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Reducing pollutant emissions in a waste collection vehicle routing problem using a Variable Neighborhood Tabu Search algorithm: A case study.

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Abstract

This paper focuses on designing waste collection routes with a single landfill using eco-efficiency as a performance indicator. In this problem there are a limited number of heterogeneous vehicles based at a single depot. Empty vehicles leave the depot, collect waste from a set of locations and drop off the collected waste at a specific landfill. Then, vehicles leave the landfill and may collect more waste from other locations or return empty to the depot. Traditional performance indicators in Vehicle Routing Problems are mainly focused on economic objectives, not explicitly considering environmental issues. In this paper, a mathematical model is presented with an eco-efficient objective function that takes into account external costs (climate change and air pollution). The COPERT model is used for estimating fuel consumption, and carbon dioxide and pollutant emissions. The problem is first heuristically solved using a semi-parallel construction algorithm. Then, solutions are improved by a variable neighborhood tabu search algorithm developed for this problem. The algorithm is validated for a real problem in the municipality of Alcalá de Guadaíra, within the metropolitan area of Seville (Spain). Results obtained on a set of case studies improve the solution that is currently implemented in the municipality, in terms of total distance traveled, carbon dioxide emissions and pollutant emissions.

Keywords: Waste collection vehicle routing problem, Variable Neighborhood Tabu Search, COPERT model equations, pollutant emissions

Mathemathics Subject Classification: 90B06 (Transportation, logistics), 90C11 (Mixed integer programming), 90C59 (Approximation methods and heuristics)

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1. Introduction

Air pollution is a general problem for all countries in the world. The rapid urban and industrial growth has resulted in the emission of considerable quantities of potentially harmful gases into the atmosphere which have affected the health and well-being of citizens, especially those living in urban and industrial areas. Although air pollutants have decreased substantially over the past decades, air pollutant concentrations are still regarded as too high and air quality problems persist, especially in cities where pollutants, such as nitrogen oxides (NO_x) or particulate matter (PM), pose serious health risks (EEA, 2012).

Relating to the transport sector, emissions from fuel consumption are composed of many types of pollutants such as carbon dioxide (CO_2), NO_x, non-methane volatile organic compounds (NMVOC) and PM among others, which are a source of serious human health problems including respiratory infections, heart disease, and cancer (Eguia et al., 2013).

From the economic point of view, these emissions have had a great influence on the gross domestic product (GDP) of the European Union (EU), representing a total of over 500 billion euros, about 4% of GDP in 2008 (CE Delft et al., 2011). Consequently, in the last decade, projects to reduce pollution from mobile sources have been implemented in the EU. They include: (1) the introduction of more energy efficient engines to reduce pollutant emissions of new vehicles (Euro standards), (2) transport mode shifts, (3) increased fuel efficiency by the use of hybrid vehicles, (4) conversion to cleaner fuels (ultra-low sulphur diesel, bioethanol, biodiesel), (5) car-free zone establishments, (6) electric vehicles and (7) the adoption of the Eurovignette Directive (European Commission, 2011), a pricing strategy where tolls are imposed for heavy goods vehicles, including an external cost charge which reflects air pollution costs. Another input for reducing pollutant emissions in urban areas is to incorporate environmental objectives in the decision-making process, especially in planning, optimizing and controlling transport activities. This is of special importance for the reduction of both operating costs and vehicle emissions.

This paper is focused on the daily solid waste collection problem performed by public or private companies in urban environments. The urban solid waste collection is a waste management activity that typically needs to collect wastes from many collection points (CPs) in order to send them to a landfill or disposal facility. This is a reverse logistics problem that is defined as a Waste Collection Vehicle Routing Problem (WCVRP), which can be treated as a vehicle routing problem (VRP) (Beliën et al., 2012). The WCVRP typically consists in routing a fleet of vehicles located at the depot to collect waste from a set of CPs with known demands. Vehicles must travel to a landfill to drop off the waste before returning empty to the depot.

In the literature, waste collection is divided into three categories: residential, commercial and skip waste collection (Benjamin and Beasley, 2013). Residential waste, which is usually located along the streets, is collected by vehicles and taken to open dumps for disposal. This WCVRP is often formulated as an arc routing problem (ARP) where streets are traveled completely by the collection vehicles and the exact location of every CP in the street is not needed. For surveys on ARPs we refer to the papers by Dror (2012) and Golden & Wong (1981). On the other hand, the commercial and the skip collection problems are typically formulated as node routing problems (NRPs). As considering each CP separately provides a more detailed model for the calculation of pollutant emissions, an NRP approach is adopted in this work. Moreover, this formulation takes into account traffic regulations (e.g. streets with unidirectional traffic).

Although there are several versions of the WCVRP, the problem often does not describe a realistic approach and does not include all the constraints and requirements of real companies.

This paper introduces the Eco-efficient WCVRP (Eco-WCVRP); it extends the WCVRP by including several realistic considerations. First, potential cost savings can be obtained by considering multiple disposal trips by collection vehicles, because companies could reduce the number of vehicles and staff needed. In this problem collection vehicles may continue to collect waste from other CPs after being emptied at a disposal facility. To the best of our knowledge, there are relatively few studies considering multiple disposal trips in the scientific literature. In most of them, each vehicle is assumed to depart from the depot, serve (pick-up or delivery) only one route consisting of multiple stops, and return to the depot (Kim et al., 2006). Second, the fleet of collection vehicles in a company is usually heterogeneous in real-life as the company incorporates vehicles of different characteristics over time (Hoff et al., 2010) and restrictions on the vehicle size and weight may be required in order to access urban areas (Semet, 1995). Finally, as the major objective of WCVRPs is to minimize the number of vehicles and total traveling time, this work also incorporates environmental issues in the objective function for the minimization of pollutant emissions, which have received relatively little attention in the scientific literature. Specifically, the total external costs of the collection routes derived from CO_2, NO_x, NMVOC and PM emissions are considered to be minimized. External costs are obtained based on the European study (INFRAS et al, 2008); by selecting this objective function, both operating costs (fuel consumption) and pollutant emissions can be reduced.

As the Eco-WCVRP belongs to the set of NP-Hard problems, the use of heuristics and metaheuristics approaches is justified. In this paper, we focus on a solution approach consisting of a semi-parallel insertion heuristic and a Variable Neighborhood Tabu Search (VNTS) metaheuristic.

This paper makes two main scientific contributions. First, the definition of the Eco-WCVRP, which combines a set of realistic constraints for real-life studies regarding pollutant emissions. It is important to note that the Eco-WCVRP not only considers CO_2 emissions as transport externalities, but also takes into account NO_x, NMVOC and PM emissions, which are of special importance in urban areas. To the best of our knowledge, there does not exist in the scientific literature any practical WCVRP application which considers these types of pollutant. The paper also introduces a mixed-integer linear programming model that considers the minimization of the external costs of transport in which pollutant emissions are estimated by the COPERT methodology (Ntziachristos and Samaras, 2012), which considers the principal influencing factors for a more accurate estimation of pollutant emissions. Such factors comprise the different vehicle speeds along the route, the load carried, the vehicle category and the engine technology. The second contribution is a VNTS algorithm which aims to efficiently solve this WCVRP. The algorithm is applied in a case study with real data, and a comparison between the performance of the current planning method and the solution obtained by the algorithm is made.

This paper is organized as follows: Section 2 presents the literature review of the research. Section 3 provides a formal description of the Eco-WCVRP. The mathematical formulation of the problem is introduced in Section 4. Section 5 explains the proposed solution methodology including the algorithmic details to solve the problem. The experimental results of the case studies are given in section 6 and finally, the conclusions are presented in the last section.

