**KES Transactions on Sustainable Design and Manufacturing I**
Sustainable Design and Manufacturing 2014 : pp.784-795 : Paper sdm14-043

# Green logistics solutions for the route design problem

Jose Carlos Molina[1], Ignacio Eguia[1], Jesus Racero[1], Fernando Guerrero[1]

[1]Escuela Superior de Ingenieria. Universidad de Sevilla. Camino de los Descubrimientos s/n. 41092 Sevilla, Spain
ies@us.es

**Abstract** Green Logistics has received considerable attention recently due to the interest in environment preservation which plays an important role in strategic and operational logistical activities. The vehicle routing problem (VRP), as part of logistics, is one of the most widely researched and has mainly focused on economic objectives, not considering explicitly environmental issues. Therefore, environmental issues are to be added to cost saving objectives, to find the right balance between these two dimensions. A multi-objective problem (MOP) model that simultaneously considers the internal costs and environmental issues can better describe the real logistics operations than a single objective model. This paper proposes an eco-efficient MOP model based on a realistic variant of the VRP with time windows constraints and a heterogeneous fixed vehicle fleet, in which vehicles are characterized by different capacities, costs and emission factors. Three objective functions are run to minimize the total internal costs, while minimize carbon dioxide ($CO_2$) and nitrogen oxides ($NO_x$) emissions. Finally, this paper presents a case of study to analyse the results of the choice of eco-efficiency routes which can help to reduce the emissions of air pollutants and greenhouse gases.

## 1. Introduction

The supply chain management is the term used to describe the set of production and logistics processes that are associated with moving goods, from raw material to finished products and their placement on the market. It is one of the most important economic activities in a business since it can increase efficiency and productivity in many different ways. An effective management has a significant impact on both service quality and product cost reduction, achieving the company´s differentiation in a competitive market. Conventionally, these activities involve different companies, which are composed by manufacturers, suppliers, transporters, warehouses, wholesalers and retailers. Transportation plays a central role in supply chains since it implies one-third of the amount in the logistics cost [11] and has influence in customer satisfaction levels. The impact of transportation in the supply chain has been increased by the production systems development that they have moved from a storage-based economy to an economy of lean production, replacing stocks by transport activities. Thus, in the period 1990-2008 the activity of road freight transport in Europe, has increased approximately 80% as a result of increased economic activity and demand for goods [10]. Moreover, the growing volume of freight transport has other consequences on the environment, which are called externalities. The internal combustion engine of a vehicle produces harmful emissions as 1) $CO_2$, a greenhouse gas (GHG) responsible for the climate change, 2) particle emissions, responsible for air pollution and 3) noise emissions. In this context, transport, is presented as a major source of air pollution in Europe, generating harmful levels of air pollutants and is responsible for approximately 24% of emissions of greenhouse gases (GHGs) in the European Union. Within the transport sector, road transport both goods and people, is still the main source of GHGs emissions, with a 17% [10]. The growing environmental concern related to the economic activity has been transferred to the field of transport and logistics in the last decade. Green logistics, has become more popular over the last years, and appears to minimize the external factors associated mainly with climate change and air pollution. 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 well-known Vehicle Routing Problem (VRP) is generally modeled as single objective optimization problem, which minimizes transportation related costs, while satisfying some restrictions. However, in real life, transportation companies should start taking into account the effects of those environmental issues in their routes design plans. In Multi-Objective Optimization Problems (MOP) the objectives may be multiple and conflicting and there does not exits just one optimal solution since two or more objectives contribute to the overall result. In this paper, we introduce a multi-objective mixed integer linear programming problem, based on the well-known Augmented Weighted Tchebycheff method, for optimizing simultaneously internal costs, $CO_2$ and $NO_x$ emissions. This eco-efficiency model is solved for the VRP with Heterogeneous Fleet and Time Windows (HF-VRPTW).With this model, transportation companies can select the most appropriate vehicles, determining the routes and schedules to satisfy the demands of the customers, reducing externalities and achieving a more sustainable balance between economic, environmental and social objectives.

