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Procedia - Social and Behavioral Sciences 160 (2014) 254 – 263

Procedia
Social and Behavioral Sciences

XI Congreso de Ingenieria del Transporte (CIT 2014)

Multi-objective vehicle routing problem with cost and emission functions

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Abstract

Among the logistics activities, transportation, is presented as a major source of air pollution in Europe, generating harmful levels of air pollutants and is responsible for up to 24% of greenhouse gases (GHGs) emissions in the European Union. The growing environmental concern related to the economic activity has been transferred to the field of transport and logistics in recent decades. Therefore, environmental targets are to be added to economic targets in the decision-making, to find the right balance between these two dimensions. In real life, there are many situations and problems that are recognized as multi-objective problems. This type of problems containing multiple criteria to be met or must be taken into account. Often these criteria are in conflict with each other and there is no single solution that simultaneously satisfies everyone. Vehicle routing problems (VRP) are frequently used to model real cases, which are often established with the sole objective of minimizing the internal costs. However, in real life other factors could be taken into account, such as environmental issues. Moreover, in industry, a fleet of vehicles is rarely homogeneous. The need to be present in different segments of the market, forcing many companies to have vehicles that suit the type of goods transported. Similarly, to have vehicles of different load capacities enables a better adaptation to the customer demand. This paper proposes a multi-objective model based on Tchebycheff methods for VRP with a heterogeneous fleet, in which vehicles are characterized by different capacities, costs and emissions factors. Three objective functions are used to minimize the total internal costs, while minimizing the CO₂ emissions and the emission of air pollutants such as NO_x. Moreover, this study develops an algorithm based on C&W savings heuristic to solve the model when time windows are not considered. Finally, a real case application is analyzed to confirm the practicality of the model and the algorithm.

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Peer-review under responsibility of CIT 2014.

Keywords: Multi-objective VRP; Green logistics; Externalities; Environmental issues

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1. Introduction

As a result of various influencing factors, European freight transport demand has faster increased, approximately an 80% in the period 1990-2008. In the year 2009, the transport sector was responsible for about 24% of the GHG emissions in the European Union. Within the transport sector, road transport both goods and people, is the main source of GHGs emissions, with a 17% (TERM 2011, European Environment Agency).

In this way, if no additional measures had been implemented, road transport emissions would have increased in the last years. Thus, in 1993, the Euro standards were introduced to limit the pollutant emissions of new vehicles sold in the European Union. Other environmental actions were the use of ultra-low sulfur diesel and car free zones. In 2011, the European Commission published a White Paper on Transport, titled "Roadmap to a Single European Transport Area- towards a competitive and resource-efficient transport system". It is a strategic document that provides the basis for the European transport policy to achieve the environmental objectives set by the European Union for 2050. The White Paper sets the target of achieving a 60 % reduction in GHG emissions from transport by 2050 compared to 1990 levels and aiming to undertake more efficient freight transport. In addition, the way in which vehicles are driven significantly affects their emissions performance. In this framework, both energy and environmental aspects have become important and it is necessary to expand the logistic cost-saving strategies, considering the environmental component in the decision-making process and not limited only to energy aspects. The incorporation of environmental aspects in transport activities, particularly in the Vehicle Routing Problem (VRP), is essential to achieve the objectives set out in the White Paper on Transport.

The well-known Heterogeneous Fleet Vehicle Routing Problem (HF-VRP) involves optimizing a set of routes for a fleet of vehicles with different costs and capacities that are to serve some customers with a known demand from a central depot. A variant of the HF-VRP arises when there is a limitation in the number of available vehicles of each type. The problem is known as HVRP. It is generally modeled as single objective optimization problem, which minimizes the overall transportation costs of vehicles, which are derived from the sum of its fixed costs and cost proportional to the total distance traveled. Apart from the traditional objective of internal cost minimization, we also explored the environmental problem of considering additional objectives functions that minimize the GHG and pollutants emissions. This problem is formulated as a Multi-objective Optimization Problem (MOP). In MOP the objectives are multiple and may be conflicting, so this prohibits choosing a solution which is optimal with respect to only one objective since different objectives contribute to the overall result. The objective is to find the solutions that give the best compromise between the different objectives functions.

