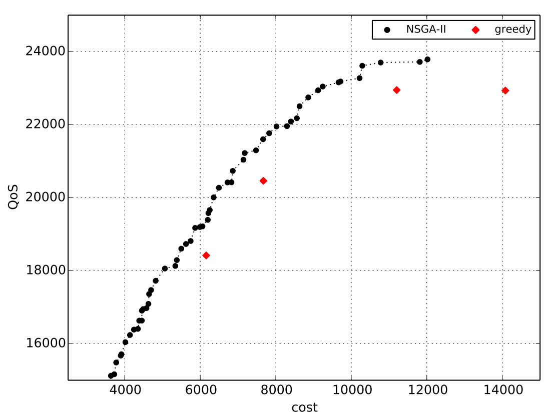

Fig. 5. Global Pareto front and heuristics results (low traffic instance)

An explicit multiobjective formulation is presented and the NSGA-II evolutionary algorithm is applied to solve real problem instances in city-scaled scenarios.

In the experimental analysis, the proposed MOEA has shown good problem solving capabilities. NSGA-II significantly improves over two greedy heuristics for the problem (which are improved versions of methods proposed and used in the literature). The NSGA-II improvements are up to **37.1%** (19.0% in average) in the cost objective and **6.0%** (5.7% in average) in the QoS objective. Additionally, NSGA-II is able to compute accurate Pareto fronts, providing different trade-off solutions for the problem.

The main lines for future work are related to extend the experimental analysis to other geographical areas and considering additional information, such as accidents, in order to model a more realistic scenario for the problem.

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