The paper is organized as follows. Section 2 reviews the literature on the HF-VRPTW, green logistics and multi-objective in VRP. The formulation of the problem under consideration is presented in Section 3. A real case application is described in section 4 and section 5 presents the results and discussion.

## 2. Literature review

This section is concerned with studies on the heterogeneous fleet VRP (HF-VRP), when the number of vehicles is limited (HVRP), with considerations of environmental aspects and in particular with a multi-objective perspective.

In the literature, the heterogeneous fixed fleet vehicle routing problem (HVRP) is a variant of the HF-VRP which considers vehicles with different costs and capacities and a limitation in the number of available vehicles of each type. The objective function is to minimize the sum of fixed vehicle costs and variable routing costs, which are related to the total distance travelled. This problem is NP-hard since it is an extension of VRP and justifies the use of heuristics and metaheuristics to solve the problem. In the literature, many authors have proposed new algorithms for tacking the HVRP. For further information on HF-VRP, a survey can be found in Baldacci et al. [1].

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 [2] was defined as a variant of the VRP using a comprehensive objective function which measures and minimizes the cost of GHG emissions. Ubeda et al. [12] presented a case study, where the $CO_2$ emissions were incorporated in the objective function of the Capacitated Vehicle Routing Problem (CVRP) with backhauls. Kara et al. [8] introduced the Energy-Minimizing VRP; an extension of the VRP where a weighted load function is minimized, trying to minimize the energy consumed. Later, Xiao et al. [13] 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. [4] proposes a linear programming mathematical model of the HVRP with time windows and backhauls (HVRPTW-B) that internalizes external costs based on conversions set by INFRAS/IWW [6].

Although numerous studies have been proposed incorporating environmental considerations on VRP, most of the authors consider a homogeneous fleet in the routes design. 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, this work not only takes into account $CO_2$ emissions, but also incorporates pollutants emissions as $NO_x$ in the objective function.

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 on multi-objective VRP can be found in Jozefowiez et al. [7]. In the field of multi-objective and green logistics, Siu et al [9] proposed a multi-objective approach of VRP incorporating the optimization of $CO_2$ 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 $CO_2$ 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 ($CO_2$), nitrous oxide ($N_2O$) and methane ($CH_4$).

$CO_2$ 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 $CO_2$ emissions can be obtained by multiplying the total fuel consumption by the $CO_2$ emission factor. The total well-to-wheel $CO_2$ emissions per unit of fuel, also called emission factor, is estimated in 2.67 kg of $CO_2$ 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 of the EMEP/EEA [5]. 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

The problem presented in this chapter is an extension of the classical Capacitated Vehicle Routing Problem, including Time Windows, and a Heterogeneous Fleet with different vehicles and fuel types (HVRPTW). The following assumptions are stated about the problem: (a) known fleet size, (b) heterogeneous fleet, with different vehicle capacities, fuel consumptions and categories, (c) single depot, (d) deterministic demand, (e) oriented network, (f) time windows, and (g) a maximum driving time. The three objectives of the model are to minimize the total internal costs, while minimizing the $CO_2$ and $NO_x$ emissions. The main contributions of this chapter deal with formulating a multi-objective mathematical model of the

HVRPTW, 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,…,n}* as a set of nodes, where node *0* represents the depot, 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,…,m}* is available to deliver the desired demand of all customers from the depot node and finally, return back. The constructing routes of each vehicle must meet the following constraints: no vehicle carries load more than its capacity, each customer is visited within its respective time window and no vehicle exceeds the maximum allowable driving time per day.