2. Literature Review

In the last decade interest in environment preservation has increased and environmental aspects play an important role in strategic and operational policies, especially in urban areas where waste generation is increasing with population growth. Thus, Green Logistics have arisen, extending the traditional definition of logistics by explicitly considering external factors associated mainly with climate change and air pollution. WCVRPs are clearly part of Green Logistics as they reduce the environmental impact by optimizing the energy usage in reverse logistics activities and by reducing waste and managing its treatment (Sbihi & Eglese, 2007). Therefore, they belong to the well-known Green Vehicle Routing Problems (GVRPs), which are characterized by the objective of harmonizing the environmental and economic costs by implementing effective routes to meet the environmental concerns and financial indexes (Lin et al., 2014). For further information on GVRPs we refer to the survey papers by Lin et al. (2014), Sbihi & Eglese (2007) and Demir et al. (2014a).

Since the transportation of waste materials (solid waste and recyclables) from the CPs to the landfill involves a high level of operational costs, a high number of works have been published with different solutions and methods for solving the WCVRP (see e.g. Angelelli and Speranza (2002), Teixeira et al. (2004), Nuortio et al. (2006), Karadimas et al. (2007), Bautista et al. (2008)). For further information we refer to the survey paper by Han & Ponce-Cueto (2015). Nevertheless, to the best knowledge of the authors, there is little research that focuses on combining economic and environmental objectives in a WCVRP. Sonneson (2000) presents a mathematical model to predict fuel consumption and time for collecting waste in different areas. In this work, the fuel consumption and consequently pollutant emissions in a collection route largely depend on the total driving distance and number of stops. Apaydin & Gonullu (2008) used a shortest path model in order to decrease the emissions in the solid waste collection process in Trabzon city (Turkey). They used a Geographic Information System (GIS) to obtain real data and to compare the optimized rote with the present one. They obtained important reductions in exhaust gas emissions. They considered constant emission factors based on travel distance for the calculation of pollutant emissions, whereas in this research, pollutant emissions are estimated depending on the vehicle speed, the engine and vehicle characteristics and the load carried by the collection vehicle. Tavares et al. (2009) propose the use of a GIS 3D route modeling software for minimizing fuel consumption in a WCVRP. The model is applied to a collection scheme in the city of Praia (Cape Verde) and considers the effects of road inclination and vehicle weight. Results show savings of 8%, compared to the approach of calculating the route of shorter distances. Zsigraiova et al. (2013) present a methodology for the reduction of operation costs and pollutant emissions. They combine vehicle routing optimization in the GIS environment and waste collection scheduling with historical data of the filling rate of trash bins. The methodology is applied to a collection system in the city of Barreiro (Portugal), obtaining beneficial impacts of the optimization on both the operation costs and pollutant emissions. Bing et al. (2014) propose a mathematical model and heuristics for redesigning the collection routes of plastic waste by adopting an eco-efficiency metric which is measured by transportation, labor and emission costs.

All these studies considered that the collection vehicle performs only one trip to the disposal facility, whereas our study considers a real-life situation, where multiple disposal trips are allowed in order to reduce the company costs. Following this consideration, Boskovic et al. (2013)

presented a methodology for vehicle route optimization using GIS, which is applied to the waste collection and transport system in the city of Kragujevac (Serbia). They presented a WCVRP with multiple disposal trips, called circuits, which are divided into four different stages in which vehicle speeds differ. This observation is also taken into account in our study, in order to calculate more precisely pollutant emissions. In their study, pollutant emissions are calculated for the optimized route and savings compared to the current situation are shown; results indicate great reductions in pollutant emissions.

In the area of GVRPs, a large number of papers have been published in the scientific literature. Some papers deal with minimizing fuel consumption, (see Kara et al. (2007), Kuo (2010), Xiao et al. (2012) and Kopfer et al. (2014)), whereas Maden et al. (2010) and Jabali et al. (2012) take into account time-dependent travel times and vehicle speeds to calculate fuel consumptions and CO_2 emissions.

Bektaş & Laporte (2011) defined the Pollution Routing Problem (PRP) as an extension of the classical VRP by using a more comprehensive objective function that accounts not just for the travel distance, but also for the amount of greenhouse gases (GHGs) emissions, fuel, travel times and their costs. They presented results of computational experiments on realistic instances that showed the trade-off between minimizing distances, minimizing the distance-load product and the minimization of energy. Extending this research, many authors considered different variants of these problems (see e.g. Franceschetti et al. (2013), Demir et al. (2014b) and Koç et al. (2014)). Other authors have presented different approaches for the PRP or its extensions (Demir et al. (2012), Tajik et al. (2014), Kramer et al. (2015a, 2015b)).

Another problem of GVRPs deals with the recharging or refueling of the vehicles, particularly, the alternative-fuel powered vehicle (AFV). Erdoğan & Miller-Hooks (2012) introduced the problem called Green VRP, under the constraints of the limited vehicle driving range in conjunction with a limited refueling infrastructure. In this problem alternative fuel vehicles may need to visit alternative fueling stations in order to continue their route. They formulated a mixed integer linear programming model and two heuristics for solving the problem. Montoya et al. (2016) proposed a two phase-heuristic for solving the problem whereas Koç & Karaoglan (2016) and Leggieri & Haouari (2017) presented mathematical formulations and branch-and-cut algorithms to solve this problem to optimality in a reasonable computation time for medium size instances. Schneider et al. (2014) introduced the Electric Vehicle Routing Problem with Time Windows and Recharging Stations (E-VRPTW), which incorporates electric vehicles that may take a significant amount of time in the recharging operation, especially when compared to the short refueling times of alternative fuels. In addition to the Green VRP and to the E-VRPTW, different variants of these problems were published (see e.g. Felipe et al. (2014), Ene et al. (2016) or Xiao & Konak. (2016)).

Oberscheider et al. (2013) implemented the minimization of GHGs emissions in timber transport. The authors used the European Environment Agency (EEA) speed-dependent formulas (EEA, 2012), based on the COPERT model, for calculating vehicle fuel consumption and therefore CO_2 emissions. Our research not only considers these formulas for the calculation of CO_2 emissions but also incorporates NO_x, NMVOC and PM emissions calculations. The Eco-WCVRP combines the minimization of those pollutant emissions through the consideration of the external costs of transport which are based on the European study (INFRAS et al., 2008).

3. Problem definition

In this section the Eco-WCVRP is presented. The description of the problem is introduced in Section 3.1 while external costs and emissions calculations are explained in Sections 3.2 and 3.3 respectively.

3.1 Formal description of the problem

The activities concerned with the collection of solid wastes at specific locations in the Eco-WCVRP can be divided into four different activity stages, which are shown in Figure 1. The activity stages are similar to those described in Boskovic et al. (2013).

