A multiobjective evolutionary algorithm for infrastructure location in vehicular networks

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Abstract. This article describes a multiobjective evolutionary algorithm applied to locating roadside infrastructure for vehicular networks over realistic urban areas. A multiobjective formulation of the problem is introduced, considering quality-of-service and cost objectives. In the experimental analysis performed over a real map of Málaga, using real traffic information and antennas, the proposed multiobjective evolutionary algorithm computes accurate trade-off solutions for the problem.

1 Introduction

Vehicular ad hoc networks (VANETs) comprise a set of communicating nodes (*vehicles*) equipped with on-board units and roadside units (RSUs) installed beside the roads. 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. Using a fixed infrastructure of RSUs is an efficient alternative in order to improve the communication capabilities of VANETs.

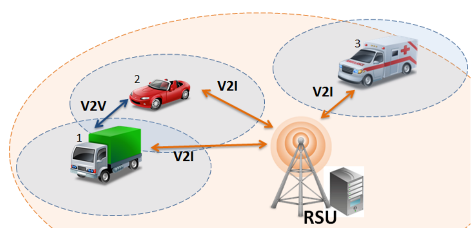

Fig. 1. Global VANET architecture.

Deploying such an infrastructure is a challenge because designers must decide about the number, type, and location of RSUs to maximize quality-of-service (QoS), while satisfying the deployment cost requirements.

The RSU Deployment Problem (RSU-DP) consists of placing a set of RSU terminals along the roads of a given area, maximizing the network QoS and minimizing the deployment costs. This is a hard-to-solve optimization problem on city-scaled areas, as the number of possible solutions is very large [4]. Heuristics and metaheuristics are promising methods to deal with the RSU-DP because they allow computing *good* infrastructure designs in reduced execution times [1, 5]. Evolutionary algorithms (EAs) have emerged to successfully deal with complex optimization problems. In this study, we propose using

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the NSGA-II evolutionary algorithm [2] to optimally design the RSU infrastructure within a city-scaled road network in Málaga (Spain). In order to obtain realistic results, we consider real information about road traffic (traffic flows and road map) and hardware (network capabilities and costs).

Our main contributions 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; *iii*) reporting accurate results for cost and QoS for the problem instances considered.

The article is organized as follows. Section 2 introduces the multiobjective version of the RSU-DP and reviews related work on the topic. Section 3 introduces evolutionary computation and the proposed MOEA to solve the problem. Section 4 reports the experimental evaluation, including a comparison against two intuitive greedy heuristics to solve the problem. Finally, Section 5 formulates the conclusions and the main lines for future work.

2 The RSU Deployment Problem

The RSU-DP considers the following elements:

- A set of *road segments* $S = \{s_1, \dots, s_n\}$ for placing RSUs along the streets. Each segment s_i is defined by a pair of points $p_j, p_k \in P = \{p_1, \dots, p_m\}$. Each point p_j is identified by its geographical coordinates (latitude, longitude). 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, $VN(s_i)$, and the average vehicle speed for each segment $sp(s_i)$.
- A set of RSU types $T = \{t_1, \dots, t_k\}$, each one with a given gain and transmission power that determines the covering area and the cost of the RSU.

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

Related works. Some works have applied EAs to RSU-DP variants. An early work studied a genetic algorithm (GA) that uses a VANET simulator to evaluate the network QoS for solving the RSU-DP in a given area of Brunswick, Germany [3], considering 100 possible predefined locations for RSUs. The results show that a *good* cost/utility trade-off is obtained using between 10 and 30 RSUs. Cavalcante et al. [1] compared a GA against a greedy approach to solve the maximum coverage with time threshold problem using real road and mobility data form four Swiss regions. The results show that the GA obtains better vehicle coverage than the greedy approach.

In the review of related works, we did not find articles using explicit multiobjective methods for this specific problem. Furthermore, the use of MOEAs to solve the problem has not been studied. Thus, there is room to contribute in this line of work by studying efficent and accurate MOEAs to solve the RSU-DP.

3 A multiobjective evolutionary algorithm for RSU-DP

This section presents the details of the proposed MOEA for RSU placement.

Solution encoding. Solutions are represented as real arrays of length $n = \#S$. Each position on the array holds the RSU information: the type is given by the integer part of the real number (0 stands for no RSU, and integers $1 \dots k$ represent types $t_1 \dots t_k$); position within the segment is given by the fractional part of the real number, mapping the interval $[0, 1)$ to points in the segment $[p_j, p_i)$. For instance, a value of 3.5 in position 5 of the tuple, means that in segment number 6 a RSU of type 3 is placed at the middle of the segment.

