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Multiobjective evolutionary optimization of traffic flow and pollution in Montevideo, Uruguay

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ABSTRACT

Traffic congestion and pollution are important problems in modern cities. As improving traffic flow via infrastructure modifications is expensive and intrusive, approaches using simulations emerge as economic alternatives to test different policies, with less negative impact on cities. This article proposes a specific methodology combining simulation and multiobjective evolutionary methods to simultaneously optimize traffic flow and vehicular emissions via traffic lights planning in urban areas. The experimental evaluation is performed over three real areas in Montevideo (Uruguay). Significant improvements on travel times and pollution are reported over the current configuration of traffic lights cycles and also over other traffic regulation techniques. Moreover, the multiobjective approach provides policy-makers with a set of alternatives to choose from, allowing the evaluation of several scenarios and the dynamic modification of traffic light cycles.

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1. Introduction

Traffic jams and air pollution are major problems in big cities nowadays. As a consequence, one of the main tasks of policy-makers and administrators consists in applying innovative ideas for developing sustainable mobility systems [1,2]. Several strategies have been proposed for developing Intelligent Transportation Systems (ITS). In general, two main strategies are applied to enhance the traffic flow: (i) changing the infrastructure of an urban area and (ii) introducing modifications in the mechanisms that rule the traffic flow.

On the one hand, those alternatives that involve modifying the traffic infrastructure have a significant monetary cost, and usually they also have negative consequences for citizens when building/testing the new infrastructure. In this context, strategies applying computational intelligence and simulation emerge as a viable option to evaluate alternative polices for traffic management [3]. Several authors and policy makers have focused on improving the traffic flow by modifying the main mechanisms to govern it, i.e., traffic lights [4]. Additionally, optimization algorithms have proven to be useful for solving problems related to traffic flow. In particular, the configuration of traffic lights cycles has been tackled using bioinspired algorithms [5]. In this line of work, our research group has recently published articles applying microscopic modeling for traffic and vehicles emissions using single-objective bioinspired optimization methods [6,7].

This article proposes a multiobjective evolutionary approach for the optimization of traffic light program cycles to improve traffic flow and reduce vehicular emissions in city-scaled scenarios. We apply an explicit Pareto-based approach, where the problem objectives are optimized simultaneously, instead of combining them in a single objective function. This approach allows exploring the whole search space of possible configurations and providing different alternatives to traffic administrators and decision makers. We introduce Multiobjective Evolutionary Algorithms (MOEAs) aimed at efficiently solving the optimization problem in large urban areas. The traffic demand is modeled using an origin-destination matrix, which is built using real data and a specific prioritization strategy of the edges of the traffic network. Additionally, we use microscopic simulations to evaluate the impact of the traffic lights cycles generated by the proposed MOEAs in both, traffic flow and vehicular emissions.

The main contributions of the research reported in this article are: (i) we integrate MOEAs with a microscopic traffic model to simultaneously optimize traffic flow and minimize vehicular emissions; (ii) we perform a comparison of four state-of-the-art MOEAs to solve the problem over realistic instances, built using

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information collected on three heterogeneous areas of Montevideo, Uruguay. The results are compared with the current configuration of traffic lights cycles programs in Montevideo and other traffic regulation techniques. The main results indicate that the best MOEA improves in more than 60% the traveling time for vehicles, in comparison with the current configuration of traffic lights. In terms of vehicular emissions, the MOEAs allow reducing pollutant emissions by more than 25% over the current situation. In comparison with standard traffic regulation techniques, the MOEAs prove to be more efficient for finding the better traffic lights cycles programs, offering to the policy-makers several alternatives to choose from.

The article is organized as follows. In Section 2 the main references about traffic lights cycles programming, vehicular emissions, and bioinspired approaches are reviewed. The mathematical formulation of the problem is presented in Section 3. The specific proposal of applying MOEAs for traffic flow and pollution optimization is presented in Section 4. Section 5 describes the experimental evaluation of the proposed evolutionary optimization techniques over real scenarios defined in Montevideo, Uruguay. The numerical results are reported and discussed in this section. Finally, Section 6 presents the conclusions and formulates the main lines for future work.

2. Literature review

Bio-inspired methods and simulations have been applied for solving traffic lights cycles programming problems.

Rouphail et al. [8] combined a microscopic simulator and Genetic Algorithms (GA) to optimize the traffic lights cycles in nine intersections of Chicago, USA. The results, in terms of total tail size, are limited due to the slow convergence of the proposed GA. Teklu et al. [9] analyzed the impact of changing the duration of traffic lights phases over vehicle drivers using simulations and a GA to determine the optimal program of traffic lights. The model anticipates the response of drivers to traffic lights changes and optimizes the traffic lights programs. The GA proposed by Sanchez et al. [5] was designed to optimize traffic lights cycles in a commercial area of Tenerife, Spain. Each intersection is treated as independent and the representation is similar to the one used by Teklu et al. [9]. The valid states strongly depended on each scenario and must be built before applying the GA. Chen and Xu [10] applied Particle Swarm Optimization (PSO) to train a Fuzzy Logic for one intersection to determine the effective green time of each traffic lights cycle. Peng et al. [11] proposed a PSO with niches for traffic lights planning, adopting a microscopic vision of vehicular flow to evaluate alternative solutions. An simple instance with only one street and two intersections is used to test the PSO. The study is focused on the capacity of niches to maintain the diversity of the swarm and not in the traffic network itself.

Empirical studies have shown the relation between vehicular emissions and delays caused by a low quality traffic lights cycles programming [12]. However, few works have directly taken into account the traffic lights cycles programming in order to minimize the pollution in urban areas. Among the most relevant ones, Li et al. [13] introduced an alert system for drivers to avoid sudden stops in intersections, potentially reducing vehicular emissions. Stevanovic et al. [14] used simulations to optimize traffic lights and minimize fuel consumption, studying 14 intersections in Utah, USA. The results showed that the estimated fuel savings were around 1.5%, a low statistical improvement. Tielert et al. [15] showed that vehicular communications help drivers to avoid sudden stops and accelerations. Asadi and Vahidi [16] reduced the fuel consumption applying a predictive cruise control, using upcoming traffic signal information. The method requires an expensive infrastructure not only for traffic lights but also for vehicles. The evaluation is performed over an instance with nine intersections and a fleet of only six vehicles equipped with a send-receive device driving in an avenue. The main problem of this approach is that it does not contemplate vehicles traveling without the device. De Coensel et al. [2] combined Paramics [17], a model for emissions, and the green wave technique to reduce the vehicular emissions. The study is focused on an urban arterial road with a speed limit of 50 km/h and five consecutive traffic signals, spaced 200 m from each other. The results showed that using green wave could potentially lower the pollutants emissions, depending on traffic flow and signal timing settings. Sun et al. [18] used NSGA-II and a mathematical model of urban traffic to solve the traffic signal timing problem over a case study only considering two traffic lights phases. Lv et al. [19] developed a GA for traffic lights optimization using an objective function that considers both vehicle delays and emissions. The emission model used real-time information of vehicles and analyzed the quality of the air for different traffic network configurations. A case study was conducted to demonstrate the application of the developed methodology to reduce traffic emissions. The results indicated that there is a trade-off between problem objectives, e.g., when using a cycle length of 120 s, emissions were reduced up to 10.9%, but in expenses of increasing the delay 14.8%. Zhou and Cai [20] optimized traffic lights cycles using a multiobjective model combining a GA with Paramics for reducing vehicular emissions, fuel consumption, and delay of vehicles in signalized intersections. The results of a case study with a single intersection reduced traffic delay and pollutant emissions, while also reducing up to 9.27% the fuel cost when compared with a traditional Webster model [21].

Lee et al. [22] combined VISSIM with a multiobjective optimization approach for optimizing traffic lights on a scenario with only four intersections in oversaturated conditions. Olivera et al. [7] applied PSO for traffic lights planning in Seville and Málaga, using a single objective function to integrate pollution and traffic flow. Two scenarios covering similar areas of 0.75 km^2 were used for the evaluation of the PSO approach, comparing with Differential Evolution. The results showed significant profits in terms of fuel consumption, time delay, and pollutant emissions. The traffic lights cycles obtained reduced the concentrations of CO by 29.3%. Similar results were observed for NO_x. For the total fuel consumption, the improvements reached 18.2%. However, the single objective approach does not allow having a global vision of the traffic network: solutions with traffic jams can be considered as “good” solutions, because vehicles that do not move produce low levels of emissions and have minimal fuel consumption.

The analysis of the related literature indicates that previous proposals about optimizing traffic flow and pollution focused on small problem instances or use a single-objective perspective of the problem. Many approaches do not consider the impact of traffic lights planning on pollution or only limited analysis and results are reported. The previous approach by Olivera et al. [7] allows computing accurate solutions using computational intelligence techniques, but it also demonstrates that the the single objective approach does not capture the main features of the traffic/pollution reality. In this article, we improve over the previous works and contribute with a fully multiobjective optimization model using MOEAs, to consider traffic flow and pollution simultaneously. In addition, we consider real-world instances, built following a specific methodology that considers up-to-date traffic data from GPS and vehicle counts.