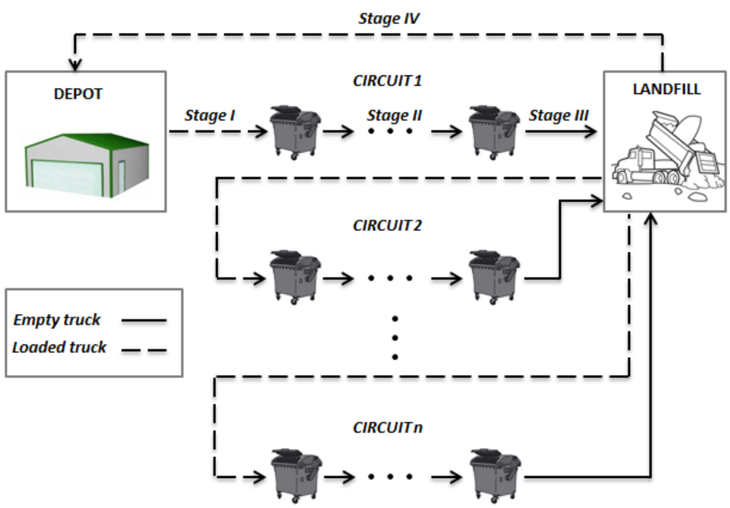

Figure.-1 Different stages in the Eco-WCVRP process

Stage I starts in the company depot from where the vehicle starts the journey travelling to the collection area. Next, Stage II starts by entering to the area. The vehicle stops at the first collection point (CP), picks up the waste and then continues to the next CP. This operation is repeated until all the CPs along a predetermined route are loaded. A CP may be composed of more than one trash bin. Stage III starts by leaving the collection area and moving to the landfill where the collected waste is dumped. At this point a circuit is finished, so the vehicle leaves the landfill and may drive to another collection area (Stage I) to collect more waste from other locations, completing a new circuit. Finally, Stage IV consists in returning the vehicle empty to the depot at the end of the workday.

This classification is motivated by the assumption that the driving conditions (speed and loading level) during the waste collection in urban areas vary across the different stages. Therefore, the calculation of fuel consumption, CO_2 and pollutant emissions must be done taking into account the different driving conditions for each stage. Thus, in Stages I and IV the vehicle is empty, unlike stages II and III where the vehicle is being loaded. On the other hand, in stages I, III and IV the vehicle drives along highways or through the major city streets, while stage II covers the waste collection in local streets at lower speeds. Based on these assumptions, different average vehicle speeds are assigned to each activity stage in a route.

3.2 External costs

In this work, we focus our attention on external costs associated with GHG emissions and atmospheric pollutant emissions, such as NO_x, NMVOC and PM. The evaluation of each component of the external costs applied to the Spanish transport setting is based on the European study (INFRAS et al., 2008).

Climate change or the global warming impacts of transport are mainly caused by emissions of GHGs: CO_2, nitrous oxide (N_2O) and methane (CH_4). The main cost drivers for the marginal climate cost of transport are the fuel consumption and carbon content of the fuel. For internalization purposes the estimated external costs related to global warming can be quantified by multiplying the total tons of CO_2 equivalent GHG by an external cost factor expressed in euros per ton of CO_2 emitted. The recommended value for the external costs of climate change obtained in INFRAS et al. (2008), expressed as a central estimate is 25€/ton.CO_2.

Air pollution costs are caused by the emission of air pollutants such as NO_x, NMVOC and PM. Emissions of a road vehicle depend on vehicle speed, the load factor, fuel type and the related combustion technology, vehicle size, the driving pattern and the geographical location of the road. For internalization purposes, the estimated external costs of each type of pollutant emissions can be obtained by multiplying the total tons of the pollutant emitted by an external cost expressed in euros per ton of pollutant emitted. The recommended air pollution costs for each pollutant in Spain (€/ton of pollutant) based on INFRAS et al. (2008) are: NO_x=3600; NMVOC=800; $PM_{2.5}$=114000; PM_{10}=45600, using PM in urban areas.

3.3 Emissions calculations

The COPERT model (Ntziachristos and Samaras, 2012) is a methodology that calculates for different types and technologies of vehicles (1) the fuel consumption and consequently the CO_2 emissions, (2) NO_x emissions, (3) NMVOC emissions and (4) PM emissions. Driving conditions such as the vehicle load and road gradient are also considered in the calculations. COPERT does not include parameters related to vehicle acceleration, which may have an impact on fuel consumption and pollutant emissions. However, the effect of considering variable operation conditions with different average vehicle speeds on each activity stage of a route should result in a more accurate estimation of the vehicle emissions.

In COPERT methodology there are three methods to estimate emissions from road transport (Ntziachristos and Samaras, 2012). These methods differ in the amount of information required for the calculation of emissions. Tier 1 methodology uses fuel as the activity indicator in combination with average fuel-specific emission factors. Tier 2 introduces different vehicle categories and considers the fuel used and their emission standards. In Tier 3 exhaust emissions are obtained using a more detailed methodology in which the total vehicle kilometers and travelling speeds per vehicle technology are available. In this paper, we focused on the Tier 3 method where speed dependent equations are available to calculate fuel consumption and pollutant emissions for different types and technologies of vehicles (Euro I to Euro V). The formulas are expressed in grams per kilometer (gr/Km) and are given for three levels of load factors (0, 50, 100%). The emission factors use up to five parameters (a, b, c, d, and e) to be calculated. These parameters are derived from statistical analyses, see Ntziachristos and Samaras (2012) annex 3. It is important to note that the fuel consumption and emission factors for a heavy-duty vehicle (HDV) are valid within the range of speed from 6 to 86 kilometers per hour.

In the Eco- WCVRP the vehicle engine operates under different loads in a route as the waste is collected at any CP and loaded into the vehicle. As road gradients are not considered in this work, the approach is only applicable to flat cities. As mentioned above, COPERT provides three different non-linear equations for the calculation of fuel consumption and emission factors at different levels of load factor (0, 50, 100%) for a specific type of vehicle. Thus, the calculation of the fuel consumption and pollutant emissions is performed by a piecewise function, where the approximation curves are determined by linear approximation between breakpoints (three different levels of load factor). Equations (1) and (2) show the calculation of the total pollutant emissions in a route R for a vehicle k, where E_k^p is the total emissions of pollutant p (gr) for vehicle k, $\varepsilon^p_{i,j,k}$ is the emission factor of the pollutant p in the arc (i,j) in (gr/Km) for vehicle k, d_{ij} is the traveled distance between nodes i and j, $v_{i,j}$ is the average speed in the arc (i,j), $z_{i,j,k}$ is the fraction of load carried for the vehicle k between nodes i and j and λ_{Lijkv} are non-negative variables needed to approximate each non-linear term, defined by the different levels of load factor L∈ (1 (0%), 2 (50%), 3(100%)) by a piecewise-linear curve.

$$E_k^p = \sum_{(i,j)\in R} \varepsilon^p_{i,j,k}(v_{i,j}, z_{i,j,k}) \cdot d_{ij} \tag{1}$$

$$\varepsilon^p_{i,j,k}(v_{i,j}, z_{i,j,k}) = \begin{cases} \lambda^p_{1i,j,k} \cdot \varepsilon^p_{i,j,k}(v_{i,j},0) + \lambda^p_{2i,j,k} \cdot \varepsilon^p_{i,j,k}(v_{i,j},0.5) & if\ z_{i,j,k} \le 0.5 \\ \lambda^p_{2i,j,k} \cdot \varepsilon^p_{i,j,k}(v_{i,j},0.5) + \lambda^p_{3i,j,k} \cdot \varepsilon^p_{i,j,k}(v_{i,j},1) & if\ z_{i,j,k} > 0.5 \\ \lambda^p_{1i,j,k} + \lambda^p_{2i,j,k} = 1; \quad \lambda^p_{3i,j,k} = 0; & if\ z_{i,j,k} \le 0.5 \\ \lambda^p_{2i,j,k} + \lambda^p_{3i,j,k} = 1 \quad \lambda^p_{1i,j,k} = 0; & if\ z_{i,j,k} > 0.5 \\ z_{i,j,k} = 0.5 \cdot \lambda^p_{2i,j,k} + \lambda^p_{3i,j,k} & \end{cases} \tag{2}$$

