Multiobjective Optimization of Greenhouse Gas Emissions Enhancing the Quality of Service for Urban Public Transport Timetabling

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***Abstract*—This paper presents a multiobjective cellular genetic algorithm to determine bus timetables using multiple vehicle types, considering restrictions of government agencies for public transport systems in the context of smart cities. The first objective is to reduce the greenhouse gas emissions by the minimization of number of vehicles wasting fuel transiting with low ridership. The second one is to minimize number of passengers that cannot move in a certain time-period increasing vehicles overload and waiting time. A set of non-dominated solutions represents different assignments of vehicles covering a given set of trips in a defined route. Our experimental analysis shows a competitive performance of the proposed algorithm in terms of convergence and diversity. It outperforms non-dominated sets provided by NSGA-II.**

***Keywords*—evolutionary algorithms; greenhouse gas; metaheuristics; multiobjective optimization; public transport.**

I. Introduction

More than half of the world population (54%) lives in urban areas, as oppose to the 30% in 1950. This abrupt growth implies deep changes in size and distribution of living space. The United Nations predict that this number will increase to 66% in 2050 [1] leading a rise in demand for all infrastructures that interact directly with the people. The increase of migrants involves several problems, increasing the demand for a limited supply of natural resources, goods, and services including energy, water, education, health and transportation among others. Harrison et al. [2] define a smart city (SC) as an "instrumented, interconnected and intelligent city". Different areas like public administration, education, health services and transportation can be improved to make them more intelligent, interconnected and efficient by computing technologies. SCs can reduce costs, make responsible use of resources and encourage the active participation of citizens in decision-making processes, to achieve a sustainable and inclusive city.

The main challenges for cities on urban mobility are often related to the inability of public transport systems to satisfy needs of a growing number of users. Though each city has different extra issues like the negative environmental impact affecting the global climate change, greenhouse gas (GHG) emission levels of the transportation activities have a significant contribution (e.g. 28% of all GHG emissions in USA) [3].

Total transportation emissions are increased due, in large part, to increased demand for mobility [3]. Figure 1 shows the average per-passenger fuel economy of different transportation systems. The transit rail attains relatively high values due to high ridership and energy efficiency of rail transport systems. Airlines are an increasingly efficient transport method due to more passengers are on planes and ticketing software (e.g. online sales or booking agency) fills most planes to capacity. Motorcycles has very high fuel efficiency achieving a high number of passenger-km per gallon. Transit buses are not very efficient because their ridership rates are less than its capacity. Demand response vehicles are the least efficient, because those vehicles use fuel just to arrive to the passengers [4, 3]. Public transport vehicles that operate with low ridership have been shown to have higher per-passenger-km emissions than cars.

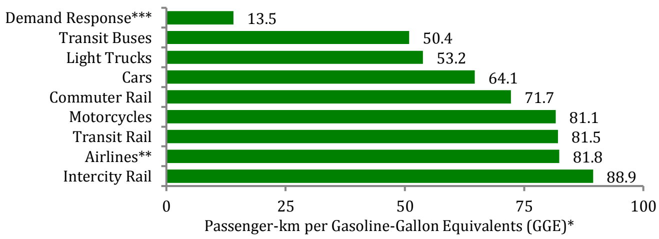


Fig. 1. Average per-passenger fuel economy. *GGEs mean a quantity of fuel or electricity with the same energy content as a gallon of gasoline. ** It includes domestic flights. *** It includes passenger cars like UBER, taxi, vans or small buses operating in response to calls or apps from users [4,3].

Nowadays the Intelligent Transportation Systems (ITSs) have conflicting objectives, the local authorities strive to minimize the environmental impact reducing GHG emissions, and the users want and expect a better service. Hence, a solution of our algorithm, for an instance of multiple vehicle-types timetabling problem (MVTTP), presents a good distribution of vehicles, reducing the number of vehicles, GHG emissions and guaranteeing the quality of service (QoS). This is essential in making the public transport more attractive and increasing its use compared to private transport methods.

Calculating the Pareto front to solve a Multiobjective Optimization Problem (MOP), in most cases, is impractical, because it may contain an infinite number of non-dominated solutions. The goal is to produce a good approximation of the Pareto front in a reasonable execution time. This paper presents a heuristic based on Multi Objective Cellular genetic algorithms (MOCell) to solve MVTTP. We do not consider the total life cycle GHG emissions (i.e. infrastructure, maintenance, etc.). We focus on operating emissions.