Evolutionary operators. Population is randomly initialized, using reals from the interval $[0,\ k + r]$ being k the number of different RSU types in T, and $r \in [0, 1)$. Given that one of the extremes of the ideal Pareto front is known (the solution that places no RSU has cost 0), we add that solution to the initial population. Future work includes adding solutions computed by greedy algorithms to the initial population as well. The crossover operator is *Intermediate Recombination*; offspring of parents $\boldsymbol{x}$ and $\boldsymbol{y}$ satisfy $\alpha_i x_i + (1-\alpha_i)y_i$ and $\beta + (1-\beta_i)y_i$ with α, β randomly chosen in $[-p, 1+p]$ for a given p. An ad-hoc mutation operator was designed to provide diversity to the search: with probability π_A we remove the RSU (if any) from the segment, with probability π_B we change the type of the RSU (if any) to a random type picked uniformly in T, and with probability $1 - \pi_A - \pi_B$ we apply a Gaussian Mutation with a standard deviation of σ.

Computing the objective functions. Computing the total cost is straightforward, by adding the cost (according to the type) of each RSU placed in the scenario. For computing the QoS, we consider the distances and values in Figure 2: the RSU placed in the point "×" covers the subsegments c_1 (in s_1), c_2 (in s_2), in street A, and c_3 (in s_3), and c_4 (in s_4) in street B. The number of effective vehicles attended is computed by $\sum_{i=1}^{i=4} NV(s_i) \times \frac{c_i}{sp(s_i)}$. This requires computing the intersections between the road segments and the circle representing the coverage of the RSU. Given that the distances involved in the problem are relatively small, we use straight lines in the latitude-longitude space as an estimation, with negligible error. This approximation makes computation faster, 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.

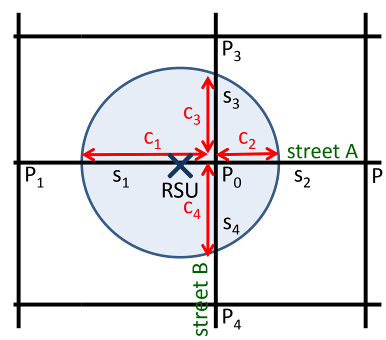

Fig. 2. Calculation of the vehicles attended by a RSU.

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, *crossover probability*=0.95, *mutation probability*=0.01, π_A=0.5, π_B=0.25, and σ=0.25.

4 Experimental analysis

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, including a number of 106 points, defining 121 segments with lengths between 55 and 1556 m. The RSUs hardware are equipped with a IEEE 802.11p network interface, connected to an external antenna to improve the communication range according to a given antenna gain. Three types of IEEE 802.11p antennas are considered, according to three commercial omni-directional antennas form *Cetacea Wireless shop* (https://shop.cetacea.com/, see Table 1).

Table 1. General information about the antennas used to define different RSUs.

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 $

In order to define the *effective radio range* (ERR) of each RSU, we evaluated the average percentage of data packets delivered correctly (*packet delivery ratio*, PDR), at different distances (from 0 to 650 m) for each RSU. Finally, 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%.

Comparison against two greedy strategies. We compare the results achieved by the proposed MOEA against two greedy heuristics. For the QoS objective, the greedy strategy places RSUs sequentially over non-covered segments starting with those with the higher ratio between number of vehicles and average speed. A segment is considered covered if it has a portion of λ inside the coverage area of any RSU. The greedy strategy for cost is analogous, but stops 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 using $\lambda = 0.75$ and $\alpha \in [0, 1]$. For the experimental analysis the greedy algorithm for QoS was executed using $\lambda \in \{0.90, 0.95, 1.0\}$ and the greedy algorithm for cost was executed using $\alpha \in \{0.70, 0.75, 0.80\}$.

Execution environment. The experimental analysis was performed using 24 cores on an AMD Opteron 6172 2.10 GHz with 24 GB RAM at Cluster Fing: the high performance computing facility at Universidad de la República. Since computing the fitness of an individual is highly CPU-intensive, the evaluation of the population is done in parallel using 24 threads, thus each thread evaluates 3 individuals of the population. For each probem instance, we performed 20 independent runs of the MOEA and of both greedy algorithms.

Numerical results. 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. Table 2 reports the best improvement of the proposed MOEA over the greedy strategies. NSGA-II is able to improve the QoS achieved by the greedy heuristic for cost in up to 73.9%

while keeping the same cost and improve up to 365.1% the cost achieved by the greedy heuristic for QoS while keeping the same QoS. Table 3 shows average, standard deviation and best results for standard multiobjective optimization metrics, where the small generational distance and spread values suggest both good convergence to an hypothetical ideal pareto front as well as good distribution among the non-dominated solutions. Finally, Figs. 3–4 show the global Pareto fronts achieved by the MOEA against the best results obtained by the greedy heuristics combining all 20 executions on normal and low traffic scenarios.

