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An Intelligent Advisor for City Traffic Policies

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Abstract. Nowadays, city streets are populated not only by private vehicles but also by public transport, fleets of workers, and deliveries. Since each vehicle class has a maximum cargo capacity, we study in this article how authorities could improve the road traffic by endorsing long term policies to change the different vehicle proportions: sedans, minivans, full size vans, trucks, and motorbikes, without losing the ability of moving cargo throughout the city. We have performed our study in a realistic scenario (map, road traffic characteristics, and number of vehicles) of the city of Malaga and captured the many details into the SUMO microsimulator. After analyzing the relationship between travel times, emissions, and fuel consumption, we have defined a multiobjective optimization problem to be solved, so as to minimize these city metrics. Our results provide a scientific evidence that we can improve the delivery of goods in the city by reducing the number of heavy duty vehicles and fostering the use of vans instead.

Keywords: Application · evolutionary algorithm · road traffic · city policy · real world · smart mobility

1 Introduction

Cities have been growing in number of inhabitants along the history, as many people are leaving the countryside to settle in urban areas [14]. Consequently, there is a noticeable increment in the number of trips that citizens have to take nowadays and their duration [18], especially because urban infrastructures are not scaling properly. Furthermore, the need of cargo space makes those services to use small trucks to perform their commercial activities [19], which represents an increment not only in the street space usage but also in the pollutant emissions.

Road traffic is a well-known source of air pollution in urban areas. The delivery of goods in a city affects air pollution, then the citizens quality of life. Local authorities are responsible for taking care of this matter despite the importance of negative or zero cost options when formulating their climate policy [10].

Some cities implement fixed speed policies where all the vehicles must observe a reduced maximum speed in the city's streets [2], while others have more green buildings, focus on pedestrian and bicycle infrastructure, or have implemented more programs to divert waste from methane-generating landfills [13].

Another type of pollution analysis is the one carried out in [8], where authors model the gas emissions of delivery trucks in urban logistics. The authors analyze the effect on greenhouse gas emissions of different trips and conclude that traveled distance and vehicles' weight have a capital impact on the pollution levels emitted. They conclude that replacing trucks by another less polluting vehicle may be a solution for reducing greenhouse gas emissions. In [12] the authors proposed banning Heavy Duty Vehicles (HDV) by 1.5 Light Duty Vehicles (LDV) among others strategies to keep the same cargo capacity while reducing gas emissions. Also, the total demand was increased by 1.035 as more vehicles were needed. We wished to go further in our study and analyze not only the optimal vehicle proportion (instead of banning some types), but also how this proportion affects travel times, gas emissions, and fuel consumption.

We have taken some small starting steps in [17] which have led us to the proposal in this article. It consists of studying different configurations of road traffic in a realistic scenario of Malaga, Spain, to better know how travel times, greenhouse gas emissions, and fuel consumption change. Common sense would suggest that reducing the number of HDV in the city's streets and incrementing the LDV should be the right thing to do. We wish to check if it is so, when the cargo capacity is a constraint to be kept and possible traffic jams are taken into account. After this study, city authorities would be capable of deciding the best strategy to apply when the pollutant levels are high or if they want to foster fuel saving or shorter travel times.

The rest of this paper is organized as follows. The problem description and our proposal are discussed in sections 2 and 3, respectively. In Section 4 we present the characteristics of the real scenarios analyzed. Section 5 focuses on the numerical study and the discussion of the results. And, finally, in Section 6, conclusions and future work are outlined.

2   Problem Description

In this article we present a new strategy to reduce travel times, gas emissions, and fuel consumption in the city by using a multi-objective evolutionary strategy. We start from the real number of vehicles measured in the city, their proportions and routes, and calculate new vehicle proportions according to an evolutionary algorithm, to improve metrics, without losing the observed cargo capacity.

Formally, let $\boldsymbol{v} = (v_s, v_{mv}, v_{fsv}, v_t, v_m)$ be a vector containing the number of vehicles in the actual city (sedans, minivans, full-size vans, trucks and motorbikes) obtained from the proportions sampled during one hour. We assumed that only the 20% of sedans ($v_{s\prime} = 0.2 \cdot v_s$) and motorbikes ($v_{m\prime} = 0.2 \cdot v_m$) are used for delivering goods so that $\boldsymbol{v}' = (v_{s\prime}, v_{mv}, v_{fsv}, v_t, v_{m\prime})$.