In this work, the authors assume that all carbon burned as fuel is emitted as CO_2 by a standard linear proportion This parameter is called the emission factor and is shown in Table 1 in kilograms per unit of fuel. The calculations of fuel consumption and CO_2 emissions are shown in Equations (3) and (4) respectively where FC_k is the total fuel consumption of a vehicle k, ρ is the mean density of the fuel and ef_k is the CO_2 emission factor of the type of fuel of vehicle k.

$$FC_k = \frac{1}{\rho} \cdot \sum_{(i,j)\in R} \varepsilon^{fc}_{i,j,k}(v_{i,j}, z_{i,j,k}) \cdot d_{ij} \tag{3}$$

$$E_k^{CO_2} = FC_k \cdot ef_k \tag{4}$$

Table 1 Calculation of CO_2 emissions for different types of fuel

Calculation of CO_2 emissions	Diesel	Gasoline	CNG
Units	Liters (l)	Liters (l)	Cubic meters (m^3)
Density (ρ)	832.5 g/l	748 g/l	778 g/m^3
Kg CO_2/Kg fuel	3.20	3.18	1.988
ef (Kg CO_2/units)	2.67	2.38	1.55

4. Problem formulation

Although mathematical models are not appropriate when solving medium to large-size VRP instances, the mathematical model introduced in this section for the Eco-WCVRP is useful to describe and to understand all constraints and it can also be used as a basis for formulating a problem with additional characteristics.

The Eco-WCVRP is defined on a graph $\mathcal{G}=\{\mathcal{N},\mathcal{A}\}$ with $\mathcal{N}=\{0,1,\ldots,N,N+1\}$ as a set of nodes, where node 0 represents the depot, node $N+1$ the landfill and the remaining nodes $\{1,\ldots,N\}$ represent the CPs and $\mathcal{A}$ is a set of arcs defined between each pair of nodes. A set of K heterogeneous vehicles, with carrying capacity of QV_k, is represented by $\mathcal{K}=\{1,\ldots K\}$ and is available from the depot. The problem introduces a maximum number of circuits of each vehicle to the landfill which is represented by $\mathcal{V}=\{1,\ldots V\}$. The objective of the Eco-WCVRP is to find a set of routes for the vehicles, minimizing the total external costs in which all CPs are visited exactly once and vehicles are not overloaded (the total waste in each visited node does not exceed the capacity of the collection vehicle). The notation adopted is the following: i,j for node indices; k for vehicle indices; v for circuit indices; s for speed indices; p for pollutant indices; QD_i is the amount of waste to be collected at node i (kg); QV_k is the capacity of vehicle k (kg); TD_{ij} represents the distance from node i to node j $(i \neq j)$; $\Psi_{i,j}^{s}$ is equal to 1 if arc (i,j) is traveled at speed s. The problem uses the following decision variables:

- X_{ijkv} : binary variable, equal to 1 if vehicle $k \in \{1,\ldots,K\}$ travels from nodes i to j $(i \neq j)$ on the circuit $v \in \{1,\ldots,V\}$.
- Z_{ijkv} : fraction of load carried by the vehicle $k \in \{1,\ldots,K\}$ from nodes i to j $(i \neq j)$ on the circuit $v \in \{1,\ldots,V\}$.
- $\lambda_{L\,ijkv}$: non-negative variables needed to approximate each non-linear term, defined by the different levels of load factor $L \in$ (1 (0%), 2 (50%), 3(100%)), by a piecewise-linear curve.
- $\gamma_{S\,ijkv}$: binary variables, equal to 1 if Z_{ijkv} corresponds to the segment $S \in$ (1 (0-50%), 2 (50-100%)).

According to the established assumptions, the constraints of the mathematical model are as follows:

$\sum_{v=1}^{V}\sum_{k=1}^{K}\sum_{\substack{j=1 \\ j\neq i}}^{N+1} X_{ijkv} = 1 \quad \forall i \neq \{0, N+1\}$ (5)	$\sum_{j=1}^{N} X_{0jk1} \leq 1 \quad \forall k$ (6)
$\sum_{j=1}^{N} X_{N+1,jkv} \leq 1 \quad \forall k, \forall v > 1$ (7)	$\sum_{j=1}^{N} X_{N+1,jkv} \leq \sum_{i=1}^{N} X_{i,N+1,k,v-1} \quad \forall k, \forall v > 1$ (8)
$\sum_{\substack{j=0 \\ j\neq i}}^{N} X_{jik1} - \sum_{\substack{j=1 \\ j\neq i}}^{N+1} X_{ijk1} = 0 \quad \forall i \neq \{0, N+1\}, \forall k$ (9)	$\sum_{\substack{j=1 \\ j\neq i}}^{N+1} X_{jikv} - \sum_{\substack{j=1 \\ j\neq i}}^{N+1} X_{ijkv} = 0 \quad \forall i \neq \{0, N+1\}, \forall k, \forall v > 1$ (10)
$\sum_{j=1}^{N} X_{0jk1} = \sum_{i=1}^{N} X_{i,N+1,k1} \quad \forall k$ (11)	$\sum_{j=1}^{N} X_{N+1,jkv} = \sum_{i=1}^{N} X_{i,N+1,kv} \quad \forall k, \forall v > 1$ (12)
$\sum_{i=1}^{N}\sum_{\substack{j=1 \\ j\neq i}}^{N+1} QD_i \cdot X_{ijkv} \leq QV_k \quad \forall k, \forall v$ (13)	

$$\sum_{\substack{j=1\\ j\neq i}}^{N+1}\sum_{k=1}^{K}\sum_{v=1}^{V} Z_{ijkv}\cdot QV_k = \sum_{\substack{j=0\\ j\neq i}}^{N+1}\sum_{k=1}^{K}\sum_{v=1}^{V} Z_{jikv}\cdot QV_k + QD_i \quad \forall i \neq \{0, N+1\} \tag{14}$$

$$QD_i \cdot X_{ijkv} \leq Z_{ijkv}\cdot QV_k \leq (QV_k - QD_j)\cdot X_{ijkv} \quad \forall i, \forall j, j\neq i, \forall k, \forall v \tag{15}$$

$$\sum_{l=0}^{N+1} Z_{ilkv} - \sum_{l=0}^{N+1} Z_{jlkv} + X_{ijkv} \leq 1 - \frac{QD_j}{QV_k} \quad \forall i \neq \{0, N+1\}, \forall j \neq \{0, N+1\}, j \neq i, \forall k, \forall v \tag{16}$$

$$Z_{ijkv} = 0.5\cdot \lambda_{2ijkv} + \lambda_{3ijkv} \quad \forall i, \forall j, j\neq i, \forall k, \forall v \tag{17}$$

$$\sum_{L=1}^{3} \lambda_{Lijkv} = 1 \quad \forall i, \forall j, j\neq i, \forall k, \forall v \tag{18}$$

$$\lambda_{1ijkv} \leq \gamma_{1ijkv} \quad \forall i, \forall j, j\neq i, \forall k, \forall v \tag{19}$$

$$\lambda_{2ijkv} \leq \gamma_{1ijkv} + \gamma_{2ijkv} \quad \forall i, \forall j, j\neq i, \forall k, \forall v \tag{20}$$

$$\lambda_{3ijkv} \leq \gamma_{2ijkv} \quad \forall i, \forall j, j\neq i, \forall k, \forall v \tag{21}$$

$$\gamma_{1ijkv} + \gamma_{2ijkv} = 1 \quad \forall i, \forall j, j\neq i, \forall k, \forall v \tag{22}$$