3. Problem formulation

An urban traffic network is composed of intersections, traffic lights, roads, and vehicles moving through following its routes. The traffic lights planning problem consists in determining a configu-

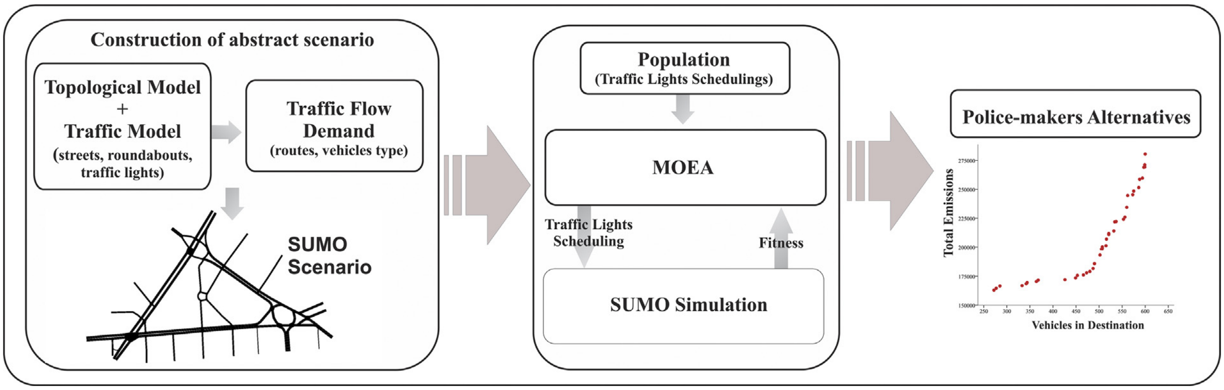


Fig. 1. General schema of the resolution strategy.

ration of traffic lights states and offsets for each intersection of an urban traffic network in order to fulfill specific goals.

Formally, consider the following elements:

- A directed graph $G(N, A)$ that represents the urban traffic network, where N are the nodes (intersections) and A are the edges (roads) in G.
- A set of input nodes $NI \subset N$ and a set of output nodes $NO \subset N$, representing the origins and destinations of vehicles, respectively.
- A set of nodes $NS = \{1, \ldots, n\}$ with traffic lights. Each node $i \in NS$ has an associated traffic lights cycle program p_i.
- A set of programs for traffic lights $P = \{p_1, \ldots, p_n\}$. Each program p_i has a set of associated states $E(p_i) = \{e_{i1}, \ldots, e_{ik}\}$ and an offset of start o_i.
- A set of vehicles $V = \{v_1, \ldots, v_m\}$. Each vehicle v_h has three attributes: (i) a type tv_h; (ii) a route r_h composed of adjacent edges, $r_h = < l_{h1}, \ldots, l_{hq} >$, with $l_{hr} \in A$; and (iii) a time of appearance in the traffic network ts_h.
- A function $VD(v, t)$, $v \in V$, indicating if the vehicle arrives to destination in a time t, according to an origin-destination matrix (O-D matrix) $M_{tv} \in \mathbb{N}^{|NI| \times |NO|}$. M_{tv} contains the number of trips between each origin and each destination, for each vehicle type tv.
- A set of pollutants $C = \{\text{CO}, \text{CO}_2, \text{NO}_x, \text{HC}, \text{PM}_x\}$ to consider in the study.
- A function $ET(V, c, t)$ that returns the emissions of all vehicles $v \in V$ for a pollutant agent $c \in C$ from time 0 to time t.
- A function $TP(v, t)$ with $v \in V$, returning the total time lost for a vehicle to travel below its ideal velocity.
- A simulation time period t_{SIM}.

The problem proposes finding, for a signalized intersection, $n_i \in NS$, the duration d_{ij} in seconds of each state e_{ij} and the offset o_i of its program p_i, to maximize the number of vehicles that arrives to destination (Eq. (1)), to minimize the time lost for vehicles traveling below the ideal velocity (Eq. (2)), and to minimize the total emissions for each pollutant (five objectives) (Eq. (3))

$$\max VDG = |\{v \in V | VD(v, t_{SIM}) = 1\}| \tag{1}$$

$$\min TPG = \sum_{v \in VD(v, t_{SIM})} TP(v, t_{SIM}) \tag{2}$$

$$\min ETG_c = ET(V, c, t_{SIM}) \forall c \in C \tag{3}$$

Instead of combining the seven problem objectives in a single function (e.g., using a linear aggregation method), we apply an explicit Pareto-based approach. In this approach, all the problem objectives are optimized simultaneously, allowing a better exploration of the space of possible traffic lights configurations. Thus, the approach allows computing different alternatives to be considered for implementation by traffic administrators and decision makers.

4. MOEAs for traffic flow and pollution optimization

This section describes the proposed optimization strategy using MOEAs and simulation for traffic lights planning in real urban scenarios.

4.1. Multiobjective evolutionary optimization

Metaheuristics are strategies that allow designing efficient and accurate methods to find approximate solutions for search, optimization, and learning problems [23]. Evolutionary Algorithms (EAs) are metaheuristics that emulate the natural evolution to solve optimization, search, and other problems [24].

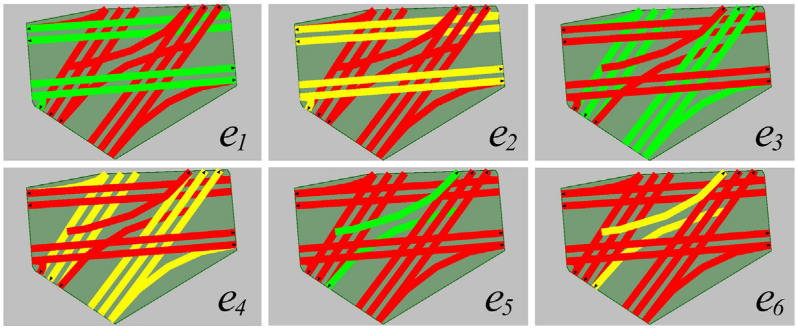
MOEAs [25] are specific EAs to solve problems with many conflicting objectives. MOEAs have obtained accurate results when solving difficult real-life optimization problems in many research areas. MOEAs allow finding a set with several solutions in a single execution, since they work with a population of tentative solutions in each generation. MOEAs are designed to fulfill two goals at the same time: (i) approximate the Pareto front, using a Pareto-based evolutionary search, and (ii) maintain diversity, instead of converging to a section of the Pareto front, using specific techniques also used in multi-modal function optimization (e.g., sharing, crowding).

This work proposes using and comparing several state-of-the-art MOEAs that have been successfully applied as optimization tools in many areas, to solve the traffic lights planning problem to improve traffic metrics and reduce pollution emission. Mobility simulation over realistic scenarios is used to evaluate traffic lights programs, as described by the general schema in Fig. 1.

4.2. Simulation tool

Simulation of Urban MObility (SUMO) [26] is an open source, highly portable, microscopic, and continuous road traffic simulator. It allows intermodal simulation including pedestrians, and has a large set of tools for creating scenarios. In SUMO, every vehicle has its own route, moves individually through the network, and has a predefined maximum velocity. In this work, we consider a model for vehicular traffic atmospheric contamination that computes pollutant emissions: carbon monoxide (CO), carbon dioxide (CO_2), nitrogen oxide (NO_x), hydrocarbons (HC), and particulate matter (PM_x); according to the *Handbook Emission Factors for Road Transport* (HBEFA) [27] to define the function *ET*.

In a SUMO network, a traffic lights cycle program has an identification, a set of ordered states, and an offset (the time when the first



e_1	rGGGrrrrGGrGrrrr
e_2	ryyyrrrryyryrrrr
e_3	rrrrGGGGrrrrGGGG
e_4	rrrryyyyrrrryyyy
e_5	GrrrrrrrrGrrrrr
e_6	yrrrrrrrryrrrrr

Fig. 2. Connections and states of traffic lights cycle program in a SUMO network junction.

state in the cycle begins). Each state has an integer value indicating its duration (in seconds) and a string of characters representing the color of the traffic lights. The characters are *r* for red light, *y* for yellow light, *g* for green light–no priority (vehicles may pass the junction if no vehicle uses a higher priority, otherwise, they decelerate and let it pass) and *G* for green light–priority (vehicles may pass the junction). Fig. 2 shows different valid states for a junction and their character representations.

4.3. MOEAs applied in the study

The MOEAs applied to optimize traffic and pollution are described next.

Non-dominated Sorting Genetic Algorithm, version II (NSGA-II) [25], is a state-of-the-art MOEA that has been successfully applied in many areas. NSGA-II applies Pareto dominance for the fitness calculation, building *fronts* of solutions. The evolutionary search on NSGA-II improves over the previous version (NSGA), by using: (i) a non-dominated, elitist sorting that reduces the complexity of the dominance check; (ii) a crowding technique for diversity preservation; and (iii) a fitness assignment that considers crowding distance values.

ϵNSGA-II [28] is a NSGA-II variant that uses adapting population size and self-termination to avoid exhaustive parameter calibration, and *ϵ-dominance archiving*, which defines a precision threshold for Pareto-optimal solutions by assigning relative priorities to each objective. A series of *connected runs* using small populations guides the MOEA to good regions of the search space. The population size is adapted as the problem becomes harder. ϵ-non-dominated solutions are stored in an external file and injected in the population to guide the search. Random generation of solutions is also used to improve diversity.

Generalized Differential Evolution, version 3 (GDE3) [29] extends Differential Evolution to solve multiobjective optimization problems. The selection operator is based on Pareto-dominance, and the DE/rand/1/bin strategy is applied to solve problems with multiple objectives and constraints.

Multiobjective Evolutionary Algorithm based on Decomposition (MOEA/D) [30] applies domain decomposition to solve several single-objective optimization problems, by means of a linear aggregation using different weights for each objective function. A cooperation schema is also used: subproblems are solved using information from neighboring subproblems. The linear aggregation approach is usually outperformed by Pareto-based methods for multiobjective optimization, but it is a common approach in the literature mainly because it is efficient and suitable for optimization problems with a convex Pareto front [31]. As a result, MOEA/D is more efficient (i.e., demands less computing time) than other state-of-the-art MOEAs.

4.4. Implementation details

The proposed MOEAs for traffic light planning were implemented in Java, using the MOEA framework [32], an open-source library for multiobjective optimization. The implementation details are described next.