In this paper, we developed a multi-objective mixed integer linear programming problem for optimizing simultaneously internal costs, CO₂ and NO_x emissions. This eco-efficiency model is solved for the Fixed Heterogeneous Fleet VRP (HVRP) adding most realistic assumptions as time windows restrictions. Furthermore, we propose a multi-objective heuristic based on Clarke and Wright (1964) saving algorithm for solving the problem proposed, when time windows are not considered.

The paper is organized as follows. Section 2 reviews the literature on the HVRP, green logistics and multi-objective in VRP. Section 3 provides the mathematical model of the problem studied in this paper and Section 4 describes a heuristic approach. A real case application is described in section 5 and section 6 presents the results and discussion.

2. Literature review

HVRP problems were first introduced by Taillard (1999) who presented a heuristic column generation method. Prins (2002) developed a heuristic for solving the HVRP with dependent routing costs (HVRPD) by extending a series of VRP classical heuristics and incorporating a local search procedure based on the Steepest Descent Local Search and Tabu Search (TS). On the other hand, Tarantilis et al. (2003, 2004) developed list-based and backtracking threshold accepting algorithm for solving the same problem. Three years later, (Li et al. 2007) developed a similar algorithm called HRTR, based on the algorithm Record-To-Record (RTR). Prins (2009) developed two heuristic procedures based on a Memetic Algorithm for the HVRPD. Recently, Brandão (2011) developed a tabu search approach for solving the HVRPD problem. For further information on HF-VRP, a survey can be found in Baldacci et al. (2008).

In the last years, following the Green Logistics emerging area, a number of studies on VRP taking account environmental considerations in their objective functions were published. The “Pollution Routing Problem (PRP)” by Bektas and Laporte (2011) was defined as a variant of the VRP using a comprehensive objective function which measures and minimizes the cost of GHG emissions. Maden et al. (2010) considered a vehicle routing and scheduling problem (VRSP) with time Windows in which speed depends on the time of the travel. They described a heuristic algorithm to solve the problem. Jabali et al. (2012) considered a similar problem but estimated the amount of emissions based on a non-linear function of speed and other factors, finding the optimal speed with respect to emissions. Kara et al. (2007) introduced the Energy-Minimizing VRP; an extension of the VRP where a weighted load function is minimized, trying to minimize the energy consumed. Figliozzi (2010) introduced the Emissions VRP (EVRP) where the amount of emissions is a function of travel speed and it will depend of the departure time in each node. He considered time windows and capacity constraints as well as time-dependent travel time. Later, Xiao et al. (2012) contemplated the Fuel Consumption Rate (FCR) as a load dependent function, and added it to the classical VRP with the objective of minimizing fuel consumption. Eguia et al. (2013), proposes a linear programming mathematical model of the HVRP with time windows and backhauls (HVRPTW-B) internalizing external costs.

This paper is distinguished from much of the previous work in this area, by incorporating environmental aspects from a multi-objective perspective under the consideration of a heterogeneous fleet. Furthermore, a heuristic algorithm for the problem resolution is presented.

In multi-objective VRP there are lower research works than relating to HFVRP but no one, to our knowledge, incorporate environmental aspects and a heterogeneous fleet. An overview of different research works can be found in Jozefowiec et al. (2008). Tan et al. (2006) considered the VRPTW as a bi-objective problem to minimize the number of vehicles and the total routes distance. Jozefowiec et al. (2009) proposed an evolutionary algorithm to address a bi-objective problem for the CVRP in which the total distances travelled and the route imbalanced are minimized. In the field of multi-objective and green logistics, Siu et al (2012) proposed a multi-objective approach of VRP incorporating the optimization of CO₂ emissions as a secondary objective of the problem as well as an additional constraint but applied to an intermodal route optimization problem.

3. Problem definition and modelling

3.1. Evaluating the environmental emissions

Transport activities give rise to environmental impacts, such as CO₂ emissions, responsible of the climate change, and particle emissions, responsible of the air pollution. In contrast to the benefits, these impacts are not taken into account by the transport users when they make a transport decision. Including environmental aspects in transport activities, particularly in the vehicle routing optimization, may result in obtaining the use of less polluting vehicles and changes in the mode of transport or in transport volumes. Climate change impacts of transport are mainly produced by emissions of the greenhouse gases: carbon dioxide (CO₂), nitrous oxide (N₂O) and methane (CH₄).