$$\lambda'_{1ijkv} \leq \lambda_{1ijkv} + \left(1 - X_{ijkv}\right) \ \forall i, \forall j, j\neq i, \forall k, \forall v \tag{23}$$

$$\lambda'_{1ijkv} \geq \lambda_{1ijkv} - \left(1 - X_{ijkv}\right) \ \forall i, \forall j, j\neq i, \forall k, \forall v \tag{24}$$

$$\begin{gathered} X_{0,N+1,kv} = 0 \quad \forall k, \forall v\ ; \quad \sum_{j=1}^{N} X_{j0kv} = 0 \quad \forall k, \forall v\ ; \quad \sum_{j=1}^{N} X_{N+1,jk1} = 0 \quad \forall k\ ; \\ X_{N+1,0kv} = 0 \quad \forall k, \forall v\ ; \quad \sum_{j=1}^{N} X_{0jkv} = 0 \quad \forall k, \forall v > 1\ ; \quad Z_{0jkv} = 0 \quad \forall j, \forall k, \forall v\ ; \\ Z_{N+1,jkv} = 0 \quad \forall j, \forall k, \forall v \end{gathered} \tag{25}$$

Constraints (5) ensure that each CP is visited exactly once. Constraints (6) state that each vehicle departs from the depot once in the first circuit. Similarly, Constraints (7) guarantee that each vehicle departs from the landfill once in any circuit. Constraints (8) ensure if a vehicle leaves the landfill, it has had to arrive there before. Constraints (9) and (10) are the flow conservation on each node. Constraints (11) ensure that if the landfill is not visited by vehicle *k* in the first circuit, then the vehicle cannot leave the depot. Similarly, Constraints (12) guarantee that if a vehicle leaves the landfill to collect more waste from other locations, then the vehicle has to return to the landfill. Constraints (13) ensure that no vehicle can be overloaded. Balance of flow is described through constraints (14). Constraints (15) are used to restrict the total load a vehicle carries. Constraints

(16) are introduced to avoid sub-tours. Constraints (17) and (18) express the fraction of load carried as a weighted combination of the different levels of load factor *(L)*. Constraints (19) - (22) impose that two consecutive variables λ_{ijkv} are different from zero. Constraints (23) and (24) are introduced in the model to take into account the fuel consumption and pollutant emissions when the vehicle travels empty. Constraints (25) impose the values of some fixed variables.

The goal of the problem is to build several routes minimizing the external costs which are composed of climate change costs and air pollution costs (Equation 26).

$$Min \sum_{v=1}^{V}\sum_{k=1}^{K}\sum_{j=0}^{N+1}\sum_{\substack{i=0\\ i\neq j}}^{N+1}\left\{\left[\frac{PE^{CO_2}\cdot ef_k}{\rho}\cdot\sum_{s=1}^{S}\psi_{i,j}^{s}\cdot\left(\lambda'_{1i,j,k,v}\cdot\varepsilon_{i,j,k,v}^{fc}(v_{i,j},0)+\lambda_{2i,j,k,v}\cdot\varepsilon_{i,j,k,v}^{fc}(v_{i,j},0.5)+\lambda_{3i,j,k,v}\cdot\varepsilon_{i,j,k,v}^{fc}(v_{i,j},1)\right)\right]\right.$$

$$\left.+\sum_{p=1}^{3}\left[PE^{p}\cdot\sum_{s=1}^{S}\psi_{i,j}^{s}\cdot\left(\lambda'_{1i,j,k,v}\cdot\varepsilon_{i,j,k,v}^{p}(v_{i,j},0)+\lambda_{2i,j,k,v}\cdot\varepsilon_{i,j,k,v}^{p}(v_{i,j},0.5)+\lambda_{3i,j,k,v}\cdot\varepsilon_{i,j,k,v}^{p}(v_{i,j},1)\right)\right]\right\}\cdot TD_{i,j} \qquad (26)$$

5. Problem-solving methodology

Due to the intrinsic difficulty of this type of routing problem, solution approaches in the literature are heuristic and metaheuristic algorithms. In this section a two-phase approach for solving the problem tackled in this paper is presented. In order to achieve diversification, in the first phase our methodology produces several initial solutions using a semi-parallel construction heuristic for only selecting a subset *F* of them based on their objective function value. Then, in a second phase, the selected initial solutions are optimized using a VNTS algorithm. Thus, the algorithm starts with an initial solution and the VNTS algorithm is repeated for all the initial solutions of the set *F*, re-starting from a new initial solution once the optimization process is finished. The proposed solution methodology is terminated when either all selected initial solutions have been examined by the VNTS algorithm or a time limit gamma (γ) is reached. The methodology is an adaptation of the solution approach presented in Paraskevopoulos et al. (2008) but introducing some differences. First, in the Eco-WCVRP scheme, TWs restrictions are not considered and consequently, vehicle capacity restrictions are only taken into account for detecting infeasible routes. Secondly, the problem introduces multiple circuits per vehicle. This issue incorporates several differences when building vehicle routes by the semi-parallel construction heuristic; such as vehicle routes may be assigned more than one circuit, which finishes at the landfill. Finally, the objective function of the Eco-WCVRP considers the minimization of the external costs.

Section 5.1 describes the steps of the semi-parallel insertion heuristic for the construction of initial solutions while Section 5.2 presents a general overview of the VNTS.

5.1 Construction of initial solutions

In this section we present a semi-parallel insertion heuristic based on the insertion framework described in Paraskevopoulos et al. (2008) which extended the algorithms previously proposed in Ioannou et al. (2001) and Solomon (1987).

Two lists containing the collection vehicles (V_k) and the unassigned CPs (C_s) are needed to be implemented in the algorithm. The proposed heuristic builds a circuit for every available vehicle at each iteration. Thus, the algorithm starts from an empty circuit and CPs are iteratively inserted until none can be inserted in the circuit due to capacity restrictions. At each iteration, the CPs of C_s are candidates for insertion to all vehicle circuits, not only once but multiple times. Next, only one vehicle circuit is selected and added to the partially final solution. Thus, the visited CPs from the selected circuit are removed from C_s and the number of circuits performed by the selected vehicle k (v_k) is increased by one unit. If the selected vehicle has reached the maximum number of circuits (V), the vehicle is removed from V_k. The overall procedure is repeated until all CPs are assigned to a vehicle circuit. According to the characteristics of the problem, the first circuit for each vehicle is built starting in the depot and finishing in the landfill. However, when a circuit is selected, the vehicle is considered to be placed in the landfill for the following circuit constructions. Finally, the route for every vehicle will be composed by the assigned circuits. In addition, the depot node will be inserted at the end of every vehicle route for considering the return trip. The semi-parallel construction heuristic is shown in Algorithm 1.