Solution representation. Given the set $P = \{p_1, p_2, \ldots, p_n\}$ of traffic lights cycle programs, an integer-based representation is used to encode the duration of each state associated to each p_i and the corresponding offset (o_i): $\left[o_1, d_{11}, d_{12}, \ldots, d_{1k_1}\right]$, $\left[o_2, d_{21}, d_{22}, \ldots, d_{2k_2}\right]$, $\ldots$, $\left[o_n, d_{n1}, d_{n2}, \ldots, d_{nk_n}\right]$, where k_i is the number of states of program p_i.

States associated to yellow lights have a constant duration of 4 s, according to traffic regulations, thus they are not included in the representation. A yellow light state always occurs between red and green state. Green and red states have durations $d_{ij} \subset \mathbb{N}$, $d_{ij} \in [5, 60]$. Offsets are defined such that $o_i \in [0, 60] \subset \mathbb{N}$. Fig. 3 presents an example of solution representation for a single crossing site (i.e., only state e_{i1} is shown. A full solution encoding simply concatenates the state representation for all crossings defined in the studied area.

Objective functions. The objective functions to optimize are: (i) minimize the total emission of pollutants (CO, CO_2, HC, PM_x, and NO_x), according to the HBEFA emission model; (ii) maximize the number of vehicles arriving to destination, as defined by Eq. (1); and (iii) minimize the total time lost due to traveling below the ideal velocity, as defined in Eq. (2), according to the mathematical model defined in Section 3.

Evolutionary operators. The *Simulated Binary Crossover* (SBX) [33] is applied to recombine solutions. This operator allows emulating the traditional single point crossover when using a real encoding. When solving the problem, SBX does not generate infeasible traffic lights states since phases are defined by the SUMO simulator.

The *Polinomial mutation* [34] is applied to generate an offspring x^{t+1} from a solution x^t according to $x^{t+1} = x^t + (x^{(U)} - x^{(L)}) \times \delta$, where $u \sim U[0, 1]$ and $\delta = (2 \times u)^{1/(\eta+1)} - 1$ if $u < 0.5$ or $\delta = 1 - [2 \times (1-u)]^{1/(\eta+1)}$ otherwise. Using this mutation operator, offspring are more likely to be generated in the neighborhood of parent x^t.

5. Experimental analysis

This section presents the experimental evaluation of the proposed MOEAs on realistic scenarios. The main numerical results are reported and discussed, including a comparison with traditional methods for traffic lights cycles program regulation.

5.1. Montevideo city scenarios

In order to test the proposed MOEAs, three topological heterogeneous zones of Montevideo city were used. The scenarios comprise

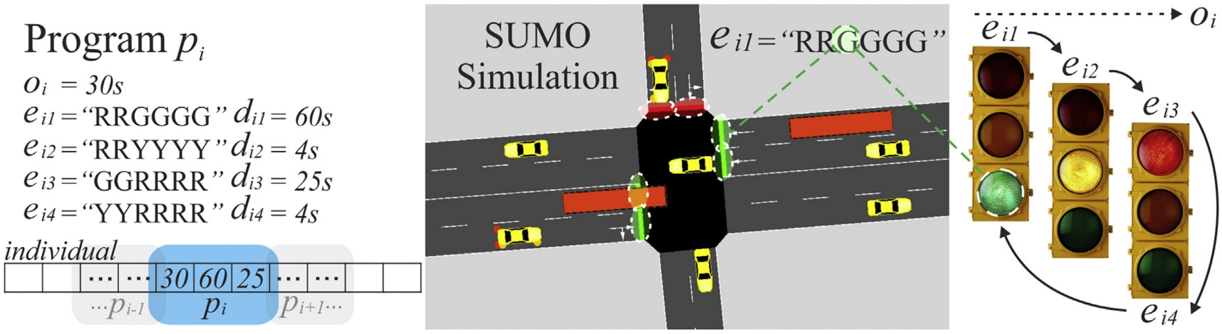


Fig. 3. Solution representation for program p_i and SUMO simulation for state e_{i1}.

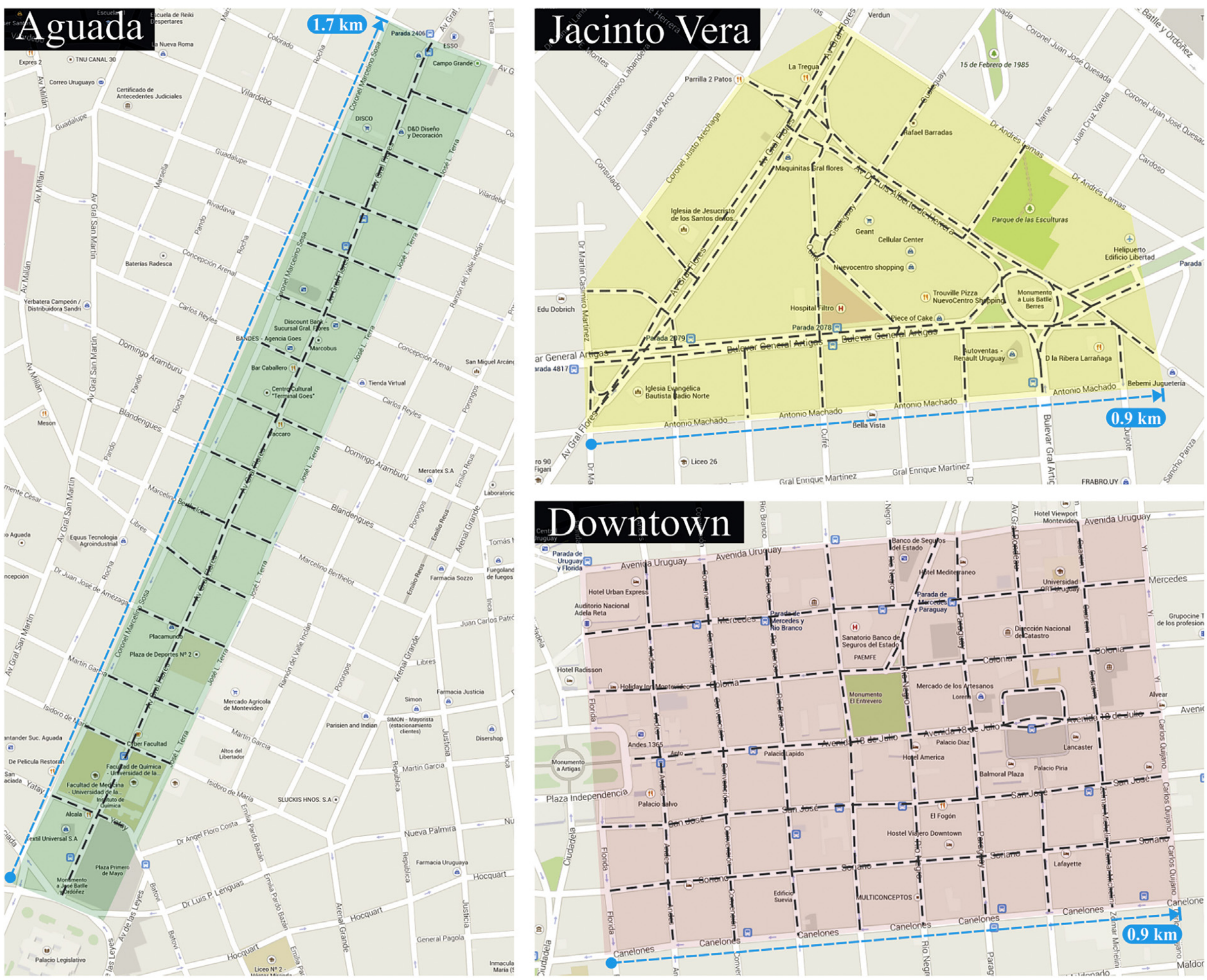


Fig. 4. Montevideo city scenarios.

zones of Aguada, Jacinto Vera, and Downtown, respectively (see Fig. 4): *Aguada* is defined along a main avenue with fourteen signalized junctions. *Jacinto Vera* has a complex topology with three main signalized intersections. *Downtown* scenario includes avenues and residential streets, having 44 junctions (41 signalized).

For each scenario, three time zones were considered: *morning* (8:00–10:00), *afternoon* (17:00–19:00) and *evening* (20:00–22:00). Thus, a total of nine scenarios are taken into account in the experimental evaluation. The OD-matrix was estimated using: (i) GPS data (a total of 11,857,521 records) from 37 bus lines from CUTCSA, the main public transportation company in Uruguay, collected in September, 2014; and (ii) GPS data from private traces of a taxi fleet in Montevideo.

Edge classification procedures and manual counts were performed for 30 junctions in each zone. According to its emissions, the vehicles were classified in *lightweight* (motorcycles), *cars*, *heavy* (trucks), and *bus*.

5.2. Computational platform

The algorithms were developed in Java 1.6 using the MOEA Framework, version 2.4 [32]. The experimental analysis was performed on a HP Proliant DL385 G7 server with AMD Opteron 6172

Table 1
Parametric setting results for each MOEA.

Parameter	NSGA-II	GDE3	MOEA/D	ϵ-NSGA-II
$\#P$	100	200	100	10
me	20,000	20,000	20,000	$\epsilon = 1$
p_C	0.9	0.1	0.2	0.9
p_M	0.05	0.2	0.05	0.05

2.10 GHz, 24 cores, 24GB RAM and Linux CentOS 6.5, from Cluster FING [35]. Simulations were carried out using SUMO version 0.21.0.

5.3. Parameters calibration

A set of parametric setting experiments were performed to determine the best parameter values for each MOEA. The parameter setting analysis were made over three topological heterogeneous instances (different from Montevideo scenarios) to avoid bias. The population size ($\# P$), the maximum number of evaluations (me), the crossover probability (p_C), and the mutation probability (p_M) were studied. For each parameter, three different candidate values were defined and all combinations were studied on 30 independent executions performed for each MOEA. Table 1 summarizes the best parameter values for each MOEA in the study.