We adopt the following notation:

- $D_i$ : load demanded by node i ∈ {1,…,t} and load supplied by node i ∈ {t+1,…,n}
- $q^k$ : capacity of vehicle k ∈ {1,…,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 ≠ 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 de following decision variables:

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

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

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

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

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

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

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

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

$$e_i \leq y_i^k \leq l_i \quad (i = 1,..., n; \quad k = 1,..., m) \tag{7}$$

$$y_0^k \leq T^k \quad (k = 1,...,m) \tag{8}$$

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

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

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

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). Any vehicle cannot exceed the maximum allowable driving time in constraints (8). 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) $CO_2$ and (3) $NO_x$ emissions. Let $F_1(x, y, f)$, $F_2(x, f)$ and

$F_3(x)$ be the internal costs, the $CO_2$ emissions and $NO_x$ emissions respectively. The expressions of each objective function are given by:

$$F_1(x,y,f)=\sum_{k=1}^{m} p^k y_0^k+\sum_{i=0}^{n}\sum_{\substack{j=0\\ j\neq i}}^{n}\sum_{k=1}^{m}\sum_{r=1}^{R} fc^r\delta^{kr} d_{ij}(fe^k x_{ij}^k+feu^k f_{ij}^k)+\sum_{i=1}^{n}\sum_{k=1}^{m} fx^k x_{0i}^k+ \sum_{i=0}^{n}\sum_{\substack{j=0\\ j\neq i}}^{n}\sum_{k=1}^{m} mn^k d_{ij} x_{ij}^k+\sum_{i=0}^{n}\sum_{\substack{j=0\\ j\neq i}}^{n}\sum_{k=1}^{m} tl_{ij} x_{ij}^k \quad (12)$$

$$F_2(x,f)=\sum_{i=0}^{n}\sum_{\substack{j=0\\ j\neq i}}^{n}\sum_{k=1}^{m}\sum_{r=1}^{R}\delta^{kr} ef^{CO2,r} d_{ij}(fe^k x_{ij}^k+feu^k f_{ij}^k) \quad (13)$$

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

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

- $p^k$ : pay of driver k per unit time.
- $fc^r$ : unit cost of fuel type r.
- $fe^k$ : fuel consumption for the empty vehicle k.
- $feu^k$ : fuel consumption per unit of additional load in vehicle k.
- $\delta^{kr}$ : equal to 1 if vehicle k uses the fuel type r.
- $fx^k$ : the fixed cost of vehicle k.
- $mn^k$ : costs of preventive maintenance, repairs and tires per km of vehicle k
- $tl_{ij}$ : costs of tolls associated with arc (i,j).
- $ef^{CO2,r}$ : emission factor, amount of $CO_2$ emitted per unit of fuel r consumed.
- $ef^{p,t}$: amount of pollutant p emitted from technology vehicle t per km travelled.
- $\gamma^{kt}$: equal to 1 if vehicle k belongs to technology t.

The Augmented Weighted Tchebycheff method formulation is given as follows:

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

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.
- $\rho$ : is a sufficiently small positive scalar assigned by the decision-maker.

In this case a “balanced” solution is found for none of the objectives deviates in excess of its optimal value. Minimizing (15) is necessary and sufficient for Pareto optimality [3]. A common approach for treating (15) is to introduce an additional parameter λ and increasing the number of constraints of the problem, one constraint for each objective function:

$$
\begin{aligned}
& \textit{Minimize} \quad \lambda + \rho \sum_{j=1}^{k} \left[ F_j(x) - F_j^0 \right] \\
& s.t. \\
& w_i \cdot \left[ F_i(x) - F_i^0 \right] - \lambda \leq 0 \qquad i = 1,2,\ldots,k \\
& \lambda \geq 0
\end{aligned} \tag{16}
$$

## 4. 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. It is a reduced example from Eguia et al. [4]. We will center on the delivery activities in the council of Huelva sited in Southeastern Spain (see figure 1). In this area, the distribution network consists of 8 delivery points (supermarkets) served directly from a depot (logistic center). The fleet of vehicles to supply these supermarkets 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, and there are no toll costs. There is also a maximum driving time of 8 hours for each vehicle and time windows are not considered. Data concerning the location in geographic coordinates and demands of the distribution and delivery points are summarized in Table 1. The parameters associated to each vehicle of the fleet can be obtained in Eguia et al. [4]. The costs of travelling between each two customers, the distances and the travelling time, have been obtained using the application of Google Maps.