Algorithm 1.- Semi-Parallel Construction Heuristic

```
Initialize available vehicle list V_k, k=1,2,…,K
Initialize collection points list C_s, s=1,2,…,N
Initialize number of vehicle circuits v_k=0,  k=1,2,…,K.
S ← InitialSolution() ,
While (C_s ≠0) do:
  For all vehicle k of V_k do:
   If (V_k ≠ 0):
        seed←FindSeedCP(C_s ,k)
        r_vk ← InitializeCircuit(v_k ,k),  r_vk←InsertSeedCP(seed),
       done←true
         While (done=true)
           done←false
            For all CPs u of  C_s-{seed}do:
                 For all insertion positions i,j of  r_vk do:
                     ϕ_i,j,u,k ←GreedyFunction(i,j,u,k,α_1,α_2), ϕ←StoreBest(ϕ_i,j,u,k),
                     done←true
                 EndFor
            EndFor
           r_vk←InsertCP_At(ij ϕ),
        EndWhile
    EndIf
  EndFor
  For all vehicle circuits r_vk do:
```

```
        ACUT_vk ← AvCostPerUnitTransfer(r_vk), x←StoreBest(ACUT_vk)
   EndFor
   S ← InsertCircuit(r_vx),  v_x ← IncrementNumberofCircuits(),  C_s ← RemoveCPs(r_vx);
   If (v_x = V):
   V_x ← Remove(x)
EndWhile
```

5.1.1 Circuit construction

Following the insertion scheme of Solomon (1987), circuits are initialized by a "seed" criterion based on the furthest CP (max(TD_{0i},TD_{i0})). If the vehicle has not been assigned any circuit yet, the distance to the depot will be taken into account. Otherwise, the distance to the landfill will be considered as the vehicle will be placed there. Then, every CP from C_s is evaluated in all possible positions between two adjacent CPs in the partially constructed circuit using a "greedy" function. As TWs restrictions are not considered, the greedy function that measures the cost of inserting a CP u between i and j in a circuit performed by vehicle k is shown in (27), where the α weights define the relative contribution of each individual metric to the overall selection (α_1+ α_2=1). When a CP u is inserted between two consecutive CPs (i,j) in a circuit, a driving time increase is produced and is given by the first metric (28). Similarly, metric (29) gives priority to the insertion of CPs with large demands on the circuit and maximizes the utilization of the vehicle capacity.

$$\phi_{ij}^{uk} = \alpha_1 \cdot C_{ij,u}^1 + + \alpha_2 \cdot C_{ij,u}^2 \qquad (27)$$

$$C_{ij,u}^1 = TT_{iu} + TT_{uj} - TT_{ij} \qquad (28)$$

$$C_{ij,u}^2 = QV_k - \left(\sum_{i \in R \cap u} QD_i \sum_{j \in R} X_{ijkv} \right) - QD_u \qquad (29)$$

Next, the CP with a smaller value of the greedy function is assigned to the partially constructed circuit in the best feasible insertion position and the procedure is repeated until no CP can be inserted in the circuit.

5.1.2 Circuit selection

At the end of the previous procedure, a circuit is selected and added to the partially final solution. For this purpose, an effective criterion for selecting the best circuit is based on minimizing the average cost per unit transferred (ACUT) (Paraskevopoulos et al., 2008), since it achieves a more efficient vehicle capacity utilization. As the Eco-WCVRP considers external costs in the objective function, the idea is to measure the amount of external costs that are involved for each unit of transported waste in a circuit performed by a specific type of vehicle. The metric is defined in equation (30).

$$ACUT_{vk} = \frac{External\_Costs(vk)}{\sum_{(i,j)\in n} QD_i \cdot X_{ijkv}} \tag{30}$$

5.2 The Variable Neighborhood Tabu Search Algorithm

In this study, the VNTS algorithm is introduced to efficiently reduce the pollutant emissions in an Eco-WCVRP. The basic VNS algorithm is upgraded by the use of TS for the local search procedure. VNS was originally proposed by Mladenović and Hansen (1997) and is a metaheuristic for solving optimization problems. VNS is a technique that tries to systematically escape from local optima by changing the neighborhood structure during the search. Thus, neighborhoods of a solution are explored during the search by jumping from one solution to another if an improvement occurs. The advantage of using several neighborhood structures is based on the fact that a local optimum for a given type of move (neighborhood structure) is not necessarily so for another, so the search must continue until a local minimum solution with respect to all neighborhood structures is reached (Hansen et al., 2010). The choice of a VNTS algorithm is motivated by the high complexity of the WCVRP, which requires an algorithm with substantial diversification possibilities as the VNS scheme. Furthermore, the use of TS for the local search is useful to indicate promising regions not yet explored and has shown that it may provide excellent results [see, e.g., Pérez et al., 2003; Repoussis et al., 2006; Paraskevopoulos et al., 2008; Molina et al. 2016].

The VNTS algorithm starts by defining a set of neighborhood structures N_q ($q = 1 \ldots q_{max}$), which are defined by local search operators that transform one solution to another. The process is based on the fact that a local minimum with respect to one neighborhood structure is not necessarily so for another. The VNTS main cycle is composed of three phases: *shaking*, *local search* and *move*. Therefore, the iterative process starts from an initial solution *s*. Then, a shaking mechanism is applied to escape from a basin of attraction. The shake procedure is a diversification mechanism that consists in perturbing a solution by applying a feasible move, to provide a new starting point (*s´*) for the local search. The objective of the shake procedure is to obtain a new starting point belonging to basin of attraction of a different local minimum than the current one. Thus, if the perturbation is too weak, the local search might bring us back to the previous solution. On the other hand, if it is too strong the new starting point could lose good features of the solution and the algorithm would degenerate into a simple random multi-start (Blum & Roli, 2003). For this reason, the selection of the neighbor in the shaking phase is determined by a random move defined in the neighborhood N_q that is being explored, as it maintains some good features of the current solution. Next, a local search based on TS is performed to determine a new solution *s´´* in N_q. If *f(s´´)* is better than the best solution *f(s)*, then *s* is replaced by *s´´*, and the search returns to N_1, otherwise the search explores the next neighborhood N_{q+1}. This is repeated until all neighborhood structures are examined ($q = q_{max}$). When the solution space from an initial solution is completely explored, the algorithm starts from a new initial solution from the set *F*. The pseudocode of the algorithm is illustrated in Algorithm 2.

Algorithm 2-Variable Neighborhood Tabu Search algorithm

```
F ← Semi-parallel_Insertion_Heuristic;
Define a set of neighborhood structures N_q, l=1, 2,…,q_max;
For all solutions s of set F do:
   While (CPU time consumed ≤ γ) do:
      Set q ← 1;
      While (q ≤ q_max) do:
     s´← Shaking (N_q)   s´´← TabuSearch (s´, N_q);
     If  f (s´´) improves f (s) then
       s ← s´´; q ← 1;
     Else
        If  q< q_max then
           q ← q+1;
      EndIf
      EndWhile
      UpdateBestSolution (s);
    EndWhile
 EndFor
```

5.2.1 Tabu search

The TS is a widely used metaheuristic that carries out the exploration of the solution space by moving successively, in each iteration, from one solution *s* to the best or first improving solution of its neighborhood $N_q(s)$, even if it may cause a deterioration in the objective function. Thus, in contrast to other descent methods, the TS allows non-improving moves to avoid getting trapped in local optima.

The central mechanism in the TS is a short-term memory known as the tabu list (TL) which stores the solutions explored throughout the search or, more commonly, some relevant attributes of these solutions. In this problem, the TL consists in storing the exchanged nodes and their initial positions in the routes before moving to other solutions. To prevent the search from returning to recently visited solutions and to drive the search towards regions of the solution space not yet explored, these selected attributes are declared as tabu and remain in the TL for a specific number of iterations (tabu tenure (TT)) unless the aspiration criterion is satisfied. The latter is applied when a move declared as tabu builds a solution that overcomes the best solution found so far. In this case, the mechanism dismisses the TL and the move is accepted.

The TL is reinitialized every time a local search process is started. Therefore, if the random move defined in the previous shaking phase belongs to the basin of attraction of the current local minimum, the search will return to the previous solution and it will be incorporated into the TL. Otherwise, the local search will have a different trajectory.