5.4. Numerical results for Montevideo city scenarios

This section reports the numerical results of the proposed MOEAs for traffic lights planning. Thirty independent executions of each algorithm were performed for each problem instance. For the evaluation of solutions, the SUMO simulation time was set in 8 min. The Mann–Whitney and Kruskal–Wallis statistical tests were applied to compare the result distributions of each MOEA. Results from the tests (p-values) confirmed that all improvements obtained by the proposed MOEAs are statistically significant (confidence level 0.95).

5.4.1. Aguada scenario

Table 2 reports the improvements for each MOEA when compared with the actual traffic lights planning in Aguada scenario. Improvements are computed considering the *best compromise solution*, which provides the best trade-off between the problem objectives. The best values for each metric and problem instance are marked in bold.

In Aguada-*morning* the OD-matrix has 866 vehicles (115 *lightweight*, 666 *cars*, 32 *heavy*, and 53 *bus*). GDE3 computed the best results, reaching pollutant emission reductions of up to **31.5%** for HC and **55.0%** for NO_x. Compared with the actual configuration of traffic lights, the improvement on time lost for vehicles reaches **77.1%** in the best case and 20.5% in average. NSGA-II obtained the best results for vehicles that arrived to destination (**10.8%**).

In Aguada-*afternoon* the OD-matrix has 950 vehicles (144 *lightweight*, 749 *pcar*, 12 *heavy*, and 45 *bus*). NSGA-II obtained the best results for vehicles that arrived to destination (**11.6%** of improvement). The traffic flow is largely improved; a reduction of **77.0%** in time lost for vehicles is reported. GDE3 and NSGA-II reache the best results regarding pollutant emissions.

Aguada-*evening* involves 463 vehicles (9 *lightweight*, 379 *pcar*, 3 *heavy*, and 22 *bus*). GDE3 computed the best results, reducing **26.2%** the HC emissions and superior for other pollutants. The time for vehicles was reduced in **62.7%**, and the improvement on vehicles arrived to destination was **63.8%**. NSGA-II and ϵ-NSGA-II obtained similar results. However, the vehicles that arrived to destination were only 5.2% with NSGA-II and 3.9% for ϵ-NSGA-II.

Figs. 5–7 present the Pareto Fronts computed by each MOEA in the study for the three Aguada scenarios. Pollutant emissions are aggregated and normalized for a better visualization in a two-dimension graphic. The Pareto fronts allow comparing the results (vehicles that arrived to destination *vs.* normalized emissions, and time lost *vs.* normalized emissions) obtained by each MOEA. Also, the objective function values corresponding to the actual traffic light configuration is reported (marked with a black square, ■).

MOEA/D obtained the lower results in pollutant emissions, but after studying the solutions we found that that the main reason

Table 2
MOEA improvements over the actual traffic lights configuration (Aguada).

		NSGA-II		GDE3		MOEA/D		ϵ-NSGA-II	
obj.	Actual	max.	avg.	max.	avg.	max.	avg.	max.	avg.
Morning									
VDG	565	**10.6%**	**10.8%**	6.1%	0.5%	−33.4%	0.0%	6.0%	0.71%
TPG	39,232.8s	**79.3%**	**20.5%**	77.1%	10.5%	0.0%	0.0%	75.0%	3.1%
CO	5934.5g	**34.1%**	**10.8%**	35.2%	3.9%	0.0%	0.0%	31.5%	5.5%
CO_2	252,717.1g	**45.6%**	**8.8%**	45.2%	6.2%	0.0%	0.0%	43.1%	6.2%
HC	421.6g	30.5%	**11.3%**	**31.5%**	0.8%	0.0%	0.0%	28.4%	1.5%
PM_x	44.5g	**38.7%**	**8.8%**	**38.7%**	5.8%	0.0%	0.0%	36.4%	4.4%
NO_x	891.3g	52.8%	6.2%	**55.0%**	**7.8%**	0.0%	0.0%	52.0%	1.5%
Afternoon									
VDG	591	**11.6%**	**1.5%**	9.8%	0.2%	−40.4%	0.0%	9.3%	0.2%
TPG	38,773.5s	**77.0%**	17.9%	76.8%	**18.9%**	0.0%	0.0%	73.5%	14.1%
CO	6026.4g	36.1%	17.3%	**36.4%**	**17.5%**	0.0%	0.0%	34.0%	12.2%
CO_2	207,726.5g	**46.2%**	**19.7%**	46.7%	19.3%	0.0%	0.0%	43.9%	13.5%
HC	443.9g	32.9%	16.5%	**34.1%**	**17.3%**	0.0%	0.0%	29.4%	11.7%
PM_x	36.4g	41.7%	**20.3%**	**43.2%**	19.6%	0.0%	0.0%	41.0%	14.0%
NO_x	491.1g	61.9%	**30.8%**	**62.9%**	29.5%	0.0%	0.0%	61.9%	22.3%
Evening									
VDG	387	5.2%	0.8%	**63.8%**	0.5%	−20.4%	0.0%	3.9%	**2.3%**
TPG	15,422.5s	49.2%	22.5%	**62.7%**	**29.5%**	0.0%	0.0%	50.2%	25.2%
CO	2048.5g	27.1%	6.3%	**27.2%**	**10.6%**	0.0%	0.0%	25.6%	5.8%
CO_2	77,785.4g	29.3%	5.2%	**39.4%**	**8.7%**	0.0%	0.0%	26.3%	5.8%
HC	151.8g	25.8%	7.1%	**26.2%**	**12.4%**	0.0%	0.0%	24.4%	8.1%
PM_x	13.2g	25.7%	5.0%	**35.5%**	**9.0%**	0.0%	0.0%	23.6%	4.7%
NO_x	190.7g	44.0%	4.8%	**64.0%**	**10.1%**	0.0%	0.0%	40.5%	6.5%

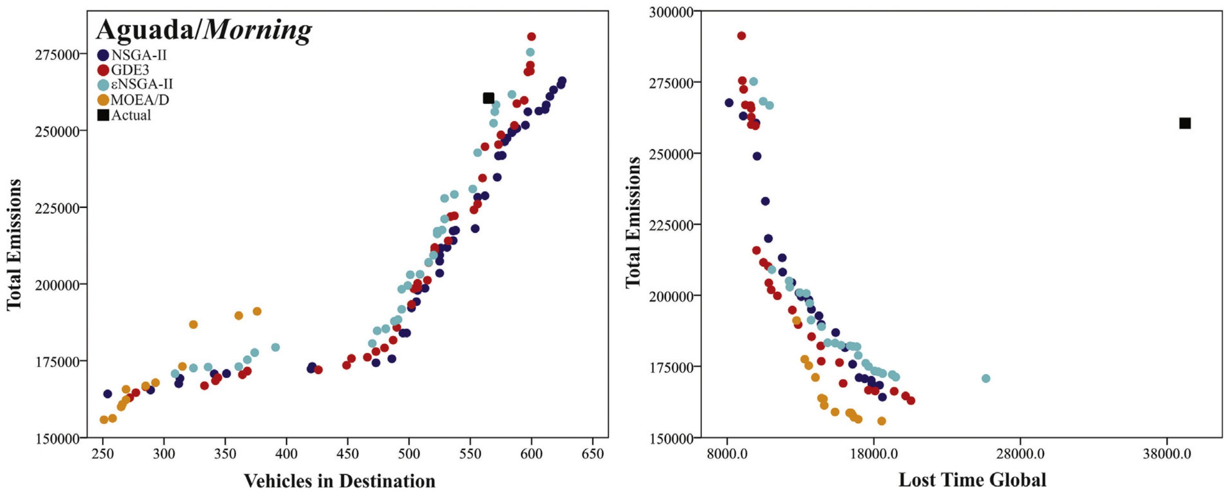


Fig. 5. Pareto fronts and actual configuration results for Aguada (*morning*).

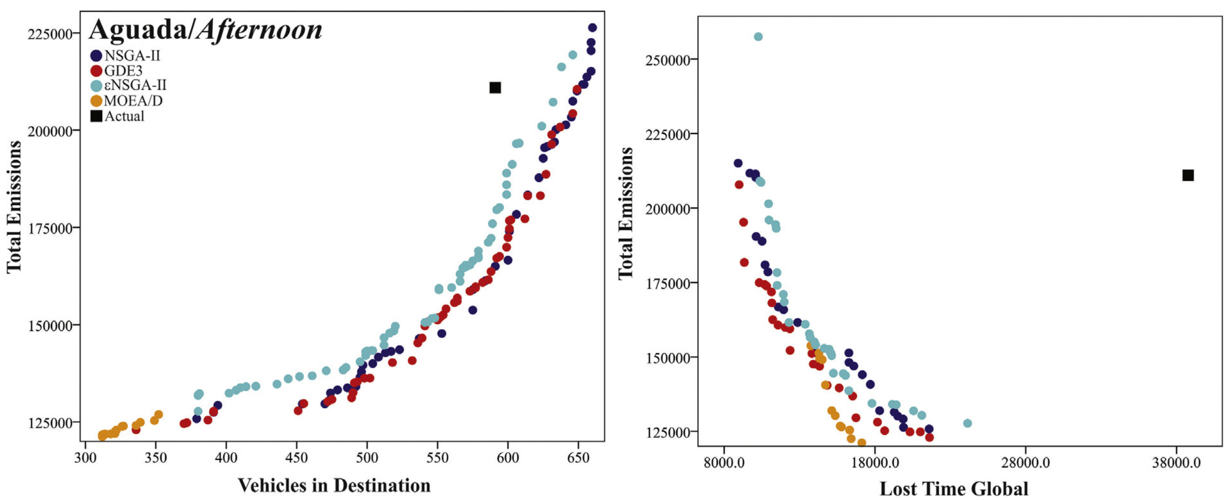


Fig. 6. Pareto fronts and actual configuration results for Aguada (*afternoon*).