Table 2. Improvements over greedy heuristics.

		instance		
		normal	*low*	*high*
improvement in cost	RG_cost_70	70.2%	67.7%	68.6%
	RG_cost_75	67.1%	68.1%	66.5%
	RG_cost_80	73.9%	69.7%	70.7%
improvement in QoS	RG_QoS_90	299.3%	307.5%	333.4%
	RG_QoS_95	337.9%	277.2%	344.7%
	RG_QoS_100	365.1%	331.4%	341.8%

Table 3. Multiobjective optimization metrics.

	normal	*low*	*high*
generational distance	2.7±0.3 (2.0)	2.7±0.4 (1.5)	2.7±0.3 (2.0)
spacing	792.5±88.1 (615.5)	739.8±68.9 (587.4)	897.7±102.0 (719.1)
spread	$0.4 \pm 4.9 \times 10^{-2}$ (0.4)	$0.4 \pm 4.3 \times 10^{-2}$ (0.3)	$0.4 \pm 4.1 \times 10^{-2}$ (0.3)
relative hypervolume	$1.0 \pm 1.7 \times 10^{-2}$ (1.0)	$0.9 \pm 1.9 \times 10^{-2}$ (1.0)	$0.9 \pm 1.9 \times 10^{-2}$ (1.0)

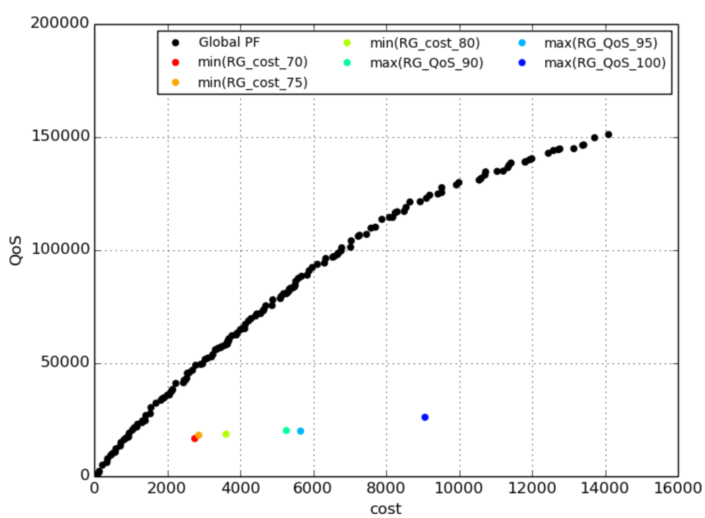

Fig. 3. Global Pareto front and heuristics results (normal traffic instance)

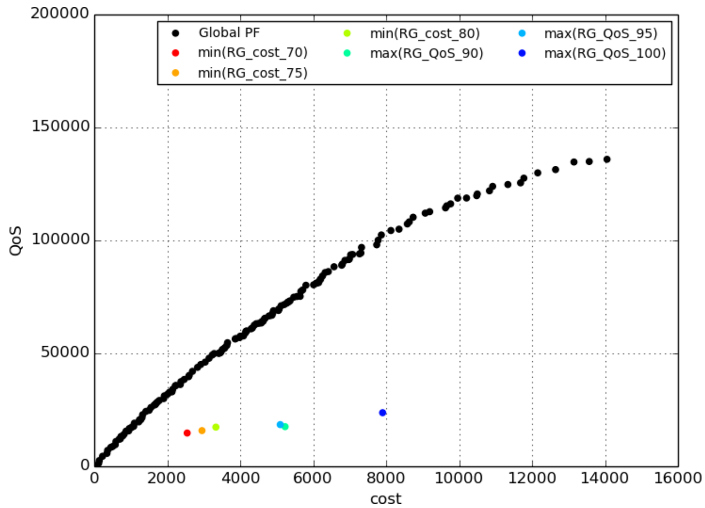

Fig. 4. Global Pareto front and heuristics results (low traffic instance)

5 Conclusions and future work

This article reports the advances on applying a multiobjective evolutionary approach to the problem of locating roadside infrastructure for vehicular networks over realistic urban areas. In the experiments performed, the proposed MOEA has shown good problem solving capabilities, computing accurate Pareto fronts and significantly improving over two greedy heuristics for the problem: up to 73.9% in cost and 365.1% in QoS. We are working now on extending the experimental analysis to other areas and considering additional information, such as accidents, in order to model a more realistic scenario for the problem.

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