II. RELATED WORK

Techniques for solving combinatorial problems can be classified into two main categories: exact and heuristic algorithms. The exact algorithms guarantee finding the global optimum. However, often, only small-sized instances can be practically solved. Heuristics and metaheuristics are more efficient and flexible, and allow approximate global optimum.

Newell [5] proposed to minimize waiting time for passengers by comparing a set of vehicles that have departure time with a smooth passenger arrival function.

Ceder [6] defined four different methods for calculating the frequency that depend on the load profile of passenger demand and the restrictions stipulated by regulators entities. He shows how to obtain optimal timetables, when selecting the maximum passenger load as a reference point. Kwan and Chang [7] presented a formulation for the scheduling problem with two conflicting objectives: the cost of transfers and cost caused by deviations from an initial schedule. The authors implement NSGA-II, combined with other methods (e.g. local search) to solve the problem.

Hassold and Ceder [8] studied scheduling issues in order to minimize waiting time for passengers (QoS) and a penalty based on the unoccupied space (operating efficiency). The main idea is to combine different types of vehicles, based on the idea proposed by Potter [9], to avoid overloads and improve the vehicles utilization. The authors implement a heuristic based on graphs, which combine different schedules to search the optimal Pareto set. Numerical results for a study case in New Zealand show significant savings in passenger waiting times, but also an acceptable passenger load on all vehicles. Griswold et al. [10] optimized the bus transit network design for a study case in Barcelona modifying a traditional continuum approximation model. They minimize costs, subject to GHG emissions constrains. The drawback of this approach is that solutions include a penalty in increased user travel time..

A. *Vehicle Specific Power (VSP)*

Jimenez-Palacios [11] developed the initial idea of Vehicle Specific Power (VSP) in the PhD thesis. The aim is to compute better the vehicle emission related with the driving (or operating) conditions. He defines VSP as the instantaneous power ($\mathbb{P}_i = FT_i.v_i$) per unit mass (m_i) of the vehicle of type i, where FT_i is the traction force (N) and v_i is the driving speed (m/s) of the vehicle of type i (see Fig 2). This mathematical model represents the engine load against aerodynamic drag (F_i^w), rolling resistance (F_i^φ), acceleration plus the kinetic (F_i^k) and potential (F_i^α) energies of the vehicle, all divided by the mass of the vehicle [12]. Where a_i is the acceleration of the bus; g is the acceleration of the gravity; φ is the coefficient of rolling resistance related to the road surface type and conditions and tire type and pressure; α is the road grade of elevation; ρ_{air} is the ambient air density.

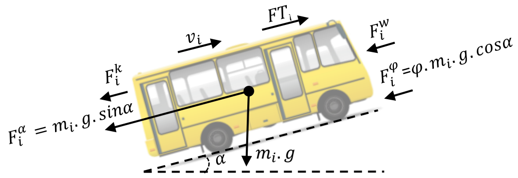


Fig. 2. Forces analysis for the vehicle of type *i*.

A_i is the frontal area of the vehicle; C_D is the drag coefficient; v_i^w is the headwind into the bus and ε_i^j is the mass factor.

Yu and Li [13] evaluated bus emissions generated by braking

$$VSP_i = \frac{\mathbb{P}_i}{m_i} = \frac{FT_i.v_i}{m_i} = \frac{v_i\left(F_i^k+F_i^\alpha+F_i^\varphi+F_i^w\right)}{m_i} = v_i\left[a_i\left(1+\varepsilon_i^j\right) + g.\sin\alpha + g.\varphi.\cos\alpha + \frac{\rho_{air}A_iC_D}{2.m_i}\left(v_i+v_i^w\right)^2\right] \quad (1)$$

and acceleration of vehicles near bus stops.

III. THE MULTIOBJECTIVE MVTTP

The ITSs include three main participants: *users* are looking for an efficient, economical, safe, comfortable and green multimodal system. *Companies* strive to reduce operating costs and maximize profits, focusing efforts on economic subjects. *Government'* policies pursue to ensure a high-quality life for its citizens, setting mobility rules that satisfy their needs and ensuring its functioning considering the environmental impact.