According to the number of cargo vehicles $\boldsymbol{v}'$ and its average cargo capacity $\boldsymbol{t} = (t_{s\prime}, t_{mv}, t_{fsv}, t_t, t_{m\prime})$, we can calculate the cargo capacity available in the real city during our study time as $T = \boldsymbol{v}' \cdot \boldsymbol{t}^{\mathsf{T}}$.

Our objective is to obtain a Pareto set [5] of N vectors $\boldsymbol{v\prime}_j^{\star} = (v\prime_{s_j}^{\star}, v_{mv_j}^{\star}, v_{fsv_j}^{\star}, v_{t_j}^{\star}, v\prime_{m_j}^{\star}), j \in N$ which contains different optimal solutions, minimizing travel times, emissions, and fuel consumption in the city subject to:

$$T_j^\star = \sum_i \boldsymbol{t}_{ij} \cdot \boldsymbol{vr}_{ij}^\star \geq T, \quad \forall j \in N \tag{1}$$

$$v_{wj}^\star \geq \tau \cdot v_w, \quad \forall j \in N \text{ and } w \in \{sedan, motorbike\} \tag{2}$$

The set of vectors $\boldsymbol{vr}_j^\star$ represents the number of vehicles delivering goods, while $\boldsymbol{v}_j^\star$ represents the total number of vehicles in the city (deliver and cargo trips). Thus, we have set $\tau = 0.8$, according to our cargo use estimation.

A set of solutions would represent different key indicators for new policies (restrictions, tax reductions, etc.) to be applied to the road traffic in the city to foster shorter travel times, less gas emissions, and saving fuel.

3   Solving the Problem

In this work, we are looking for the best proportion of vehicle types in the city so as to optimize different aspects of the entire road traffic in the city. Modifying the number and type of vehicles used in transportation of goods while keeping the total demanded cargo will allow us to change the whole traffic characteristics to improve the quality of life of drivers and citizens. We use a realistic scenario of Malaga featuring different vehicle proportions (Table 1) to be optimized. Using each new configuration we calculate the amount of cargo $T^\star$ for this new scenario (subject to the restriction in Equation 1).

Fig. 1 shows the architecture of our proposal. The algorithm calculates the optimal proportions of vehicles evaluating its individuals by using the SUMO traffic simulator [11]. This evaluation comprises a realistic city model made of data measured *in situ*, open data published by the local city council, and the city map obtained from OpenStreetMap [15] (see our case study in Section 4). The different parts of the architecture are explained as follows.

3.1   Solution Encoding

We have encoded each solution as a vector of real numbers $\boldsymbol{x} = (x_s, x_{mv}, x_{fsv}, x_t, x_m)$ in which each component is the proportion of sedans,
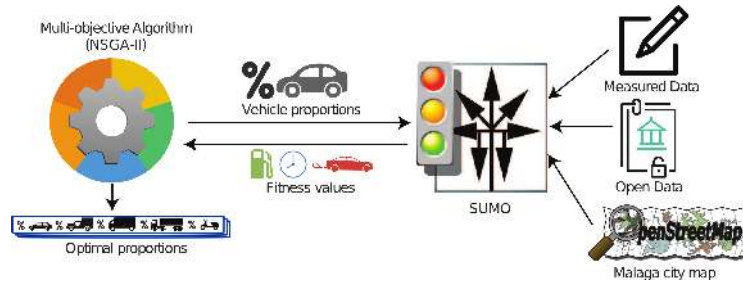

Fig. 1. System architecture.

minivans, full-size vans, trucks, and motorcycles intended to transport goods. However, a gas oil engine does not have the same fuel consumption as a gasoline engine, nor the same amount of gas emissions. Because of these differences, and to get closer to reality, before evaluating a solution $\boldsymbol{x}$ we transform it into more detailed proportions $\boldsymbol{x}^{\star}$ according to the volume of engine types (fuel and gas emissions characteristics) existing in the car fleet. These proportions will be used by our evaluation function. We have two possibilities for fuel: gas oil and gasoline, and we have different gas emission classes according to the European emission standard [6]. Below we describe the steps to obtain $\boldsymbol{x}^{\star}$:

Step 1 Calculate the amount of cargo vehicles $N_c = T/(\sum_i^{|\boldsymbol{x}|} x_i \cdot t_i)$ that we need to supply the tonnage demand T (constraint).