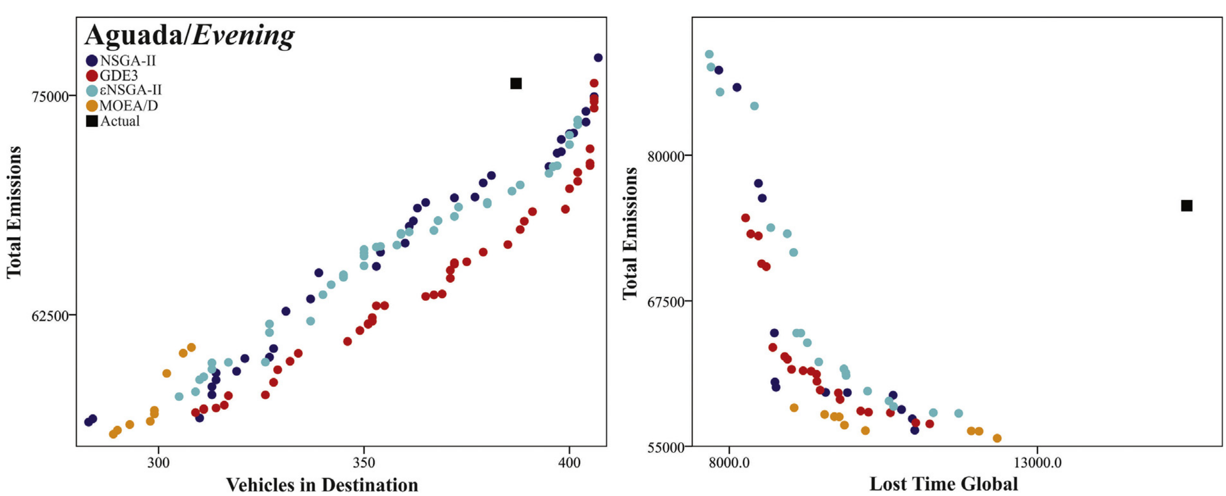


Fig. 7. Pareto fronts and actual configuration results for Aguada (*evening*).

for this behavior is that the vehicles do not move much, provoking traffic jams. As a consequence, a large number of vehicles do not arrive to destination. Thus, MOEA/D solutions are not considered in the analysis for any scenario (we report 0.0% improvement for pollutant emissions). These solutions cannot be implemented in practice due to they do not provide a minimal quality of service for citizens.

Table 3
MOEA improvements over the actual traffic lights configuration (Jacinto Vera).

obj.	actual	NSGA-II max.	NSGA-II avg.	GDE3 max.	GDE3 avg.	MOEA/D max.	MOEA/D avg.	ϵ-NSGA-II max.	ϵ-NSGA-II avg.
Morning									
VDG	478	**21.5%**	0.6%	21.3%	**3.97%**	−11.1%	0.0%	19.2%	0.42%
TPG	32,503.7s	**57.0%**	3.7%	55.5%	**8.7%**	0.0%	0.0%	52.1%	2.7%
CO	5707.5g	**34.5%**	**24.6%**	34.4%	21.8%	0.0%	0.0%	30.9%	23.1%
CO_2	204,606.6g	**34.4%**	**20.6%**	34.3%	19.9%	0.0%	0.0%	32.7%	19.1%
HC	477.1g	35.9%	**26.9%**	**36.4%**	24.5%	0.0%	0.0%	31.9%	26.4%
PM_x	35.6g	32.7%	**20.4%**	**33.2%**	20.1%	0.0%	0.0%	31.7%	19.8%
NO_x	604.1g	43.5%	16.1%	**45.5%**	**20.2%**	0.0%	0.0%	41.1%	17.6%
Afternoon									
VDG	367	**40.3%**	3.3%	38.4%	**14.4%**	−12.0%	0.0%	36.5%	3.0%
TPG	36,800.3s	68.0%	2.0%	**69.4%**	1.5%	0.0%	0.0%	67.5%	**15.6%**
CO	8237.0g	33.4%	25.9%	**34.3%**	**22.2%**	0.0%	0.0%	32.0%	22.1%
CO_2	240,943.5g	29.3%	**22.5%**	**29.9%**	19.5%	0.0%	0.0%	27.9%	20.1%
HC	726.2g	35.7%	**28.4%**	**35.9%**	26.0%	0.0%	0.0%	32.8%	24.0%
PM_x	42.4g	29.9%	**22.4%**	**30.5%**	19.8%	0.0%	0.0%	27.4%	19.6%
NO_x	519.2g	34.0%	17.1%	**34.4%**	**19.1%**	0.0%	0.0%	30.1%	16.2%
Evening									
VDG	442	**9.5%**	**0.4%**	9.3%	**0.4%**	−10.6%	0.0%	7.7%	**0.4%**
TPG	30,651.5s	54.9%	17.8%	**55.7%**	**20.6%**	0.0%	0.0%	52.6%	13.9%
CO	4723.8g	**23.8%**	16.0%	23.7%	**16.7%**	0.0%	0.0%	21.7%	15.6%
CO_2	173,565.9g	21.1%	10.7%	**21.3%**	**12.8%**	0.0%	0.0%	20.1%	11.2%
HC	396.1g	25.8%	18.3%	**26.3%**	**20.4%**	0.0%	0.0%	24.1%	19.4%
PM_x	30.1g	**23.3%**	12.8%	22.8%	**14.7%**	0.0%	0.0%	22.4%	12.9%
NO_x	493.6g	**31.3%**	7.3%	31.0%	**13.5%**	0.0%	0.0%	29.5%	9.2%

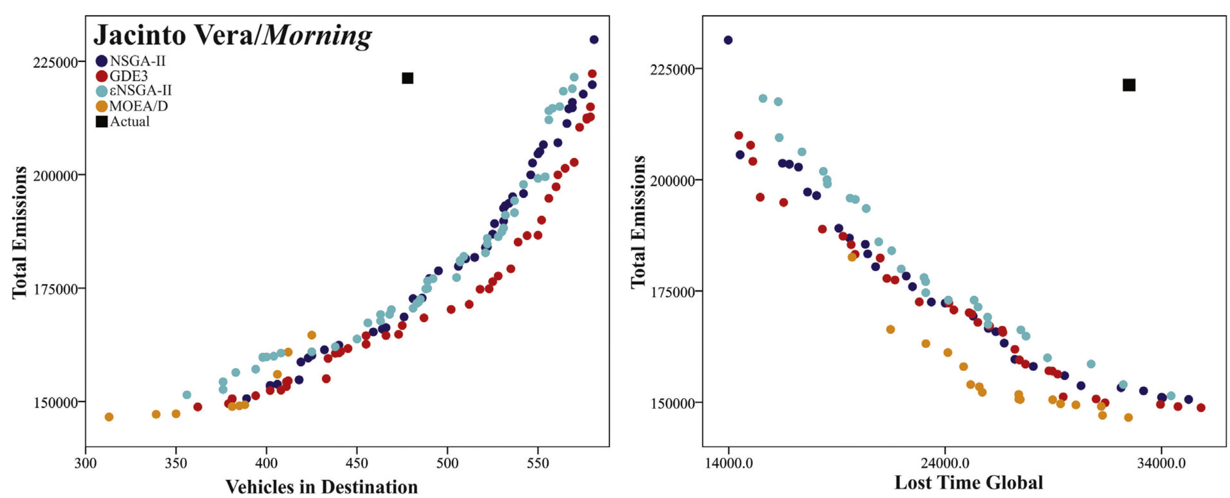


Fig. 8. Pareto fronts results for Jacinto Vera (*morning*).

5.4.2. Jacinto Vera scenario

Jacinto Vera has specific topological characteristics that makes it very interesting for traffic engineers. This scenario allows testing the capabilities of the proposed methodology to improve the traffic flow in a small but complex scenario that does not have a single major traffic road, but three important ways connected in a triangular shape.

Table 3 reports the improvements for each MOEA (best compromise solution) when compared to the actual configuration of traffic lights cycles in Jacinto Vera scenario.

Jacinto Vera-*morning* has an OD-matrix with 943 vehicles (89 *lightweight*, 770 *pcar*, 41 *heavy*, and 43 *bus*). All the MOEA found configurations with more than 30.0% reduction of pollutant emissions. Using NSGA-II, **21.5%** of vehicles arrive to destination and **57.0%** and the travel time is improved up to **21.5%**. GDE3 obtains between **33.2–45.5%** of improvements on pollutant emissions and **21.3%** of improvements in vehicles arriving to destination.

Jacinto Vera-*afternoon* has 1168 vehicles (121 *light*, 979 *pcar*, 25 *heavy*, and 43 *bus*). The average reduction on emissions is over **19.1%** for all MOEAs. GDE3 reaches the best percentage of improvements for travel time (**69.4%**).

The OD-matrix in Jacinto Vera-*evening* has 719 vehicles (67 *light*, 584 *pcar*, 14 *heavy*, and 54 *bus*). NSGA-II, GDE3 and ϵ-NSGA-II computed similar results, improving over **20.0%** in pollutant emissions, over **7.0%** in vehicles that arrived to destination, and reducing **52.6%** the travel time. GDE computed the best improvements in five out of seven metrics.

Figs. 8–10 present the Pareto fronts computed by the studied MOEAs and the (reference) actual traffic lights configuration for Jacinto Vera scenario. A significant improvement on the vehicles that arrived to destination is clearly shown in Pareto fronts. GDE3 found the best solutions, improving over the ones computed by the other MOEAs.