A. *Problem description*

MVTTP models a realistic scenario, where a set of vehicles of different types is assigned for covering trips of a route. The MOP is to find an appropriate distribution of multiple vehicle-types, with the goal of to simultaneously to minimize two vital objectives: GHG emissions related to the fuel consumption from vehicles used for a specific route and unsatisfied user demand. Minimizing the impact function f_1, additionally, we contribute to reducing the operational cost and improving the traffic flow due to we reduce the fuel consumption and needless bus circulation. The unsatisfied user demand function impacts on the perceived delay to board the vehicle and the comfort associate to the load factor, i.e. number of passengers on board.

Ceder [6] proposed four basic steps for a transit planning problem: 1) Network route design, 2) Timetable development, 3) Vehicle scheduling, and 4) Crew scheduling. We divided the second step in two tasks: frequency determination and timetable design. Therefore, we assume that the route with their stops is defined with additional information like traffic volume, average speed and altimetry (i.e. the elevation of the route see Fig. 3).

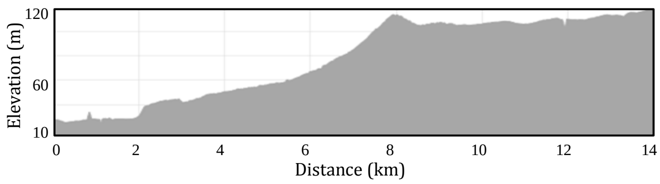


Fig. 3. Elevation profile of Los Angeles bus route 217 northbound with a gradient ascending of 7% at 7.3 km and maximum altitude of 114 meters.

Passenger demand for each period in every stop is available. Unsatisfied demand defines the amount of passenger that cannot be moved satisfactory. It implies more waiting time and congestion in the selected set of vehicles to cover the route in this period based on Peña et al. [14]. The vehicle impact is based on fuel consumption. It can be calculated using the elevation-profile, acceleration, and speed.

B. Mathematical formulation

Given the following elements: A set of vehicles $B = \{b_1, \dots, b_n\}$, where b_i shows the vehicles number of type i, n is the different types of vehicles, and $\sum_{i=1}^{n} b_i$ is the total fleet. T is a set of required trips $T = \{t_1, \dots, t_m\}$ of a defined route R.

The MVTTP is based on two objective functions f_1 and f_2 :

Minimize $$f_1 = \sum_{t_k \in T} FC_i \quad (2)$$

and $$f_2 = \sum_{t_k \in T} \sum_{s \in R} LQ_s \quad (3)$$

subject to:

$$FC_i = \tau_R \beta_i VSP_i, \quad (4)$$

$$f_j \geq f_j^{min}, \quad (5)$$

$$LF_j \leq LF_j^{max}, \quad (6)$$

$$LQ_s = max\left(P_j^s - \sum_{i \in M_j} LF_j \times CAP_i, 0\right) \quad (7)$$

Where: FC_i is fuel consumption of vehicle type i, covering a trip of the route; β_i is the vehicle fuel coefficient consumption rate; τ_R is the time spent to cover the route R; P_j^s is the number of passengers on a stop in the route R; f_j is the frequency for period; f_j^{min} is the minimum required frequency in every period; LF_j is the load factor during a period; LF_j^{max} is the maximum load factor. M_j is the set of vehicles used during the period j; CAP_i is the capacity of a vehicle of type i and LQ_s is the passengers demand at the s stop that exceed capacity

IV. Multiobjective Evolutionary Algorithms

The problem tackled in this paper is composed of two conflicting objectives that must be optimized at the same time. The formulation of a MOP is the following: Find a vector $x^* = [x_1^*, \dots, x_n^*]^T$, which satisfies m inequality constraints $g_i(x) \geq 0, i = 1, \dots, m$, p equality constraints $h_i(x) = 0, i = 1, \dots, p$, and minimizes the vector function $f(x) = [f_1(x), \dots, f_k(x)]^T$, where $x = [x_1, \dots, x_n]^T$ is the vector of decision variables.

A MOP consists of k objectives reflected in the k functions, m + p constraints on the objective functions, and n decision variables. The set of all the values satisfying the constraints defines the feasible region (or solution space) S. Any point x ∈ S is a feasible solution. A key concept in multiobjective optimization [15] is Pareto dominance, which is defined as: given two vectors $u = (u_1, \dots, u_k)$ and $v = (v_1, \dots, v_k)$, we say that u dominates v (denote by $u \prec v$) iff u is partially less than v, i.e., $\forall i \in \{1, \dots, k\}, u_i \leq v_i$ and $\exists i \in \{1, \dots, k\}: u_i < v_i$.