Step 2 Compute the total amount of vehicles $N^{\star} = N_p + N_c$, being $N_p = v_s + v_m$ the number of vehicles intended for private use (constraint).

Step 3 Get the correction factor ϕ in the number of vehicles $\phi = N^{\star}/N$, being N the total amount of vehicles in the base solution.

Step 4 For each proportion, we correct its value for the new total of vehicles: $x_i' = x_i \cdot N_c/N^{\star}$, obtaining the new vector $\boldsymbol{x}'$.

Step 5 Calculate the new proportion of private use vehicles (sedans and motorcycles) and add it to the solution $x_j' = x_j' + v_j/N^{\star}, j \in \{s, m\}$.

Step 6 According to the proportions of each vehicle classes in Table 1 we calculate the extended solution $\boldsymbol{x}^{\star} = \{x' \cdot f \cdot e | \forall x' \in \boldsymbol{x}', f \in Fuels, e \in Emissions\}$ where $Fuels$ is the proportion of gasoline and gas oil of each vehicle, and $Emissions$ the proportion of engine according to the data published in [4].

Step 7 Return the extended solution $\boldsymbol{x}^{\star}$ and the factor ϕ.

3.2   Evaluation Function

We evaluate the quality of each solution making use of the SUMO traffic microsimulator [11]. SUMO is a free and open traffic simulation suite developed by the German Aerospace Center[1]. It allows modeling of intermodal traffic systems including road vehicles, public transport and pedestrians.

Each solution to be evaluated consists of a solution $\boldsymbol{x}^{\star}$. Additionally, an increment factor ϕ is used to increase (or decrease) the total number of vehicles N (measured amount of vehicles). Note that the realistic scenario to be optimized has a factor $\phi = 1.00$.

Also, since Malaga has a large number of vehicles, solutions which notably increase this number could end in several traffic jams with many vehicles enqueued, waiting to enter the city after the analysis ends. To prevent that, we have calculated the proportion of vehicles entering the city in our realistic scenario (84%) and slightly penalized with the term k, those configurations that are under this threshold. Concretely, we have set a threshold $\theta = 0.8$ to allow up to 20% of vehicles waiting in the queue when the analysis time ends.

We show in Equation 3 the fitness function used in the optimization process and in Equation 4 the penalty term.

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[1] http://dlr.de/ts/sumo

$$\mathbf{f}(\boldsymbol{x}) = \left(k + \frac{1}{n}\right) \cdot \sum_{i=1}^{n} \left(travel\ time(x_i), emissions(x_i), fuel(x_i)\right), \qquad (3)$$

$$k = \begin{cases} 0 & \text{if } \frac{n}{N} \geq \theta, \\ \frac{100}{n} \cdot \left(\frac{n}{N} - \theta\right) & \text{otherwise.} \end{cases} \qquad (4)$$

3.3   Algorithm

In order to solve our optimization problem, we use a well-known multi-objective metaheuristic algorithm: the NSGA-II algorithm proposed by Deb et al. [3]. Our goal is not to research in the algorithm itself, but to make a first model of this real problem and see if we can create an intelligent advisor for city managers. As described above, each individual is represented as a vector of real numbers. This allows us to use simple and fast operators as the following ones:

- Crossover: Simulated binary crossover with probability 0.9.
- Mutation: Polynomial mutation with probability 0.25.
- Selection: Same selection applied in [3].
- Replacement: Elitist without including repeated individuals.