This work proposes a scheme for the TT that provides a balance between diversification and intensification search strategies by using a particular mechanism described in Paraskevopoulos et al. (2008). Initially, the TT is set equal to a lower value TT_{min}. A diversification mechanism is provided by incrementing at each iteration the TT in one unit up to an upper bound TT_{max} while no improvement is observed. Therefore, at each iteration, the best solution of $N_q(s)$, which is not included in the TL or satisfies the aspiration criterion, is chosen as the new current solution. Then, this solution is added to the TL, the TT is incremented in one unit (only if $TT< TT_{max}$) and the oldest solution already included in the TL is removed (only if $TT=TT_{max}$). In contrast, the intensification mechanism is performed when an improvement in the objective function is achieved. For this purpose the TT is reinitialized to TT_{min} removing the oldest solutions from the TL. The termination condition used in TS is the maximum number of iterations (MaxIters) without observing improvement in the objective function. The pseudocode of the Tabu Search algorithm is presented in Algorithm 3.

Algorithm 3.-Tabu_Search algorithm

```
Initialize TL of TT_min size;
 fitness ← s, counter=0, TT_size ← TT_min;
   While (counter ≤ MaxIters) do:
      Find s' ∈ N_q(s) | s' subject to tabu & aspiration conditions
      AllowedSet(s) ← s';
        s ← ChooseFirstImproving(AllowedSet(s));
         Update_TL();
        If f (s) improves f (fitness) then
           fitness ← s; counter =0, TT_size ← TT_min,;
        Else
           counter =counter + 1;
            If (TT_size < TT_max) then
                TT_size = TT_size + 1;
            EndIf
         EndIf
   EndWhile
 Return (fitness)
```

5.2.2 Neighborhood structures

The process of changing neighborhoods in case of no improvements corresponds to a diversification of the search. The effectiveness of this dynamic neighborhood strategy can be explained by the fact that a solution that is locally optimal with respect to a neighborhood is probably not locally optimal with respect to another neighborhood (Blum & Roli, 2003).

The scheme implemented in this paper oscillates between eight neighborhood structures (q_{max}=8) which are defined as a blend of well-known local search move operators that transform one solution into another. The order of the neighborhoods was selected after some experiments considering the impact in the final solution and their cardinality, and are applied in the following order: Relocate (inter-route) (Savelsbergh, 1992), Exchange (inter-route) (Kindervater and Savelsbergh, 1998), GENI (Gendreau et al., 1998), 2-Opt (Croes, 1958), Relocate (intra-route), Exchange (intra-route), Double insertion (Brandão, 2011) and CROSS-exchange (Taillard et al., 1997).

- Relocate: This neighborhood structure is applied on pairs of circuits (inter-route) and on single circuits (intra-route). The Relocate operator aims to generate a solution by removing a CP from a circuit and inserting it into another circuit (Relocate-2) or into another position within the circuit (Relocate-1).
- Exchange: This neighborhood structure is applied on pairs of circuits (inter-route) and on single circuits (intra-route). The Exchange operator aims to generate a solution by swapping a pair of CPs from two different circuits (Exchange-2) or from the same circuit (Exchange-1).
- GENI: This neighborhood structure is applied only on pairs of circuits and is only composed of the Generalized Insertion (GENI) operator. It basically consists in removing a CP from a circuit and inserting it into any two CPs of another circuit. The insertion of a CP in a circuit does not necessarily take place between two CPs which are consecutive in a circuit. For this purpose, two possible orientations of the tour for each possible insertion are considered. For a more detailed description see Gendreau et al. (1998).
- 2-Opt: This neighborhood structure is applied only on single circuits (intra-route) and it aims to generate feasible solutions by examining all possible moves defined by removing two non-adjacent arcs and constructing two new arcs in a circuit. The main idea is to build a new circuit by crossing over itself and reordering it, maintaining the tour structure.

- Double insertion: In a double insertion move, the operation is similar to a single insertion (Relocate-2) except for removing a segment length of two consecutive CPs respectively in a circuit.
- CROSS-Exchange: This neighborhood structure is also applied only on pairs of circuits and swaps segments of CPs between two circuits. The different segments may contain an arbitrary number of CPs but due to the typically vast number of neighbors that would result, the segment length is limited to three CPs. Thus, sets of 1-2, 2-2, 1-3, 2-3 and 3-3 swaps are defined and executed in the listed order. Furthermore, these moves usually increase the chances of finding high quality solutions and avoid getting trapped in a local minimum.

6. Computational results

This section describes the computational experiments carried out to validate the effectiveness of the algorithm developed to solve the Eco-WCVRP. Moreover, a real WCVRP in the municipality of Alcalá de Guadaíra (Seville) is presented to analyze and improve the current solution in terms of total distance traveled, CO_2 and pollutant emissions. The algorithm was developed in C++ and run on a 3.30 GHz Intel® Core(TM) i5-2400 CPU. First, the parameters used within the algorithm are adjusted. Then, a comparative analysis with the best results from the literature corresponding to closely related VRP instances is performed to validate the effectiveness of the proposed algorithm. Next, the quality and performance of the neighborhood structures are evaluated within a computational study, where local search operators are combined in different configurations in the algorithm. Then, the VNTS algorithm is compared with VNS and TS approaches. Finally, a real WCVRP is presented and four case studies are solved to evaluate the reduction of pollutant emissions in the route planning when different vehicle types are taken into consideration.

6.1 Parameter settings

This section reports the best values selected for the parameters of the VNTS algorithm proposed in this work. The parameter setting has been done in order to show whether two control parameters (TT_{max} and MaxIters) play a significant role in finding improved solutions. As the Eco-WCVRP can be considered as a VRP with a fixed heterogeneous fleet (HVRP), with a special depot behavior (depot and landfill) and a piece-wise linear objective function, the benchmark data sets of Taillard (1999) have been used to do the parameter setting. They consist of eight problems, numbered from 13 to 20 with a fixed fleet and 50-100 nodes. Vehicles are characterized by different capacities and variable costs, which depend on the distance traveled. Services times on nodes are not considered.

Both control parameters are expressed as a fractional size of the number of nodes (*N*). The TT_{max} is a control parameter that restricts the length of the TL while MaxIters represents the number of iterations without improvement in the local search. We set TT_{max} and MaxIters to different values ranging from 20% to 40% and from 20% to 50% respectively and run the proposed methodology with the selected problems. Each problem is solved 20 times for each combination of control parameters.

Table 2 presents the results obtained from the parameter setting. It shows the percentage deviation between the average solution obtained by the VNTS and the best-known solution (BKS) value, averaged over the eight instances.

Table 2. Average percentage deviations of the results obtained by the VNTS from the best known solutions with varying TT_{max} and MaxIters

TT_{max} fraction	MaxIters fraction			
	20% *N*	30% *N*	40% *N*	50% *N*
20% *N*	0.96	0.75	0.71	0.70
30% *N*	0.82	0.79	**0.66**	0.66
40% *N*	1.12	0.81	0.75	0.71

The experiments showed that both parameters have an impact on the solution quality, obtaining the best results when the TT_{max} =30%**N* and MaxIters ranged between (40%-50%)**N*. The obtained value for TT_{max} is in accordance with the work of Paraskevopoulos et al. (2008), who performed experiments to generate robust and satisfactory parameter values for the VNTS on closely related HVRP and TWs (HVRPTW) instances with 100 customer nodes. On the other hand, these authors suggested a value of 30% for MaxIters, but our experiments resulted in a more appropriate value of 40% (see Table 3).