CO₂ emissions estimations are based on the assumption that all carbon content of the fuel is burned and emitted as carbon dioxide. For internalization purposes the estimated CO₂ emissions can be obtained by multiplying the total fuel consumption by the CO₂ emission factor. The total well-to-wheel CO₂ emissions per unit of fuel, also called emission factor, is estimated in 2.67 kg of CO₂ per liter of diesel. The fuel consumption depends only on three factors: the distance travelled, the vehicle type, and the load carried.

Air pollution costs are caused by the emission of air pollutants such as particulate matter (PM), NO_x and non-methane volatile organic compounds (NMVOC). For internalization purposes the estimated each pollutant emissions can be obtained by multiplying the distance travelled by the grams of the pollutant per kilometer travelled. The estimation of pollutant emissions from road transport are based on the Tier 2 methodology (EMEP/EEA, 2010). This approach considers the fuel used for different vehicle categories and technologies according to emission-control legislation.

3.2. A multi-objective eco-efficiency model for HVRPTW

This study treats the HVRPTW in a different way from the classical VRP, considering the environmental impact in the search for a solution from a multi-objective perspective. The mathematical model used is derived from that used in Eguía et al. (2013). The problem is defined as constructing routes for a set of known heterogeneous vehicles, with different vehicles and fuel types, to meet the demands of all customers. Vehicles must depart from and return to the depot node, no vehicle can exceed its capacity and each customer is visited within its respective time window. Routes must also meet a maximum allowable driving time per day. The three objectives of the model are to minimize the total internal costs, while minimizing the CO₂ and NO_x emissions. This chapter deals with formulating a multi-objective mathematical model of the HVRPTW, based on Tchebycheff methods, considering environmental aspects as part of the route design in the delivery activities of a company.

The HVRPTW is defined on a graph $G=\{N,A\}$ with $N=\{0,1,\dots,n\}$ as a set of nodes, where node 0 represents the depot, and nodes numbered 1 to n represent delivery points, and A is a set of arcs defined between each pair of nodes. A set of m heterogeneous vehicles denote by $Z=\{1,2,\dots,m\}$ is available to deliver the desired demand of all customers from the depot node. We adopt the following notation:

- D_i : load demanded by node $i \in \{1,\dots,n\}$
- q^k : capacity of vehicle $k \in \{1,\dots,m\}$.
- $[e_i, l_i]$: earliest and latest time to begin the service at node i .
- s_i^k : service time in node i by vehicle k .
- d_{ij} : distance from node i to node j ($i \neq j$).
- t_{ij} : driving time between the nodes i and j .
- T^k : maximum allowable driving time for vehicle k .

Our formulation of the problem uses the following decision variables:

- x_{ij}^k : binary variable, equal to 1 if vehicle $k \in \{1,\dots,m\}$ travels from nodes i to j ($i \neq j$).
- y_i^k : starting service time at node $i \in \{0,1,\dots,n\}$; y_0^k is the ending time.
- f_{ij}^k : load carried by the vehicle $k \in \{1,\dots,m\}$ from nodes i to j ($i \neq j$).

According to the established assumptions, the constraints of the mixed-integer linear programming model are as follows:

$$\sum_{j=1}^n x_{0j}^k \leq 1 \quad (k = 1, \dots, m) \quad (1)$$

$$\sum_{\substack{j=0 \\ j \neq i}}^n x_{ij}^k - \sum_{\substack{j=0 \\ j \neq i}}^n x_{ji}^k = 0 \quad (k = 1, \dots, m; \quad i = 1, \dots, n) \quad (2)$$

$$\sum_{k=1}^m \sum_{\substack{j=0 \\ j \neq i}}^n x_{ij}^k = 1 \quad (i = 1, \dots, n) \quad (3)$$

$$\sum_{i=1}^n D_i \sum_{\substack{j=0 \\ j \neq i}}^n x_{ij}^k \leq q^k \quad (k = 1, \dots, m) \quad (4)$$

$$y_i^k + s_i^k + t_{ij} \leq y_j^k + T^k(1 - x_{ij}^k) \quad (i = 1, \dots, n; \quad j = 0, \dots, n; \quad j \neq i; \quad k = 1, \dots, m) \quad (5)$$

$$t_{0j} \leq y_j^k + T^k(1 - x_{0j}^k) \quad (j = 1, \dots, n; \quad k = 1, \dots, m) \quad (6)$$

$$e_i \leq y_i^k \leq l_i \quad (i = 1, \dots, n; \quad k = 1, \dots, m) \quad (7)$$