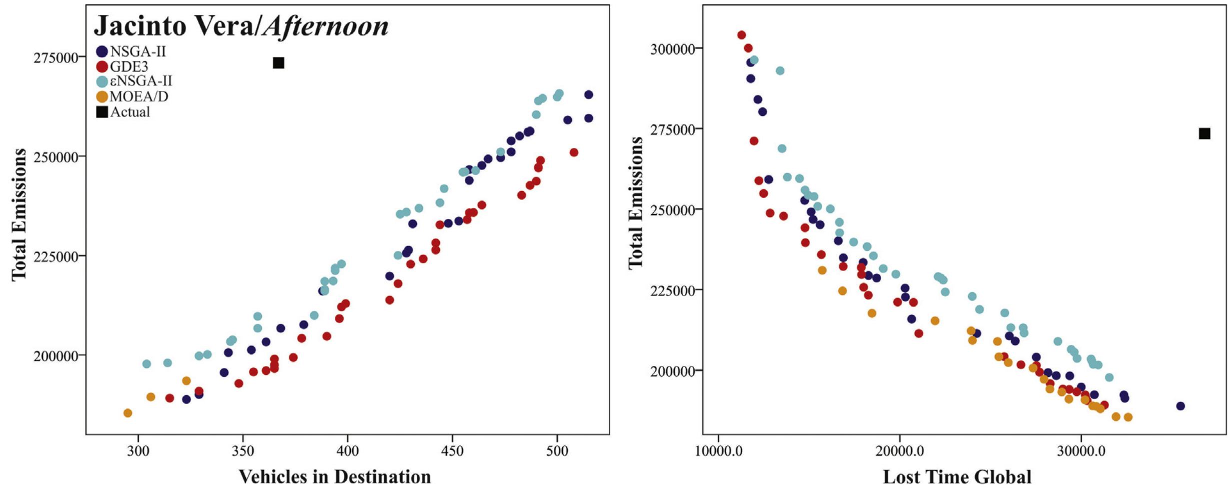


Fig. 9. Pareto fronts results for Jacinto Vera (*afternoon*).

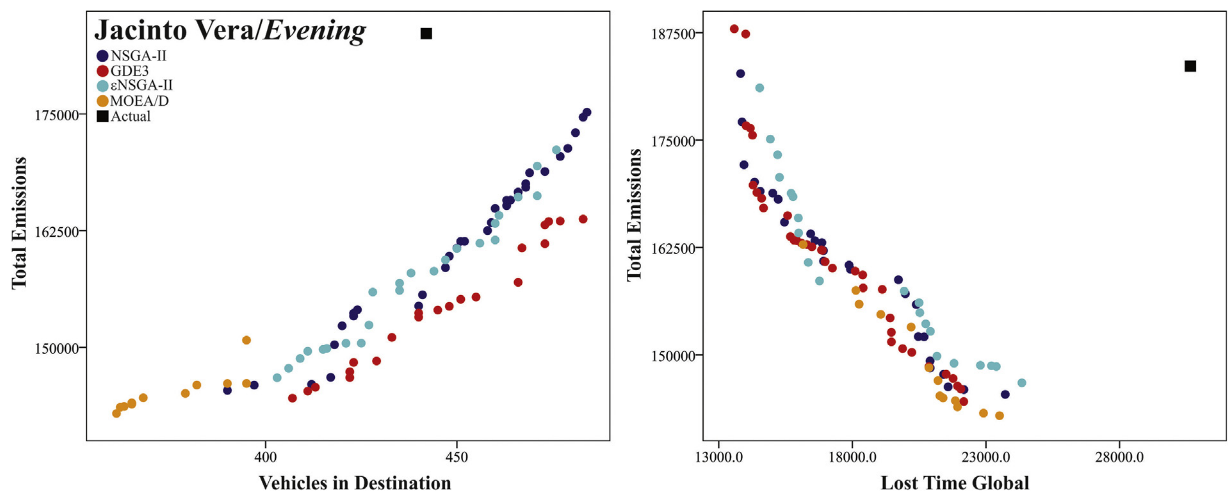


Fig. 10. Pareto fronts results for Jacinto Vera (*evening*).

5.4.3. Downtown scenario

Downtown contains 41 signalized junctions organized in a regular grid topology (common in modern American cities). Table 4 reports the improvements for each MOEA (best compromise solution) compared to the actual configuration of traffic lights cycles in Downtown.

Downtown-*morning* has 1130 vehicles (94 *lightweight*, 892 *pcar*, 7 *heavy* and 137 *bus*). NSGA-II computed the best values for vehicles arriving to destination (**43.6%**). All MOEAs obtained significant reductions of pollutant emissions: GD3 up to **20.4%** in CO and NSGA-II up to **23.9%** in HC. ϵ-NSGA-II improved over the actual configuration, but not over the results computed by the other three MOEAs.

In Downtown-*afternoon* the OD-matrix includes 1007 vehicles (75 *lightweight*, 814 *pcar*, 4 *heavy*, and 114 *bus*). Interestingly, while NSGA-II focused on maximizing the number of vehicles that arrive to destination and minimizing the time lost, GDE mainly reduced the emission of all pollutants. ϵ-NSGA-II obtained intermediate values, with large time improvements and acceptable pollution reductions. The best result of NSGA-II for travel time was **58.1%**, reducing the average travel time of vehicles to more than a half. GDE3 obtained the best results in six out of seven metrics, and improved up to **30.2%** for NO_x emissions and more than **7.3%** in average for all pollutants.

Downtown-*evening* has 586 vehicles (41 *lightweight*, 485 *pcar*, 2 *heavy*, and 58 *bus*). Regarding travel time, NSGA-II computed the best improvements: **46.3%** for time lost and for vehicles arriving to destination ϵ-NSGA reaches the best result (**22.6%**). All MOEAs computed similar results for emissions, with ϵ-NSGA-II obtaining slightly better reductions for CO_2, HC, PM_x and NO_x, and NSGA-II for CO, and GDE3 for HC.

Figs. 11–13 present the Pareto fronts computed by the studied MOEAs and the (reference) actual traffic lights configuration for Downtown scenario. The graphics show that NSGA-II, GDE3, and ϵ-NSGA-II improved over the current urban traffic lights configuration regarding all objectives. MOEA/D computed poor results in comparison with the actual configuration for *morning* and *afternoon* instances.

5.5. Comparison with standard traffic lights planning methods

This subsection compares the solutions computed by the proposed MOEAs for each scenario with two standard traffic lights planning methods: *green wave* (GW) and *street decongestion* (SD).

The green wave methodology consists of coordinating the traffic lights cycles in a road to allow for a continuous traffic flow in one direction. A vehicle traveling in a road with the green wave will find—when driving at a given fixed velocity—a progressive sequence of green traffic lights [36]. This technique is usually

Table 4
MOEA improvements over the actual traffic lights configuration (Downtown).

		NSGA-II		GDE3		MOEA/D		ε-NSGA-II	
obj.	actual	max.	avg.	max.	avg.	max.	avg.	max.	avg.
Morning									
VDG	633	**43.6%**	0.3%	38.5%	**0.8%**	−6.9%	0.0%	38.9%	0.3%
TPG	57,307.6s	**57.6%**	22.6%	52.8%	**23.4%**	0.0%	0.0%	53.0%	16.1%
CO	7396.3g	19.3%	15.5%	**20.4%**	**16.8%**	0.0%	0.0%	17.6%	13.0%
CO_2	304,699.0g	23.8%	11.4%	**25.9%**	**15.0%**	0.0%	0.0%	21.0%	11.5%
HC	631.6g	**23.9%**	21.1%	23.6%	**22.3%**	0.0%	0.0%	20.6%	17.8%
PM_x	53.9g	18.0%	10.2%	**20.5%**	**13.6%**	0.0%	0.0%	16.4%	8.6%
NO_x	1060.0g	30.3%	9.9%	**32.6%**	**16.3%**	0.0%	0.0%	28.9%	10.8%
Afternoon									
VDG	652	**30.4%**	**3.2%**	25.6%	0.1%	−12.1%	0.0%	27.5%	1.1%
TPG	50,626.9s	**58.1%**	16.7%	54.5%	**19.4%**	0.0%	0.0%	55.8%	4.5%
CO	6369.5g	17.7%	10.0%	**18.4%**	**14.6%**	0.0%	0.0%	15.0%	8.1%
CO_2	268,274.7g	20.9%	6.5%	**21.3%**	**10.3%**	0.0%	0.0%	18.8%	5.2%
HC	532.1g	**16.9%**	11.9%	17.3%	**15.8%**	0.0%	0.0%	15.2%	9.7%
PM_x	46.6g	**20.9%**	8.8%	20.6%	**11.0%**	0.0%	0.0%	17.2%	7.6%
NO_x	890.7g	28.0%	6.3%	**30.2%**	**7.3%**	0.0%	0.0%	28.1%	5.0%
Evening									
VDG	439	21.9%	**2.3%**	20.0%	1.1%	0.4%	0.5%	**22.6%**	3.4%
TPG	30,012.0s	**46.3%**	25.6%	42.0%	**26.1%**	32.5%	7.5%	39.5%	18.7%
CO	3282.1g	**8.7%**	**7.8%**	8.5%	7.7%	4.6%	1.7%	8.0%	7.4%
CO_2	144,205.6g	9.7%	5.3%	9.9%	5.7%	**13.2%**	1.5%	7.8%	**6.1%**
HC	268.2g	13.4%	11.9%	**13.8%**	11.5%	5.7%	5.0%	12.5%	**12.1%**
PM_x	24.8g	10.0%	6.8%	9.7%	6.6%	**11.8%**	2.5%	8.1%	**7.5%**
NO_x	483.7g	22.3%	7.3%	20.9%	7.5%	**27.8%**	4.2%	19.5%	**10.0%**