To avoid unfeasible solutions, before evaluating each solution, we normalize it and then calculate $\boldsymbol{x}^{\star}$ and ϕ. We also perform 200 evaluations of the algorithm with a population of 48 individuals (the initial population was randomly generated). These values were selected after a preliminary study in which we tested two population sizes: 24 and 48, and two maximum number of evaluations: 100 and 200. Then, we selected the best configuration in order to maximize the diversity of the calculate Pareto set, taking into account the limitation of time (the mobility scenarios require long computation times).

4   Case Study

We have chosen as our case study an area comprising the East side of the city of Malaga (Spain), including those zones where traffic jams are common. The geographical area studied encompasses an area of about 32 km^2.

The city map (shown in Fig. 2) was imported from OpenStreetMap into the SUMO traffic microsimulator. This allows us to work with a real scenario, e.g., streets, traffic lights, left turns, and roundabouts. From our observations, we have defined five types of vehicle for representing the road traffic in the streets of Malaga. The average characteristics of vehicles according to the manufacturers are shown in Table 1. The vehicle distribution was obtained by counting and classifying the type of vehicles at four different locations in the city (blue labels in Fig. 2). We observed that 68.9% of vehicles are sedans, 6.4% are minivans, 7.0% are full-size vans, 2.9% are trucks, and 14.9% are motorcycles. Some types are divided into gasoline and gas oil variants (Table 1) as stated by the data for Andalusia [4], and into their equivalent emission classes in SUMO (HBEFA3 [9]).

Fig. 2. Case study: East Malaga. The measurement points are the red numbers and the sampling points are the blue letters.

Using the data published by the local council of Malaga [1] corresponding to 23 measurement points (red numbers in Fig. 2) and the Flow Generator Algorithm (FGA) [16], we have obtained the average traffic per hour for working days in the third quarter of 2015. The FGA assigns vehicles to the traffic flows generated by the program DUARUTER included in the SUMO software package, and adjusts its number and routes in the simulation map to the values measured by the 23 real sensors in the city. After this process, we ended up with a scenario, consisting of 10,438 vehicles (7,193 sedans, 616 minivans, 768 full-size vans, 297 trucks, and 1,564 motorbikes), to be optimized with the aim of finding the best policies for reducing travel times, gas emissions and fuel consumption.

Each vehicle type has an assigned capacity t obtained from standard commercial models of vehicles as shown in Table 1. By multiplying the number of vehicles n by their capacity t, we obtained a total cargo of 4,101 tons, which is the lower bound T of the problem (Equation 1). Each solution generated by our algorithm must be able to provide the total of vehicles needed to delivery this tonnes of goods, so that the city is not losing cargo capacity.

Table 1. Characteristics of the vehicles in our case study, the observed proportions, the cargo availability, and the individual and total cargo capacity.

Type	Accel. (m/s^2)	Decel. (m/s^2)	Length (m)	Max.Spd. (m/s)	Gasoline (%)	Gas Oil (%)	Rate (%)	Cargo (%)	Capacity t (ton)	Total T (ton)
Sedan	0.720	12.341	4.500	25.25	44.86	55.15	68.9	20	0.20	288
Minivan	0.720	12.341	4.500	25.25	10.88	89.12	6.4	100	1,00	616
Full-size van	0.720	12.341	4.878	25.25	10.88	89.12	7.0	100	2.00	1,536
Truck	0.263	3.838	7.820	16.67	0.00	100.00	2.9	100	5.50	1,633
Motorcycle	0.460	8.147	2.200	16.67	100.00	0.00	14.9	20	0.09	28

5   Results

After presenting our problem we are going to study the different solutions obtained by the algorithm and compare our improvements on the city with other strategies carried out by traffic managers for reducing pollution.

5.1   Pollutants Correlations

Since SUMO provides different types of pollutants (CO_2, CO, HC, etc.), we wished to select the ones with the lowest correlations to travel time and fuel consumption. After carrying out the simulation and measuring these emissions we calculated the Pearson correlation coefficients where hydrocarbons (HC) presented the lowest correlation with travel times (0.23) and fuel consumption (0.40). Hence, we have chosen HC as a gas emission measure in our experiments. The rest of metrics will be also reduced since there also exist relations between HC and CO_2 (0.38), CO (0.67), NO_x (0.25), PM_x (0.30), and fuel (0.40).