$$y_0^k \leq T^k \quad (k = 1, \dots, m) \quad (8)$$

$$\sum_{k=1}^m \sum_{\substack{j=0 \\ j \neq i}}^n f_{ji}^k - \sum_{k=1}^m \sum_{\substack{j=0 \\ j \neq i}}^n f_{ij}^k = D_i \quad (i = 1, \dots, n) \quad (9)$$

$$f_{ij}^k \leq (q^k - D_i)x_{ij}^k \quad (i = 0, \dots, n; \quad j = 0, \dots, n; \quad j \neq i; \quad k = 1, \dots, m) \quad (10)$$

$$D_j x_{ij}^k \leq f_{ij}^k \quad (j = 1, \dots, n; \quad i = 0, \dots, n; \quad i \neq j; \quad k = 1, \dots, m) \quad (11)$$

Constraints (1) mean that each vehicle departs from the depot once or doesn't, that is, no more than m vehicles (fleet size) depart from the depot. Constraints (2) are the flow conservation on each node. Constraints (3) guarantee that each customer and supplier is visited exactly once. Constraints (4) ensure that no vehicle can be overloaded. Starting service times are calculated in constraints (5) and (6), where y_0^k is the ending time of the tour for vehicle k if these variables are minimized in the objective function. These constraints also avoid sub-tours. Time windows are imposed by constraints (7). Constraints (8) avoid exceeding the maximum allowable driving time. Balance of flow is described through constraints (9) which model the flow as increasing by the amount of demand of each visited customer. Constraints (10) and (11) are used to restrict the total load a vehicle carries depending on whether it arrives or leaves a customer. Then, the routing solutions should minimize the criteria of (1) internal costs (cost of drivers, energy costs, fixed cost of vehicles–depreciation, inspection, insurance, maintenance costs and toll costs), (2) CO₂ and (3) NO_x emissions. Let $F_1(x, y, f)$, $F_2(x, f)$ and $F_3(x)$ be the internal costs, the CO₂ emissions and NO_x emissions respectively. The expressions of each objective function are given by:

$$F_1(x, y, f) = \sum_{k=1}^m p^k y_0^k + \sum_{i=0}^n \sum_{\substack{j=0 \\ j \neq i}}^n \sum_{k=1}^m \sum_{r=1}^R f c^r \delta^{kr} d_{ij} (f e^k x_{ij}^k + f e u^k f_{ij}^k) + \sum_{i=1}^n \sum_{k=1}^m f x^k x_{0i}^k + \sum_{i=0}^n \sum_{\substack{j=0 \\ j \neq i}}^n \sum_{k=1}^m m n^k d_{ij} x_{ij}^k + \sum_{i=0}^n \sum_{\substack{j=0 \\ j \neq i}}^n \sum_{k=1}^m t l_{ij} x_{ij}^k \quad (12)$$

$$F_2(x, f) = \sum_{i=0}^n \sum_{\substack{j=0 \\ j \neq i}}^n \sum_{k=1}^m \sum_{r=1}^R \delta^{kr} e f^{CO_2, r} d_{ij} (f e^k x_{ij}^k + f e u^k f_{ij}^k) \quad (13)$$

$$F_3(x) = \sum_{i=0}^n \sum_{\substack{j=0 \\ j \neq i}}^n \sum_{k=1}^m \sum_{r=1}^R \sum_{t=1}^T \sum_{p=1}^P \delta^{kr} \gamma^{kt} e f^{p, t} d_{ij} x_{ij}^k \quad (14)$$

Where the set of parameters used in the above expressions are:

- p^k : pay of driver k per unit time.
- $f c^r$: unit cost of fuel type r .
- $f e^k$: fuel consumption for the empty vehicle k .
- $f e u^k$: fuel consumption per unit of additional load in vehicle k .
- δ^{kr} : equal to 1 if vehicle k uses the fuel type r .
- $f x^k$: the fixed cost of vehicle k .
- $m n^k$: costs of preventive maintenance, repairs and tires per km of vehicle k
- $t l_{ij}$: costs of tolls associated with arc (i, j) .
- $e f^{CO_2, r}$: emission factor, amount of CO₂ emitted per unit of fuel r consumed.
- $e f^{p, t}$: amount of pollutant p emitted from technology vehicle t per km travelled.
- γ^{kt} : equal to 1 if vehicle k belongs to technology t .