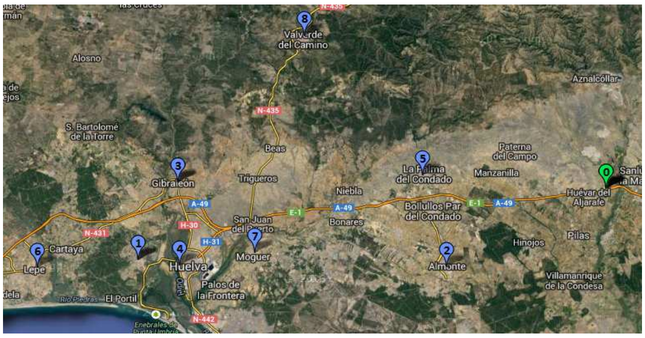


Figure 1. Distribution and delivery points locations

Specifically, in this section routes are designed by solving the multi-objective optimization model based on the Augmented Weighted Tchebycheff method. We have proposed three different objective functions: minimizing internal costs (1), minimizing $CO_2$ emissions (2) and minimizing pollutants emissions such as NOx (3), taking into account capacity and driving time constraints. Several simulations of the problem have been made varying the objective functions weights (Table 2), in order to analyze their impact on the final solution. The value of parameter ρ= 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.

To solve the Augmented Weighted Tchebycheff model, it is first necessary to obtain the values that optimize each objective function separately. Table 2 shows these values and the utopia points used. The latter are chosen so that they are close to their optimal values.

Table 1. Distribution and delivery point locations and demands.

| Node | Denomination | Demand (Ton) | Geographic Coordinates |
|---|---|---|---|
| 0 | Depot | ---- | 37.36777,-6.251307 |
| 1 | Aljaraque | 2.00 | 37.269481,-7.028072 |
| 2 | Almonte | 2.50 | 37.2602,-6.515853 |
| 3 | Gibraleón | 1.50 | 37.376795,-6.963138 |
| 4 | Huelva | 4.00 | 37.262245,-6.959466 |
| 5 | La Palma del Condado | 1.00 | 37.385996,-6.556054 |
| 6 | Lepe | 3.00 | 37.258957,-7.196568 |
| 7 | Moguer | 2.50 | 37.279747,-6.834899 |
| 8 | Valverde del Camino | 1.50 | 37.578435,-6.752129 |

Table 2. Optimal, utopia points and objective function weights for problem types

| | INTERNAL COSTS ($W_0$) | | $CO_2$ EMISSIONS ($W_1$) | | $NO_x$ EMISSIONS ($W_2$) | |
|---|---|---|---|---|---|---|
| | Optimal | Utopia | Optimal | Utopia | Optimal | Utopia |
| $F_i^0$ | 468,69 | 465,00 | 216,38 | 210,00 | 1222,99 | 1200,00 |
| T00 | 100 | | 0 | | 0 | |
| T01 | 0 | | 100 | | 0 | |
| T02 | 0 | | 0 | | 100 | |
| T03 | 70 | | 20 | | 10 | |
| T04 | 80 | | 15 | | 5 | |
| T05 | 90 | | 5 | | 5 | |

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 ($F_i^0$)

$$F_i^{trans}(x) = \frac{F_i(x) - F_i^0}{F_i^0} \tag{17}$$

Tables 3 and 4 show the results. The gap value obtained for the problems ensure that the solutions are optimal. We can observe that the solution found for the problem that minimizes only internal costs (T00) differs of those that take into account the environmental aspects, regardless of the assigned weights.