5.2   Solution Analysis

After performing 30 independent runs the average hypervolume is 95,736, the standard deviation is 6,550, their average ϵ-indicator is 12.6 and the deviation is 6.3. From these indicators, we assume the fronts were similar to each other.

We studied the different solutions using the attainment surfaces [7] technique. We selected the 25%-attainment surface to ensure the quality of the selected solutions (Fig. 3). By analyzing the individuals in this Pareto front, we were able to spot the differences in the number of vehicles in each class (Fig. 4(a)).
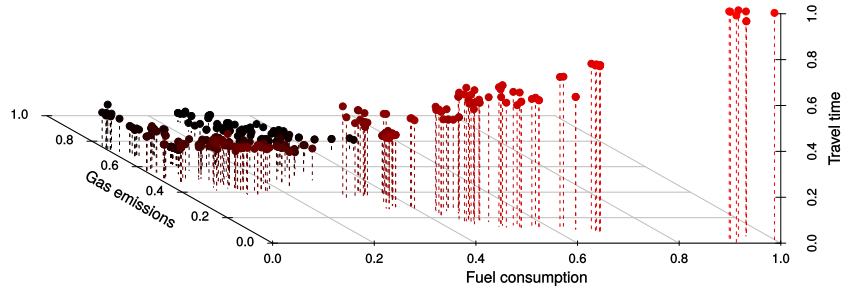

Fig. 3. 25%-attainment surface. Fitness values are scaled to the [0,1] range.

The most used cargo vehicles were vans: 1,419 minivans (median) and 1,332 full-size vans. Their speed and cargo capacity thus are an ideal choice for delivery goods throughout the city. However, HDV, like trucks, and also motorcycles were not good options, as the former are too slow and pollutant and the latter have too little cargo capacity. Sedans had a greater presence than motorcycles and trucks, but were still overshadowed by the utility of vans for delivering goods.

5.3   Solution Improvement

Next, after discussing the solutions obtained by the algorithm, we will analyze the fitness values of each one of them. Fig. 4(b) shows the percentage improvement of each solution of the front with respect to the current situation (scenario) in the city of Malaga. Although travel time was improved by 10%, fuel and all the emissions (not only HC) were considerably better than the ones measured in Malaga. This is good news for the city's environment, as not only there were fewer emissions of polluting gases, but also fewer fossil fuels were consumed.
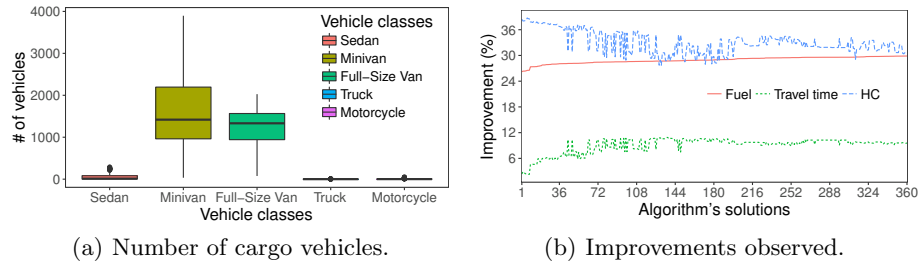
(a) Number of cargo vehicles.   (b) Improvements observed.

Fig. 4. 25%-attainment surface analysis.

5.4   Comparing with other Strategies

This new way of improvement in the transport of goods is different from previous strategies applied by the city managers for reducing the carbon footprint and get a more fluid traffic in the roads [12]. We compared our solution with other strategies used in the cities in Table 2, where the fitness value of each objective (travel times, gas emissions, and fuel) obtained by our algorithm (minimum and maximum values found among all the Pareto sets) are shown.

Table 2. Fitness values in the different strategies.

Strategies	Travel time	Gas emissions	Fuel
NSGA-II Min	**633.77**	**434.15**	**406.20**
NSGA-II Max	**698.66**	**523.08**	**434.06**
Malaga	711.12	708.68	579.19
Limit 30 km/h	2048.74	1412.43	1089.75
Limit 70 km/h	709.47	621.21	499.71

Even in the worst case, our proposal achieved better fitness (434.06, 698.66, 523.08) than the rest of the strategies (30% improvement on average). These results show that employing intelligent techniques can help city managers to discover new ways of improving traffic flows and reducing air pollution.