Solving a MOP is the process of finding a set of solutions that dominate every other point in the solution space. This means that the solutions in this set are Pareto optimal for the problem. A set of all the Pareto optimal solutions is known as the Pareto Optimal Set. Each vector in the Pareto Optimal set has a correspondence in objective function space, getting the so-called Pareto front. Formally: A solution $x^* \in S$ is Pareto optimal if and only if it is non-dominated by any other solution $x' \in S$. For a given MOP, $f(x)$, the Pareto Optimal Set, $\mathcal{P}_S$, is defined as:

$$\mathcal{P}_S = \{x \in S | \nexists x' \in S\ f(x') \prec f(x)\} \quad (8)$$

For a given MOP, $f(x)$, and $\mathcal{P}_S$. Pareto Front $\mathcal{P}_F$ is defined as:

$$\mathcal{P}_F = \{f(x) \in \mathbb{R}^k | x \in \mathcal{P}^*\} \quad (9)$$

As discussed before, MOPs can have a Pareto front composed of a huge (possibly infinite) number of solutions, we only aim for a $\mathcal{P}_F$ approximation. When stochastic techniques are used, the goal is to obtain a $\mathcal{P}_F$ approximation.

A. Evolutionary algorithms and MOCell

Evolutionary algorithms (EAs) are nature-inspired search methods that emulate the evolution process of species to solve optimization problems. The evolution is the result of the interaction between the creation and evaluation of new genetic information, and its behavior for a future selection. Everyone is affected by other individuals and the environment, with different probabilities depending to population settings. When an individual exhibits a better fitness, it has a greater chance to live for a longer and generate genetic inheritance. These techniques apply an iterative and stochastic process on a set of individuals, where everyone represent a potential solution to the problem. To measure their aptitude in every problem objective, a fitness value is assigned to everyone and used by the algorithm to guide the search. Most EAs use a single population of individuals and apply the operators as a whole. On the other hand, in the case of distributed EAs or cellular EAs (cGAs), the individuals in a population can just interact with a reduce number of individuals partitioned in islands or located in a nearby neighborhood.

The multiobjective EAs (MOEAs) have been applied to solve hard MOPs obtaining accurate results, when solving problems in many research areas. Due to their population nature, they can find a set with several solutions that approximate to the whole $\mathcal{P}_F$ of a MOP in one single run. MOEAs are designed considering two features at the same time: satisfactory convergence and diversity properties. This means that they not only look for finding the approximate $\mathcal{P}_F$, with a high degree of convergence (be as close as possible to the $\mathcal{P}_F$), but also the solutions must be uniformly spread along the $\mathcal{P}_F$.

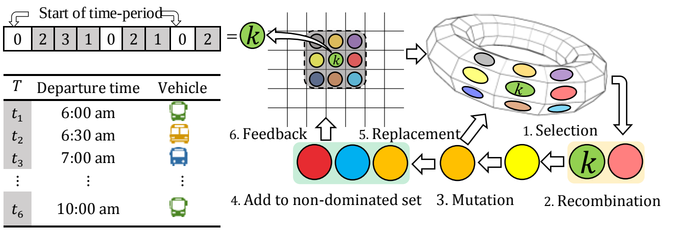


Fig. 4. Solution representation for the MVTTP and reproduction steps.

In this work, we focus on the cGAs, particularly, on MOCell [16]. The main feature of this type of algorithm is that population is distributed in a tow-dimensional toroidal grid, where each individual belongs to a cell and can only be recombined with the surrounding cells. The main idea of this limitation is to perform a greater exploration of search space, because the overlapped neighborhoods induce a slow diffusion of solutions through the population, while a kind of exploitation takes place inside each neighborhood by genetic operations. MOCell (see Fig. 4) keeps an external file to store non-dominated solutions using the crowding distance of NSGA-II [17] to maintain a diverse set of solutions, and a feedback mechanism to replace individuals in the population after each iteration. Encoding and solution representation

Solutions are encoded as arrays of integers, representing the type of vehicle assigned to cover one trip of T. Zeros mark new time-periods. The order of departures is specified in the sequence; Figure 4 shows an example of solution encoding for an instance with three different type of vehicles, six trips $t_k \in T$, and three periods of one hour. The array size is taken from prior demand study and preliminary frequency determination based on a load profile [5]. We consider a lower-bound level on the frequency (F_j) for each time-period, given the same vehicle-capacity constraint, $\overline{CAP}$ (average of capacities of vehicles).

$$F_j = max\left[\frac{A_j}{LF_j \cdot \overline{CAP} \cdot L}, \frac{P_j^{max}}{\overline{CAP}}, f_{min}\right] \quad (10)$$

$$A_j = \sum_{s \in R} P_j^s \ell_s, \quad (11)$$

$$L = \sum_{s \in R} \ell_s \quad (12)$$

Where A_j is the area in passenger-km under load profile during time-period j, ℓ_s is the distance between the stops s and $s+1$, and L is the route length. The zeros distribution can be changed but cannot be consecutive and every j has a same size.