Table 3. Route and travel time solutions

| PROBLEM | OBJ FUNCTION | WEIGHTS | VEHICLE | ROUTE | TIME (h) |
|---|---|---|---|---|---|
| T00 | Int. Costs | 100 | 1 | 0-2-3-6-1-0 | 6,90 |
| | $CO_2$ Emissions | 0 | 2 | | |
| | $NO_X$ Emissions | 0 | 3 | 0-4-7-8-5-0 | 6,85 |
| T01 | Int. Costs | 0 | 1 | 0-2-5-8-0 | 5,35 |
| | $CO_2$ Emissions | 100 | 2 | 0-7-4-1-6-3-0 | 7,83 |
| | $NO_X$ Emissions | 0 | 3 | | |
| T02 | Int. Costs | 0 | 1 | 0-2-8-5-0 | 5,33 |
| | $CO_2$ Emissions | 0 | 2 | 0-7-4-1-6-3-0 | 7,83 |
| | $NO_X$ Emissions | 100 | 3 | | |
| T03 | Int. Costs | 70 | 1 | 0-2-5-8-0 | 5,35 |
| | $CO_2$ Emissions | 20 | 2 | 0-7-4-1-6-3-0 | 7,83 |
| | $NO_X$ Emissions | 10 | 3 | | |
| T04 | Int. Costs | 80 | 1 | 0-2-5-8-0 | 5,35 |
| | $CO_2$ Emissions | 15 | 2 | 0-7-4-1-6-3-0 | 7,83 |
| | $NO_X$ Emissions | 5 | 3 | | |
| T05 | Int. Costs | 90 | 1 | 0-2-5-8-0 | 5,35 |
| | $CO_2$ Emissions | 5 | 2 | 0-7-4-1-6-3-0 | 7,83 |
| | $NO_X$ Emissions | 5 | 3 | | |

Figures 2(a) and 2(b) represent respectively the routes obtained by minimizing internal costs (T00) and when the environmental objectives are taking into account (T01, T03, T04 and T05). Vehicles number 1, 2 and 3 are associated with colors blue, red and yellow respectively. The marks represent the different delivery points and numbering corresponds to the order of visit of the customer per vehicle. The green mark represents the depot. It is observed that minimizing only internal costs provides routes made by smaller capacity vehicles. In these types of vehicles, driver costs, fuel consumption, fixed costs and maintenance costs are lower than in the vehicle with greater capacity. The inclusion of environmental aspects in the objective function result in routes with lower total length in distances, since they involve lower $CO_2$ and $NO_x$ emissions. The result of this inclusion with the assigned weights is to find solutions close to the ideal point that optimizes internal costs, but with fewer emissions.

Table 4. Solution values for the problem

| PROB. | OBJ FUNCT | λ | INT. COSTS (€) | $CO_2$ EMIS. (Kg) | $NO_x$ EMIS. (gr) | DIST. (Km) | GAP (%) |
|---|---|---|---|---|---|---|---|
| T00 | 0,7988 | 0,7927 | 468,69 | 250,68 | 1.689,45 | 429,10 | 0,01 |
| T01 | 3,0392 | 3,0386 | 470,05 | 216,38 | 1.223,25 | 365,20 | 0,01 |
| T02 | 1,9161 | 1,9154 | 470,20 | 218,03 | 1.222,99 | 365,10 | 0,01 |
| T03 | 0,7602 | 0,7596 | 470,05 | 216,38 | 1.223,25 | 365,20 | 0,01 |
| T04 | 0,8687 | 0,8681 | 470,05 | 216,38 | 1.223,25 | 365,20 | 0,01 |
| T05 | 0,9772 | 0,9766 | 470,05 | 216,38 | 1.223,25 | 365,20 | 0,01 |

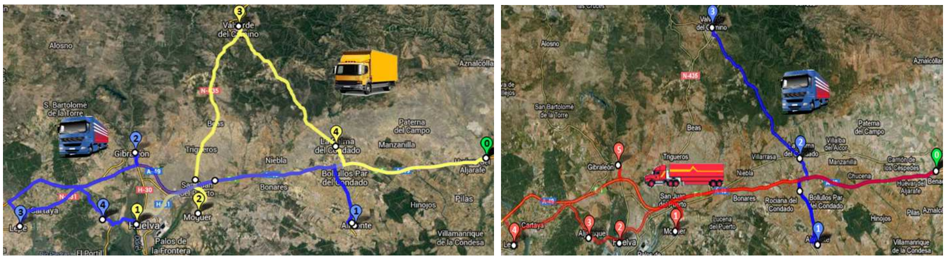

Figure 2. Routes obtained for {T00} (left) and {T01,T03,T04,T05} (right)