It is also interesting to compare the number of vehicles in each solution found with those currently moving in Malaga. Fig. 5 shows the number of vehicles of each algorithm's run. The red line marks how many vehicles (10,438) were in Malaga according to our case study. We can see that the total number of vehicles is lower than in Malaga (74.09% of solutions are under the red line). But, this
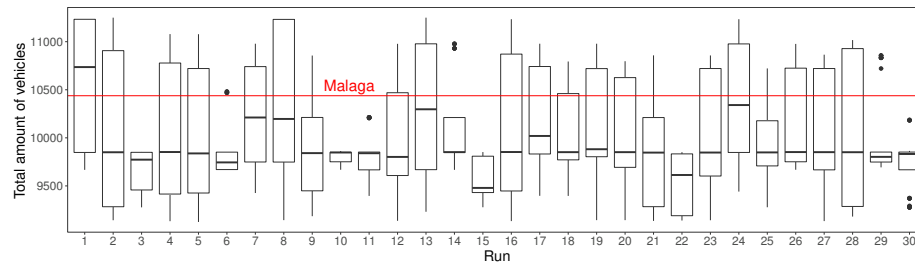

Fig. 5. Total number of vehicles in each run.

does not mean that more trucks need to be added instead of LDV, as we saw in the 25%-attainment surface. The original, realistic scenario (Malaga), is close to the maximum capacity of vehicles that fits into the analyzed area of the city without producing traffic jams. Consequently, our solutions do not only have less emissions while improving the efficiency of transport operators, but also citizens and drivers are enjoying less congestion on the roads.

5.5 City Improvements

The global improvements achieved on Malaga are shown in Table 3. Being Malaga our realistic case study, we have improved all the metrics using the algorithm, although we report only the best solutions for each objective. We can see that the shortest travel times are obtained when there are 1,734 full-size vans as they are faster than trucks an their emissions are lower. The less emitting solution is the one that uses 3,193 minivans for delivering cargo instead of the other vehicles. Finally, citizens would save more fuel in a more equilibrate distribution of both van types. Note that the algorithm has definitely banned trucks from the city as they are large, slow, and pollutant. Additionally, we present the metrics for 30 and 70 km/h, and conclude that their improvements are marginal despite being commonly used by city councils when the emissions are high.

Table 3. Improvements of metrics when using the analyzed strategies in Malaga and the number of vehicles of each type.

Strategy	T.Time (s)	G. Emiss. (g HC)	Fuel (l)	Distance (m)	Sedan	Minivan	Full-size van	Truck	Motor-cycles	Total
Malaga	696.3	626.7	513.8	5552.0	6095	521	649	254	1307	8826
Limit 30 km/h	912.7	629.2	485.5	5261.4	5655	484	600	237	1224	8200
Limit 70 km/h	709.5	621.2	499.7	5527.5	6004	512	643	246	1302	8707
NSGA-II T.Time	**633.8**	504.8	412.9	5605.5	5118	109	**1734**	1	1084	**8046**
NSGA-II G. Emiss.	694.5	**434.1**	425.6	**5532.9**	5034	**3193**	76	1	1011	9315
NSGA-II Fuel	642.9	491.7	**406.2**	5593.7	5027	**1274**	**1153**	0	1093	8547

6 Conclusions

After studying how changing the proportions of HDV and LDV affects the metrics in the city we have obtained results that show that the number of trucks should be kept at a minimum inside the city. However, due to the limited capacity of the city's streets, the number of LDV vehicles cannot be considerably increased as this makes traffic jams very likely to occur. The multi-objective algorithm was capable of identifying this restriction and obtained solutions where using minivans and full-size vans for delivering goods is advisable.

It does not mean that companies have to sell all their trucks, but HDVs should be used as freight transport by highways and then use vans for local delivery. All this information would be extremely useful for city managers and these results would serve as goals for the creation of municipal strategies to promote the well-being of drivers, workers and citizens.

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