B. Objective functions and fitness evaluation

The optimization problem is formulated as having two different objective functions. f_1 (2) includes of the sum of the fuel consumption of every vehicle assigned to cover a trip t_k, which is calculated according to the timetable and FC_i depend on the vehicle type and (1). f_2 (3) is the number of passenger that cannot be transported by the fleet assigned for each trip t_k.

C. Evolutionary operators

Population initialization: it is generated by randomly assigning different vehicles to each departure considering the size of schedule and zeros distribution previously defined. Individuals are distributed in a toroidal grid of cells (see Fig. 4).

Selection: A tournament selection (tournament size: 9 individuals) is chosen to select the parents (two individuals survive) in the neighborhood about the studied individual.

Recombination: Single Point Crossover (SPX) consists in selecting a randomly zero position as crossover point, time periods from the beginning of chromosome to the point is copied from one parent, the rest is copied from the second parent.

Mutation: Uniform mutation (UM): In this method, from the entire chromosome, a subset of genes is randomly chosen, and their values are swapped for other random value from the set of allowable values (set of different type of vehicles).

V. Experimental Results

A. Quality indicator

Hypervolume (I_{HV}) [18] assesses convergence and uniform distribution along the front together. I_{HV} calculates the multi-dimensional region enclosed between the individuals in a computed approximation front and a reference point in the objective function space. The closer the approximation is to the Pareto front, the higher the value of this indicator. On the other hand, if the spread of the individuals along the front is good (desirably uniform), the higher the value of this indicator.

Hence, a solution that produces the higher value of this indicator is desirable. I_{HV} can be calculated as follows. First, given an approximation set $\mathcal{P}$ placed in objective space and a reference point W, a hypercube (Hc_k) for each solution ($k \in \mathcal{P}$) is constructed taking as corners the reference point and the solution point. After that the union of all these hypercubes is found and its hypervolume is calculated using (13).

$$I_{HV} = volume\left(\bigcup_{k=1}^{|\mathcal{P}|} Hc_k\right) \quad (13)$$

B. Experimental setup

This section presents the experimental setup, including bus route and passenger's demand. The passenger demand is retrieved from 217 Metro Local Line of Los Angeles Metro Bus. For the considered problem instance, we run 30 independent executions of 10^4 fitness evaluation. I_{HV} is calculated for each run using the upper bounds for every objective function due to the extreme cases are used for normalizing the objective space. Parameter settings are described in Table I.

To compare the proposed algorithm with other techniques for multiobjective combinatorial optimization, we implement NSGA-II, proposed by Deb et al. in 2002 [17]. The same parameters are used in recombination and mutation operators and their probabilities (see Table I). The size of the initial population is 100 individuals, for selection we use binary tournament and 2000 generations as stopping criteria, assessing the performance by using the I_{HV}, as a quality indicator.

TABLE I. PARAMETERIZATION OF THE ALGORITHMS

Stopping condition	10000 function evaluation
Population size	100 individuals (10x10)
Neighborhood	8 surrounding neighbors
Selection parents	(9,2)
Recombination	SPX
Probability of recombination	0.9
Mutation	UM
Probability of mutation	0.2
Density estimator	Crowding distance
Replacement	Replace if better ranking and crowding
Feedback	20 individuals

C. Results and discussion

In this section, we focus on quality of solutions and performance. Figure 5 shows an observed FC for each trip, using vehicles of the same type [6], and a set of obtained solutions. We appreciate that for each time-period, obtained FC is less for all trips. However, the QoS worsens as fuel consumption decrease.