## 5. Conclusion and discussion

In this paper, a MILP model for the VRP with realistic assumptions (Heterogeneous Fleet and Time Windows) has been presented with multiple objective functions that account for internal costs and environmental considerations. To our knowledge, this is the first work which incorporates pollutant emissions in a multi-objective VRP with heterogeneous fleet. We have also optimized the delivery activities from a real case, taking into account costs, $CO_2$ and $NO_x$ emissions. The solutions obtained present lower values in terms of distances and emissions than optimizing only internal costs. With this model, transportation companies can select the most appropriate vehicles, determining the routes and schedules to satisfy the demands of the customers, reducing externalities and achieving a more sustainable balance between economic, environmental and social objectives. Future works may lead to the development of metaheuristics multi-objective optimization method that allows solving large-scale problems with time windows restrictions. Another way of research can be considering fuzzy sets to find optimal solutions to HVRP.

**Acknowledgements**

This research is funded by Andalusia Government through grants P10-TEP-6332.

**References**

[1] Baldacci, R., Battarra, M., Vigo, D. (2008). Routing a heterogeneous fleet of vehicles. In: The vehicle routing problem: latest advances and new challenges. Springer, US, pp. 3–27.

[2] Bektas, T. and Laporte, G. (2011). The Pollution-Routing Problem. Transportation Research Part B: Methodological, 45, (8), pp. 1232-1250.

[3] Choo, E.U.; Atkins, D.R. 1983: Proper efficiency in nonconvex multicriteria programming. Mathematics of Operation Research 8(3), 467–470.

[4] Eguia, I., Racero, J., Molina, J.C., Guerrero, F. (2013). Environmental Issues in Vehicle Routing Problems. Sustainability Appraisal: Quantitative Methods and Mathematical Techniques for Environmental Performance Evaluation. Springer, Berlin Heidelberg: pp.215-241.

[5] EMEP/EEA (2010). Emission inventory guidebook 2009, updated June 2010. European Environment Agency (EEA).

[6] INFRAS/IWW (2004) External costs of transport: update study, Zurich.

[7] Jozefowiez, N., Semet, F., Talbi, E.G. (2008). Multi-objective vehicle routing problems. European Journal of Operation Research, 189(2), pp.293-309.

[8] Kara, I., Kara, B.Y., Yetis, M.K., (2007). Energy minimizing vehicle routing problem. In: Dress, A., Xu, Y., Zhu, B. (Eds.), Combinatorial Optimization and Applications, Lecture Notes in Computer Science, vol. 4616. Springer, Berlin Heidelberg, pp. 62–71.

[9] Siu, W.S., Chan, C.K., Chan, H.C. (2012). Green cargo routing using genetic algorithms. In Proceedings of the International Multi-Conference of Engineers and Computer Scientists, (Volume 1), Hong Kong, March 2012.

[10] TERM (2011). Transport indicators tracking progress towards environmental targets in Europe. European Environment Agency (EEA).

[11] Tseng Y. Y., Yue W.L., Taylor M.A. (2005). The role of transportation in logistics chain. Proceedings of the Eastern Asia Society for Transportation Studies, 5 pp.1657‑1672.

[12] Ubeda, S., Arcelus, F.J., Faulin, J.(2011). Green logistics at Eroski: A case study. International Journal of Production Economics, 131(1): 44 –51.

[13] Xiao, Y., Zhao, Q., Kaku, I., Xu, Y. (2012). Development of a fuel consumption optimization model for the capacitated vehicle routing problem. Computer and Operation Research 39(7): pp. 1419–1431.