The Augmented Weighted Tchebycheff method has been used to solve the multi-objective problem. This methodology avoids weakly non-dominated points (Steuer and Choo, 1983) and has the main advantage of solving only one single optimization problem to determine one solution. A “balanced” solution is found for none of the objectives deviates in excess of its optimal value. The formulation of this method is given as follows:

$$\text{Minimize } U; \quad U = \max_i \{w_i \cdot [F_i(x) - F_i^0]\} + \rho \sum_{j=1}^k [F_j(x) - F_j^0] \quad (15)$$

Where:

- w_i : is the assigned weight to the objective function i .
- F_i^0 : is the ideal or utopia point of the objective function i .
- k : is the number of objective functions in the problem.
- ρ : is a sufficiently small positive scalar assigned by the decision-maker.

A common approach for treating (21) is to introduce an additional parameter λ and increasing one constraint of the problem for each objective function:

4. A heuristic multi-objective algorithm to solve the HVRP with environmental considerations

This section presents an algorithm for solving the multi-objective HVRP when time windows and backhauls are not considered. Our approach to solving the multi-objective HVRP is derived from that used in Eguia et al. (2013), but includes the ability to perform with a multi-objective problem. They proposed an algorithm, based on the savings heuristic of Clarke and Wright (1964) but designed for a heterogeneous fleet problem including capacity constraints.

Let Z the set of vehicles, N the set of customers to delivery, R the set of routes and F the set of objective functions. The algorithm starts by forming for each client a route that connects it to the depot, having a set R of N tours. These routes are iteratively joined until the algorithm stops when R has only one route or when unfeasible joining routes occurs.

In the beginning or after each fusion routes process, the algorithm calculates for each vehicle and for each objective function the savings between each pair of routes from set R (16), obtaining a $F \times Z$ matrix, whose elements are formed by a matrix that contains the savings for each pair of routes. Vehicle availabilities and capacities conditions are not taken into account in savings calculation.

$$S_{ab}^{k,f} = C_a^{k,f} + C_b^{k,f} - C_{ab}^{k,f} \quad \forall k \in Z; \quad \forall f \in F \quad \forall a, b \in R \quad (16)$$

Where:

- $S_{ab}^{k,f}$ is the saving between routes a and b of the objective function f , when performed with a vehicle k .
- $C_{ab}^{k,f}$ is the result of the objective function f , when routes a and b are fused, performed with a vehicle k .

In order to compare the different objective functions, the next step is to transform every saving matrix into a normalized and weighted matrix. For this purpose, every saving matrix, which belongs to an objective function and a vehicle, is divided by its maximum saving element and multiplied by its corresponding weight. The next step is to form, for each vehicle, a saving matrix whose elements are calculated for each pair of routes, by the maximum value between the savings of the different objective functions. Once the savings matrix for each vehicle is obtained, average values (17) are calculated. The candidate routes to be fused are selected by the highest value of this matrix.

$$S_{ab} = \frac{\sum_{\forall k} S_{ab}^k}{m} \quad \forall k \in Z; \quad \forall a, b \in R \quad (17)$$

To guarantee feasibility, a fusion route check procedure is considered. It verifies that exist a solution that could be feasible in subsequent iterations or routes fusions. It orders the routes from higher to lower demand and

sequentially routes are assigned to the smaller capacity feasible vehicle. If all routes demands are linked into vehicles, the solution is feasible and routes are joined; otherwise the next largest saving value is chosen and the check procedure is repeated. If a pair of routes is joined, then an assignment problem is solved to get the best assignment of vehicles to routes (based on cost criteria). Every time the number of routes in R is less or equal to the number of available vehicles, it is possible to obtain a new feasible solution for the problem and keep it if is better than a previous found. For this purpose, the Hungarian Algorithm is used. It is a combinatorial optimization algorithm which solves the assignment problem in polynomial computing time. The algorithm takes as cost for a route, the maximum normalized value between all objectives functions. In the initial iteration process, any temporary generated solution has a high probability to be unfeasible, because the number of routes may exceed the number of available vehicles. Also, in the last algorithm iterations, routes cannot be fused because demands exceed the vehicle capacities. Once the algorithm is finished, a local search is run. 2-optimal and 3-optimal procedures are applied to each of the found routes from the feasible solution for improving them.