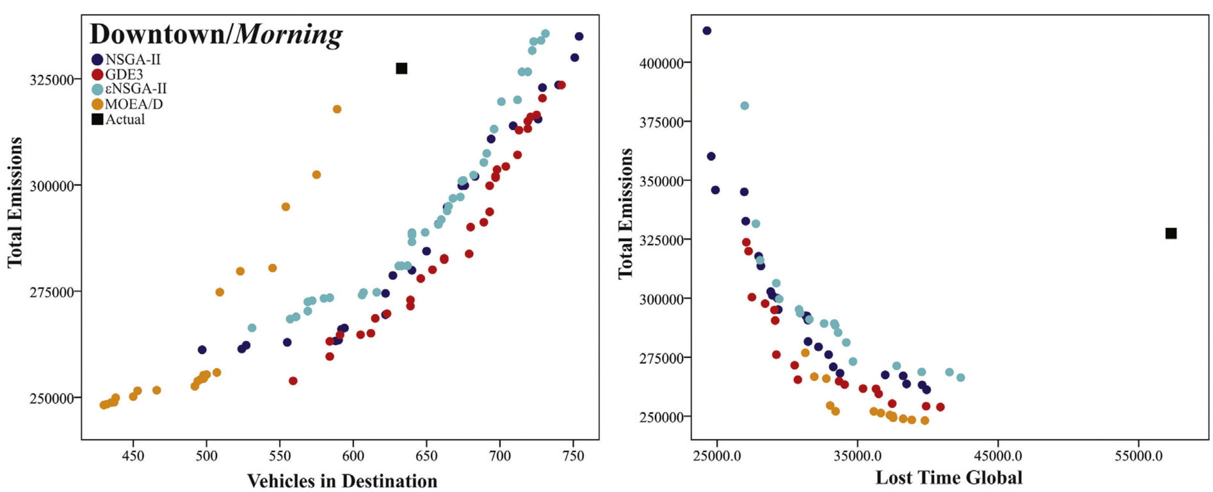


Fig. 11. Pareto fronts results for Downtown (*morning*).

applied in urban areas with specific road topologies and certain traffic lights characteristics. For example, the green wave technique is especially useful for one-way traffic organization in scenarios having few phases at traffic lights.

Taking into account these considerations, we use the GW methodology for Aguada and Downtown. The topology of both scenarios (i.e., a large avenue with intersections for Aguada and a rectangular grid for Downtown) makes them good candidates to apply GW to improve the traffic speed [37]. The topology of Jacinto Vera (three main avenues interconnected, neither avenue has priority over the others) and the complexity of the traffic lights phases are not appropriate for the application of the green wave methodology.

The street decongestion method proposes modifying the normal operation of traffic lights. When a congestion is detected (e.g., using intelligent cameras, sensors, or other vehicle tracking systems), a special configuration of traffic lights cycles, having a duration for green phases that is longer than usual (normally, a few minutes), is activated. Just like for the green wave technique, there are some specific requirements over both the urban area and the traffic light phases for the successful application of the street decongestion method. This methodology is currently used by the local administrators in Montevideo in order to reduce bottlenecks, especially in scenarios with more traffic density (e.g., Downtown).

The duration of green phases in the street decongestion technique applied in Montevideo is two minutes. In our study, we consider using both green wave and street decongestion combined (GW+SD) for Downtown scenario, to perform a comparative evaluation of the proposed MOEAs for traffic lights planning.

GW and GW+SD compared to actual configuration. Table 5 reports the percentage of improvement obtained by GW over to the actual configuration of traffic lights in Aguada scenario. Table 6 reports the percentage of improvement obtained by GW+SD with respect to the actual configuration of traffic lights in Downtown scenario.

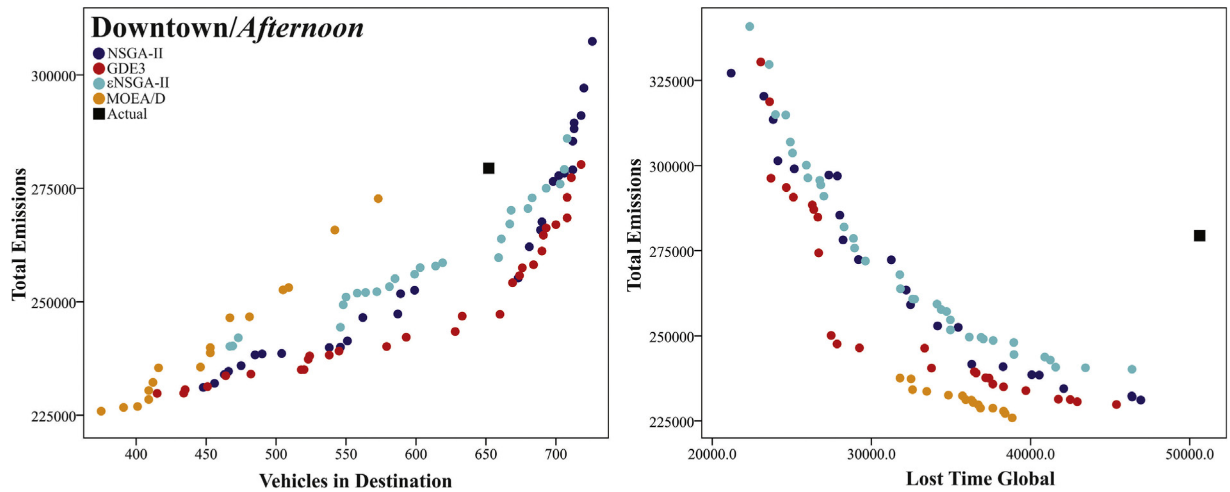


Fig. 12. Pareto fronts results for Downtown (*afternoon*).

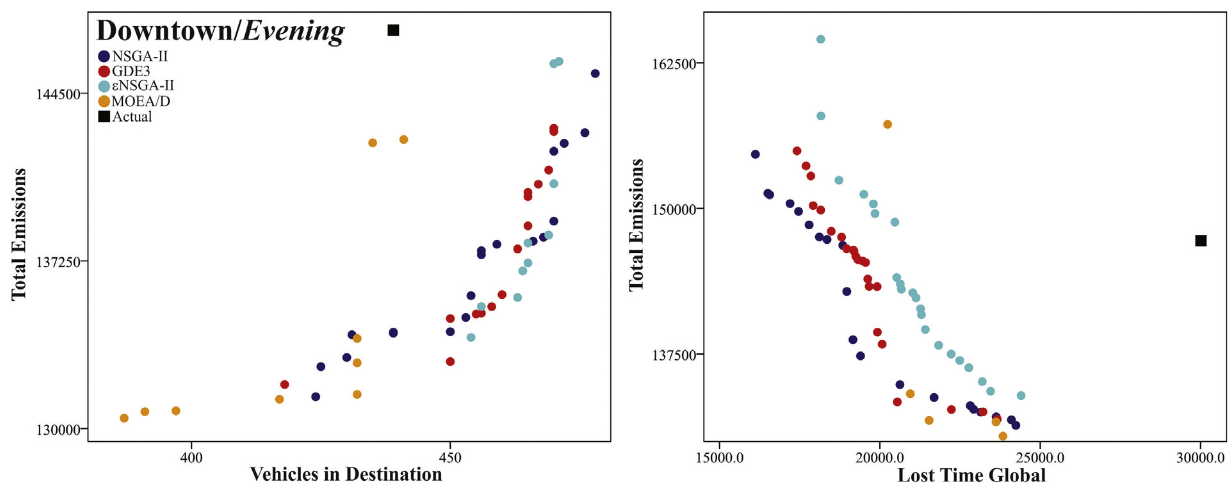


Fig. 13. Pareto fronts results for Downtown (*evening*).

Table 5
GW improvements over the actual traffic lights configuration (Aguada).

	Morning		Afternoon		Evening	
obj.	Actual	GW impr.	Actual	GW impr.	Actual	GW impr.
VDG	565	5.7%	591	7.3%	387	−2.6%
TPG	39,232.8s	56.7%	38,773.5s	65.7%	15,422.5s	24.4%
CO	5934.5g	13.7%	6026.4g	14.5%	2048.5g	16.2%
CO_2	252,717.1g	27.8%	207,726.5g	21.7%	77,785.4g	16.4%
HC	421.6g	12.4%	443.9g	14.5%	151.8g	15.3%
PM_x	44.5g	20.8%	36.4g	17.4%	13.2g	14.6%
NO_x	891.3g	36.4%	491.1g	42.4%	190.7g	22.0%

Table 6
GW+SD improvements over the actual traffic lights configuration (Downtown).

	Morning		Afternoon		Evening	
obj.	Actual	GW impr.	Actual	GW impr.	Actual	GW impr.
VDG	633	16.0%	652	12.1%	439	6.8%
TPG	57,307.6s	34.8%	50,626.9s	31.2%	30,012.0s	24.5%
CO	7396.3g	12.1%	6369.5g	9.1%	3282.1g	8.5%
CO_2	304,699.0g	6.0%	268,274.7g	7.1%	144,205.6g	5.3%
HC	631.6g	18.7%	532.1g	15.3%	268.2g	14.3%
PM_x	53.9g	6.0%	46.6g	8.6%	24.8g	6.9%
NO_x	1060.0g	5.0%	890.7g	13.0%	483.7g	10.3%

GW allows, in general, enhancing the actual configuration of the traffic lights. The number of vehicles that arrives to its destinations reaches 5.7%, for the morning scenario, and the contamination is reduced up to 12.4% for HC and better for other pollutants. However, in the evening scenario, GW get a slightly worse results on the number of vehicles that arrives to its destinations when compared with the actual configuration, while the emission of pollutants get better. The values obtained by GW+DS improve the emission of pollutants by up to 15.3% with respect to the current configuration. The lost time reduces more than 24.5% for all instances and the number of vehicles arrives its destinations improves up to 16.0% in the morning scenario (Downtown).

MOEAs vs GW and GW+SD. Table 7 reports the percentage of improvement obtained by each MOEA against a traditional GW scheduling technique for Aguada scenario.

Results indicate that all MOEAs are able to outperform the GW results for Aguada scenario. Regarding traffic flow, NSGA-II obtains the best improvements for vehicles arriving to destination and GDE3 computes the best TPG values. GDE also improves over 20% for all pollutants in the three instances of Aguada scenario. Overall, we conclude that the studied MOEAs are able to improve significantly the traffic flow (over 4.96% for VDG and over 33% in TPG) and the pollutant emissions over 21.8% compared with the green wave technique. The better results computed using MOEAs in comparison to the green wave results can be explained by considering

Table 7
MOEA improvements over green wave technique for Aguada Scenario.