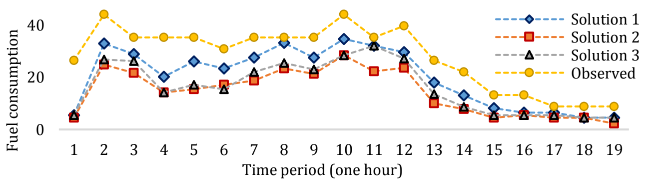
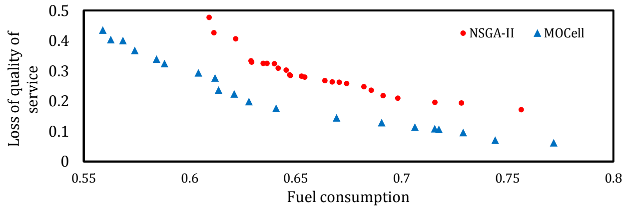


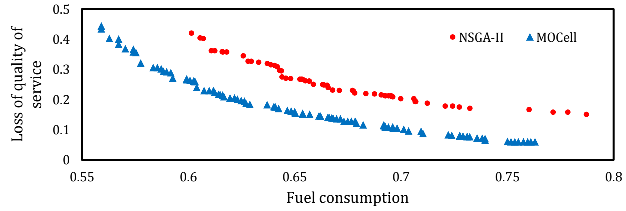
Fig. 5. Fuel consumption in liters of three solutions (best crowding distance in $\mathcal{P}_F$) against observed frequency of route 217 in LA (90 seats vehicle).

The values obtained after applying I_{HV} to each front collected from 30 independent runs show a good performance of the proposed algorithm with maximum I_{HV} value of 0.38 (0.37 on average). It shows a competitive behavior of the recombination and mutation operators to explore the search space and achieve an approximation set close to the $\mathcal{P}_F$. Figure 6 shows the $\mathcal{P}_F$ approximation obtained in the better run for

NSGA-II ($I_{HV} = 0.27$) and our algorithm ($I_{HV} = 0.38$) for the same instance after 10^4 fitness function evaluations.



(a)



(b)

Fig. 6. Loss of QoS. (a) Best cases for NSGA-II and proposed algorithm. (b) Pareto front approximation for 30 best cases for the route 217 in Los Angeles.

Also, we compare the non-dominated set formed by 30 best approximation sets for each run. We analyze the Pareto front approximations for the two algorithms. It is easy to see that NSGA-II has difficulties in convergence and diversity. It has poor I_{HV} value. The comparison shows that cellular algorithm outperform NSGA-II, achieving better values of I_{HV}, in average and best case. Our approach provides a good approximation to $\mathcal{P}_F$, and solution sets preserve diversity (see Table II).

TABLE II. METRIC I_{HV} COMPUTED FOR MOCELL AND NSGA-II

Metric	MOCELL			NSGA-II		
	max	mean	σ	max	mean	σ
Non-dominated points	24	19.7	1.7449	**39**	30.233	3.4209
Hypervolume (I_{HV})	**0.3814**	0.3709	0.0067	0.2766	0.2663	0.0096

In real-world applications, the decision maker is normally interested in certain types of trade-offs based on regulations and restrictions usually framed by ITS. From this point of view, the approximation sets produced by our algorithm (see Fig. 6) repeat a lot of values for the fitness functions. It happens because there exist identical timetables but the order of the vehicles is not the same. The decision maker can choose one of the two solutions, then, through a detailed study (e.g. local search) in specific times of the day (e.g. peak hours), to select the best timetable.

VI. CONCLUSIONS

In this paper, we have studied the multiobjective MVTTP. The problem has been formulated by considering two conflicting objectives: fuel consumption and QoS for users. After describing the problem formulation in detail and presenting the chosen algorithm, we explain a method to solve MVTTP based on MOCell that is a very competitive technique for MOP.

The experimental analysis demonstrates the capacity of the studied heuristic to find a set of different vehicle types to cover a specific route with a reduced fuel consumption in comparison to other methods. It also guarantees the level of service defined by government entities. We conclude that our approach is very useful tool for vehicle timetabling problems. It provides a wide range of trade-off timetables applicable in diverse cases, considering regulation of the ITS.

The main lines of future work include a timetabling and vehicle scheduling that considers real-time traffic information to improve the assignation of vehicles and to produce adaptive solutions for each time-period. Another interesting research is to use the knowledge of the problem to adjust the operators of recombination or mutation to provide more appropriate timetables of vehicles of different type. An important topic is the implementation of parallel techniques that allow speed up the optimization process.

ACKNOWLEDGMENT

The work is partially supported by RFBR, project no. 16-07-00931, Council for Grants of the President of Russian Federation, project NSh-8081.2016.9, and CONACYT, México, grant no. 178415.

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