5. A real case application

In this paper, a real case application has been developed for a leading company in the food distribution sector in Spain, with the purpose of validating the model and the heuristic. This problem was firstly exposed in Eguia et al. (2013). The problem consists of 17 delivery points (supermarkets) served directly from a depot. The fleet of vehicles consists of three different rigid trucks with sufficient capacity to deliver the customers' demands. Service times are set to 1 hour in all nodes by all vehicles, time windows are not considered and there are no toll costs. Specifically, in this section routes are designed by solving the MOP model based on the Augmented Weighted Tchebycheff method. We have proposed three different objective functions: minimizing (1) internal costs, minimizing (2) CO₂ emissions and minimizing (3) pollutants emissions such as NO_x, taking into account the capacity constraints. Several simulations of the problem have been made varying the number of nodes (problem dimension). Problems with 8, 13 and 17 nodes have been solved and a maximum computing time of 1, 7 and 10 hours have been established respectively. The value of parameter $\rho = 0.01$ has been adopted for all problem types. The optimal solution of the model has been found using CPLEX 11.1 with default parameters in a 3.30 GHz Intel(R) Core(TM) i5-2400 CPU. Data concerning the location in geographic coordinates and the parameters associated to each vehicle of the fleet can be obtained in Eguia et al. (2013). Table 1 shows the supermarkets belonging to each problem and their corresponding demands. For all problems, nodes are renumbered starting from 1, and following the increasing order.

Table 1. Nodes, demands, optimal and utopia points for the different problem types

N°	Nodes number from Eguia et al.(2013)	Demands (Ton)	Internal Costs (€)		CO ₂ Emissions (Kg)		NO _x Emissions (gr)	
			(F_0^0)		(F_1^0)		(F_2^0)	
			Optimal	Utopia	Optimal	Utopia	Optimal	Utopia
8	{1,2,7,8,12,13,15,17}	{2, 2.5, 1.5, 4, 1, 3, 2.5, 1.5}	457.04	457.00	206.04	206.00	1164.67	1164.00
13	{1,2,3,4,5,6,7,8,12,13,15,16,17}	1 Ton per node	616.79	600.00	281.67	280.00	1678.38	1600.00
17	{1..17}	1 Ton per node	779.88	750.00	316.74	315.00	1606.96	1600.00

Moreover, the Augmented Weighted Tchebycheff method belongs to the category of a priori methods where weights related to each objective function are known in advance. Therefore, six versions for each problem (T00 ... T05) have been performed varying the weights to each objective function to analyze their impact on the final solution. The weights component {100,0,0}, {0,100,0}, {0,0,100}, {70,20,10}, {80,15,5} and {90,5,5} have been assigned to problems T00, T01, T02, T03, T04 and T05 respectively; where the first, second and third number correspond to the weight of internal costs, CO₂ emissions and NO_x emissions.

To solve the Augmented Weighted Tchebycheff model, it is first necessary to obtain the values that optimize each objective function separately. Table 1 shows these values and the utopia points used. The latter are chosen so that they are close to their optimal values. In order to compare the different objective functions, the following function transformation has been made in order to normalize them, where it has been used the utopia point. (F_i^0)

$$F_i^{trans}(x) = \frac{F_i(x) - F_i^0}{F_i^0} \quad \forall i \in F \quad (18)$$

The second set of experiments is aimed at evaluating the accuracy of the heuristic with respect to optimality, comparing the results with those obtained by the resolution of the model. The results obtained for all problems by the heuristic are shown in table 3, where it is also represented for every objective function, the relative percentage difference between the solutions obtained by the heuristic and CPLEX. In some instances, it is observed that the solution provided by the heuristic is the same as that obtained by the model. In general, the values of the different objective functions of the problem do not differ excessively from the model resolution.

Table 3. Heuristic routes solutions and relative percentage difference between solutions.