	NSGA-II		GDE3		MOEA/D		ϵNSGA-II	
obj.	max.	avg	max.	avg.	max.	avg.	max.	avg.
	Morning							
VDG	**4.96%**	−12.0%	2.3%	−13.7%	−44.5%	−36.4%	1.9%	−16.1%
TPG	34.0%	32.9%	35.2%	32.4%	44.0%	−3.5%	34.5%	22.7%
CO	23.6%	8.0%	**24.9%**	12.5%	32.5%	23.1%	20.6%	16.7%
CO_2	**24.7%**	19.5%	24.1%	23.2%	43.5%	28.5%	26.2%	21.2%
HC	20.7%	−0.1%	**21.8%**	5.3%	26.4%	11.9%	18.3%	10.0%
PM_x	**22.6**%	14.7%	22.6%	18.6%	39.3%	26.5%	22.0%	19.7%
NO_x	25.8%	23.4%	**29.2%**	26.9%	49.3%	32.5%	29.1%	24.5%
Afternoon								
VDG	**4.0%**	−12.0%	2.3%	−13.7%	−44.5%	−36.4%	1.9%	−16.1%
TPG	**32.9%**	34.0%	32.4%	35.2%	44.0%	−3.5%	34.5%	22.7%
CO	25.3%	13.2%	**25.6%**	19.2%	37.6%	25.3%	22.8%	20.2%
CO_2	31.3%	18.7%	**31.9%**	25.0%	44.2%	34.7%	28.4%	27.0%
HC	21.5%	8.5%	**22.9%**	15.3%	33.6%	15.6%	17.4%	16.6%
PM_x	29.4%	18.0%	**31.2%**	24.7%	42.7%	33.4%	28.6%	26.1%
NO_x	33.9%	27.3%	**35.6%**	37.5%	55.6%	35.9%	40.0%	33.9%
Evening								
VDG	**8.0%**	−1.0%	7.6%	−0.8%	−18.3%	−15.0%	6.7%	−2.9%
TPG	32.8%	28.8%	**50.7%**	33.9%	22.4%	32.0%	34.1%	31.7%
CO	17.9%	13.0%	**24.4%**	13.1%	28.2%	9.9%	20.7%	11.2%
CO_2	17.8%	15.4%	**27.5%**	21.9%	31.9%	18.3%	18.9%	11.8%
HC	18.3%	12.4%	**26.4%**	12.9%	27.4%	8.3%	22.0%	10.7%
PM_x	18.0%	13.0%	**24.5%**	22.4%	30.1%	14.8%	19.2%	10.5%
NO_x	28.2%	22.1%	**53.8%**	24.3%	39.4%	28.8%	23.7%	20.7%

that the proposed MOEAs optimize *all signalized intersections at the same time*, not only the main avenue in Aguada scenario. A similar situation happens when comparing the MOEA results against the GW results for Downtown scenario.

Table 8 reports the percentage of improvement obtained when using the proposed MOEAs compared against the combination of green wave and street decongestion for Downtown scenario.

The results for Downtown scenario indicate that the proposed MOEAs are effective tools in order to improve the traffic flow and pollutant emissions in Downtown scenario, when compared against green wave combined with street decongestion. NSGA-II obtains significant improvements for vehicles arriving to destination, especially for *morning* (23.8%) and *evening* (14.0%) instances. GDE3 reaches the best pollutant emissions results, improving more than 4.9% over the green wave combined with street decongestion, for all scenarios.

From the reported results, we conclude that the proposed MOEAs provide effective solutions for optimizing traffic flow and reducing the pollutant emissions in the studied scenarios.

6. Conclusions

This work presents a multiobjective evolutionary approach to improve the traffic flow and reduce pollutant emissions by traffic lights planning on heterogeneous urban areas in Montevideo, Uruguay.

The mathematical model for optimization considers two metrics related to traffic flow (vehicles arriving to destination and time lost for vehicles traveling below the ideal velocity) and the emissions of five pollutants (CO, CO_2, NO_x, HC, and PM_x). A novel multiobjective approach is proposed, optimizing all problem objectives simultaneously. A methodology for approximating the OD-matrix is also applied to generate realistic traffic demand using GPS information and manual counts.

Four MOEAs, (NSGA-II, GDE3, MOEA/D and ϵ-NSGA-II), are proposed to solve the problem. A strategy applying micro simulations in SUMO, including a model for pollutant emissions, is used for evaluating traffic lights configurations. The experimental analysis is performed over three scenarios corresponding to real urban areas in Montevideo, Uruguay (Aguada, Jacinto Vera, and Downtown). These scenarios account for different road network topologies, traffic patterns, and traffic lights configurations. Additionally, three time zones are considered for each scenario.

The proposed MOEAs are compared with the actual traffic lights scheduling and also with two standard techniques for traffic light cycles planning that are currently applied in Montevideo: green wave and street decongestion.

The main results from the experimental evaluation show that the proposed MOEAs are able to compute traffic lights configurations that improve significantly over the actual configuration and standard traffic lights planning techniques. The improvements were obtained consistently for all the problem objectives in all scenarios.

The comparison between the four MOEAs in the study indicates that GDE3 computed the best results, considering the trade-off between the problem objectives. NSGA-II computed accurate values for traffic-related metrics, but GDE3 is superior when considering the optimization of pollutant emissions.

Regarding the numerical results, in Aguada (afternoon) the MOEAs reduced up to **77.0%** the time lost by vehicles and **11.6%** more vehicles arrive to destination, in comparison with the current traffic lights configuration. Simultaneously, the MOEAs reduced the pollutant emissions up to **36.4%** (CO), **46.2%** (CO_2), **34.1%** (HC) and **43.2%** (PM_x). For Jacinto Vera (afternoon) the best improvements were **69.4%** for vehicles that arrive to destination and a reduction larger than **29.9%** for all pollutants. In the case of Downtown (morning) the MOEAs improve up to **43.6%** on vehicles that arrive to destination, while reducing **20.4%** the CO emissions and superior values for other pollutants.

The MOEAs also computed significant improvements in comparison with traditional traffic lights scheduling techniques, e.g., green wave in Aguada and green wave combined with street decongestion in Downtown.

Table 8
MOEA improvements over green wave combined with street decongestion for Downtown scenario.

	NSGA-II		GDE3		MOEA/D		ϵNSGA-II	
obj.	max.	avg	max.	avg.	max.	avg.	max.	avg.
	Morning							
VDG	**23.8%**	**18.7%**	18.3%	18.0%	−19.7%	0.0%	17.1%	16.8%
TPG	**35.0%**	**21.5%**	27.6%	**21.5%**	0.0%	0.0%	27.9%	16.0%
CO	8.2%	1.3%	**9.4%**	**8.2%**	0.0%	0.0%	6.5%	6.3%
CO_2	18.9%	9.4%	**21.2%**	**15.4%**	0.0%	0.0%	16.0%	13.2%
HC	6.4%	−0.7%	**8.2%**	**6.0%**	0.0%	0.0%	6.8%	2.3%
PM_x	12.7%	6.5%	**15.4%**	**12.3%**	0.0%	0.0%	11.1%	10.5%
NO_x	26.6%	14.1%	**29.1%**	**20.8%**	0.0%	0.0%	25.2%	18.2%
	Afternoon							
VDG	**0.8%**	0.2%	1.8%	**1.1%**	−21.6%	0.0%	−3.1%	−17.6%
TPG	**39.1%**	14.0%	33.9%	**14.2%**	0.0%	0.0%	35.8%	9.2%
CO	9.5%	3.1%	**10.2%**	**9.9%**	0.0%	0.0%	7.7%	6.5%
CO_2	14.9%	9.0%	**15.3%**	**12.7%**	0.0%	0.0%	12.6%	10.6%
HC	1.9%	−1.0%	**7.7%**	**2.4%**	0.0%	0.0%	5.4%	−0.1%
PM_x	**13.5%**	8.3%	13.1%	**12.5%**	0.0%	0.0%	10.3%	9.4%
NO_x	17.2%	11.6%	**19.8%**	**14.4%**	0.0%	0.0%	17.4%	11.8%
	Evening							
VDG	**14.0%**	**2.1%**	11.1%	7.4%	−6.0%	0.0%	11.6%	9.2%
TPG	**28.7%**	12.4%	23.2%	**13.2%**	0.0%	0.0%	19.9%	12.1%
CO	**0.1%**	−3.6%	0.0%	**−2.5%**	0.0%	0.0%	−0.5%	−5.1%
CO_2	4.6%	3.9%	**4.9%**	**4.3%**	0.0%	0.0%	2.7%	2.6%
HC	**−1.1%**	−6.6%	−0.6%	**−5.4%**	0.0%	0.0%	−2.1%	−8.8%
PM_x	**3.3%**	2.4%	3.0%	**2.7%**	0.0%	0.0%	1.3%	0.9%
NO_x	**13.4%**	**8.9%**	11.8%	8.4%	0.0%	0.0%	10.3%	6.6%

The findings from this study make several contributions to the current literature: the prioritization strategy for edges of the traffic network to establish the locations where manual counts need to be performed; the multiobjective approach for the simultaneous optimization of traffic flow and pollutant emissions, considering the scheduling of traffic light cycles following a global and realistic approach; and the experimental evaluation and promising results that generated a set of solutions for decision-makers.

The main lines for future work are related to improve the proposed approach by incorporating a dynamic model to automatize the vehicle counts, using sensors and other computational intelligence techniques; perform a comparison with exact multiobjective approaches for small instances, e.g. ε-constraint and augmented ε-constraint (AUGMECON); extending the experimental evaluation in order to assess the impact of other pollutants and also noise contamination and including other sources of information—such as meteorological data–and an improved physical modeling of pollutant dispersion in street canyons to determine the impact of traffic flow in citizens.

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