N ^a	Prob.	Veh	Routes	Heuristic results			Deviation		
				I.C.(€)	CO ₂ (Kg)	NO _x (gr)	I.C.(€)	CO ₂ (Kg)	NO _x (gr)
8	T00	1	0-2-0						
		2	0-7-4-1-6-3-8-5-0	462,09	206,04	1.164,67	1,10%	-12,26%	-29,03%
	T01	1	0-2-0	462,09	206,04	1.164,67	0,00%	0,00%	0,00%
		2	0-7-4-1-6-3-8-5-0						
	T02	1	0-2-0	467,27	214,42	1.206,03	1,12%	4,07%	3,55%
		2	0-4-1-6-3-7-8-5-0						
	T03	1	0-2-0	462,09	206,04	1.164,67	0,00%	0,00%	0,00%
		2	0-7-4-1-6-3-8-5-0						
	T04	1	0-2-0	462,09	206,04	1.164,67	0,00%	0,00%	0,00%
		2	0-7-4-1-6-3-8-5-0						
13	T00	1	0-2-0	462,09	206,04	1.164,67	0,00%	0,00%	0,00%
		2	0-7-4-1-6-3-8-5-0						
	T01	1	0-2-0	462,09	206,04	1.164,67	0,00%	0,00%	0,00%
		2	0-7-4-1-6-3-8-5-0						
	T02	1	0-2-0	462,09	206,04	1.164,67	0,00%	0,00%	0,00%
		2	0-7-4-1-6-3-8-5-0						
17	T00	1	0-5-9-2-11-8-12-1-6-10-4-7-13-3-0	616,79	281,67	1.748,78	0,00%	0,00%	0,00%
		2	0-5-9-2-11-8-12-1-6-10-4-7-13-3-0						
	T01	1	0-2-5-9-11-8-12-1-6-10-4-7-13-3-0	619,07	284,62	1.759,50	0,37%	1,05%	0,61%
		2	0-2-5-9-11-8-12-1-6-10-4-7-13-3-0						
	T02	1	0-5-9-13-3-7-4-10-6-1-12-8-11-2-0	626,23	301,53	1.736,52	-6,66%	-4,73%	3,46%
		2	0-5-9-13-3-7-4-10-6-1-12-8-11-2-0						
	T03	1	0-5-9-2-11-8-12-1-6-10-4-7-13-3-0	616,79	281,67	1.748,78	0,00%	0,00%	0,00%
		2	0-5-9-2-11-8-12-1-6-10-4-7-13-3-0						
	T04	1	0-5-9-2-11-8-12-1-6-10-4-7-13-3-0	616,79	281,67	1.748,78	0,00%	0,00%	0,00%
		2	0-5-9-2-11-8-12-1-6-10-4-7-13-3-0						
17	T00	1	0-5-12-2-0	779,08	316,74	1.911,15	2,45%	-9,03%	-13,68%
		2	0-15-10-11-9-8-16-1-6-13-14-4-7-17-3-0						
	T01	1	0-2-0	784,17	319,13	1.921,86	1,30%	0,70%	5,44%
		2	0-5-12-15-10-11-9-8-16-1-6-13-14-4-7-17-3-0						
	T02	1	0-5-0	801,97	362,70	1.930,00	0,84%	3,28%	5,60%
		2	0-12-17-3-7-4-14-13-6-1-16-8-9-11-10-15-2-0						
	T03	1	0-5-0	786,78	325,82	1.942,26	1,06%	-1,22%	6,56%
		2	0-12-2-15-10-11-9-8-16-1-6-13-14-4-7-17-3-0						
	T04	1	0-5-12-2-0	779,08	316,74	1.911,15	1,87%	-9,99%	-12,22%
		2	0-15-10-11-9-8-16-1-6-13-14-4-7-17-3-0						
17	T05	1	0-5-12-2-0	779,08	316,74	1.911,15	1,69%	-11,06%	-11,94%
		2	0-15-10-11-9-8-16-1-6-13-14-4-7-17-3-0						

6. Conclusion and discussion

In this paper, a new mixed-integer linear programming model for the Multi-Objective Vehicle Routing Problem with some realistic assumptions (Heterogeneous Fleet and Time Windows) has been presented. The three objectives

functions considered are to minimize the total internal costs, while minimizing some environmental considerations as the CO₂ and NO_x emissions. The model makes a positive contribution towards a more sustainable balance between economic, environmental and social objectives. Moreover, this paper has described a route building procedure based on Clarke and Wright (1964) savings heuristic for the Capacitated Vehicle Routing Problem, when time windows are not considered. It can simultaneously minimize some number of objectives functions in the design of the routes and has been tested on the internal costs, CO₂ and NO_x emissions. Finally, we have also optimized the delivery activities from a real case to illustrate and validate the model and the heuristic. Computational results show good quality solutions for the heuristic. Further research may lead to the development of a new metaheuristic multi-objective optimization method that allows solving large-scale problems with time windows restrictions.

Acknowledgements

This research has been fully funded by the Andalusia Government through grants P10-TEP-6332.

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