Finally, as the production of 100 initial solutions using the semi-parallel construction heuristic commonly takes less than 5 seconds, the values of α_1 and α_2 ranged between 0-100 via increments of 1. The selected parameters are shown in Table 3, where *N* represents the number of nodes of the problem.

Table 3. Parameter settings

	VNTS parameters			
	F	MaxIters	TT_{min}-TT_{max}	γ *(sec)*
Parask et al. (2008)	20	30 (0.3**N*)	10-30 (0.1-0.3)**N*	1200
This work	20	40 (0.4**N*)	10-30 (0.1-0.3)**N*	1200

6.2 Comparisons with VRP instances

In order to evaluate the proposed solution method, various experiments were carried out and comparisons over benchmark data sets from the scientific literature are presented. They are taken from Taillard (1999) and from Paraskevopoulos et al. (2008).

Table 4 illustrates a summary of the performance of the proposed solution method, abbreviated as VNTS, on Taillard (1999) benchmark data sets. The first two columns of the table show the instance number and the number of customers to be served. Then, the BKS among most best published works are provided. They include Taillard (1999), Li et al. (2007), Brandão (2011), Subramanian et al. (2012) and Penna et al. (2013). The last row indicates the percentage deviation (% Dev) of the results obtained by the VNTS with respect to the BKS. For each problem, a bold face refers to the match with current BKS.

The results in Table 4 show that the VNTS approach used in this research is able to generate competitive solutions for the HVRP. In addition, the algorithm obtained the best-known solution for four out of eight problem instances with an average deviation of 0.68% and a worst case performance of 2.41%.

The second benchmark data sets used in this work for the evaluation of the VNTS were proposed by Paraskevopoulos et al. (2008). These data sets are derived from Liu and Shen´s (1999) benchmark data sets, originally proposed for solving the Heterogeneous VRP with unlimited fleet and TWs, known as the Fleet Size and Mix VRPTW (FSMVRPTW). They extended a fixed fleet for each problem with the best known solutions of these authors. They proposed 24 benchmark instances grouped into six types of data sets (R1, C1, RC1, R2, C2, RC2). Customers are randomly distributed in instances of type R, clustered in type C and semi-clustered in instances of type RC.

Problem sets shown by R1, C1 and RC1 have a short scheduling horizon and small vehicle capacities, contrary to R2, C2 and RC2. The total cost of a route is obtained by the sum of the fixed vehicle cost and of the total en route time which includes travelling and waiting times.

Table 4. Comparison between different approaches for Taillard (1999) instances

Instance	Nodes	Taillard (1999)	Li et al (2007)	Brandão (2011)	Subramanian et al.(2012)	Penna et al. (2013)	VNTS	BKS	% Dev.
13	50	1518.05	**1517.84**	**1517.84**	**1517.84**	**1517.84**	**1517.84**	**1517.84**	0.00
14	50	615.64	**607.53**	**607.53**	**607.53**	**607.53**	**607.53**	**607.53**	0.00
15	50	1016.86	**1015.29**	**1015.29**	**1015.29**	**1015.29**	**1015.29**	**1015.29**	0.00
16	50	1154.05	**1144.94**	**1144.94**	**1144.94**	**1144.94**	**1144.94**	**1144.94**	0.00
17	75	1071.79	**1061.96**	**1061.96**	**1061.96**	**1061.96**	1066.40	**1061.96**	0.42
18	75	1870.16	**1823.58**	**1823.58**	**1823.58**	**1823.58**	1843.26	**1823.58**	1.08
19	100	**1117.51**	1120.34	1120.33	1120.34	1120.34	1144.47	**1117.51**	2.41
20	100	1559.77	**1534.17**	**1534.17**	**1534.17**	**1534.17**	1557.15	**1534.17**	1.50
Avg.		1240.48	1228.18	1228.21	1228.21	1230.73	1237.11		0.68

Table 5 presents the results obtained by VNTS compared to the current state-of-the-art solution approaches for the HVRPTW. The first line of the table lists the authors using the following abbreviations: PRSK for Paraskevopoulos et al. (2008) and KOC for Koç et al. (2015).

The first column of the table shows the instance category. Then, the total costs obtained by each method are shown. Next, for each problem instance the BKS with respect to Paraskevopoulos et al. (2008) and Koç et al. (2015) are provided. Finally, the last column indicates the percentage deviation (% Dev) of the results obtained by the VNTS with respect to the BKS. As in Table 4, a bold face refers to the match with the current BKS, whereas a bold face with a '*' indicates a new BKS.

Table 5. Comparison between different approaches for Paraskevopoulos (2008) instances

Instance	PRSK	KOC	VNTS	BKS	% Dev.	Instance	PRSK	KOC	VNTS	BKS	% Dev.
R101	**4583,99**	4588.76	4654,72	4583,99	1,54	R201	**3779,12**	3782.49	3823,44	3779,12	1,17
R102	4420,68	**4376.54**	4449,05	4376,54	1,66	R202	**3578,91**	3583.92	3616,66	3578,91	1,05
R103	**4195,05**	4201.71	4198,80	4195,05	0,09	R203	3582,51	**3553.92**	3590,10	3553,92	1,02
R104	4065,52	4027.69	**4016,17***	4027,69	**-0,29***	R204	3143,68	**3081.80**	3092,29	3081,80	0,34
C101	**8828,93**	**8828.93**	**8828,93**	8828,93	**0,00**	C201	**6140,64**	**6140.64**	**6140,64**	6140,64	**0,00**
C102	7137,79	7153.13	**7119,35***	7137,79	**-0,26***	C202	7752,88	**7623.96**	**7623,96**	7623,96	**0,00**
C103	7143,88	7122.57	**7105,39***	7122,57	**-0,24***	C203	**7303,37**	**7303.37**	7303,70	7303,37	0,00
C104	7104,96	7083.74	**7081,51***	7083,74	**-0,03***	C204	5721,09	**5680.46**	**5680,46**	5680,46	**0,00**
RC101	5279,92	5266.36	**5257,67***	5266,36	**-0,16***	RC201	**5523,15**	5534.59	5550,88	5523,15	0,50
RC102	5149,95	5099.55	**5083,08***	5099,55	**-0,32***	RC202	**5132,08**	5150.23	5192,38	5132,08	1,17
RC103	5002,41	4991.29	**4990,94***	4991,29	**-0,01***	RC203	4508,27	**4471.92**	4473,13	4471,92	0,03
RC104	5024,25	5016.97	**5006,16***	5016,97	**-0,22***	RC204	4252,87	4241.83	**4240,35***	4241,83	**-0,03***

Note that the proposed solution method is not supposed to be the most competitive over these instances, since they present TW constraints that have had to be incorporated into the VNTS algorithm. Therefore, in order to obtain feasible solutions, the algorithm checks, in every movement of the shaking and local search phases, if the new solution is compatible with TW constraints. In the same way, the TW compatibility is also checked in the semi-parallel construction heuristic; specifically when a CP is inserted in a circuit in the construction phase. The VNTS algorithm provides solutions that overcome the best known results for nine instances (R104, C102, C103, C104, RC101, RC102, RC103, RC104, RC204) and obtain the same value of BKS on four problems (C101, C201, C202, C204). The VNTS algorithm provides reasonably good solutions with an average percentage deviation of 0.29% with respect to the BKS, with cost reductions from -0.32% and a worst case performance of 1.66%. Moreover, the comparison of the results with respect to the BKS shows that the VNTS algorithm is competitive in the case of C1, C2 and RC1 instances, but not for random problems (R1 and R2 instances).

6.3 Computational studies

In the remainder of this section, the performance of the proposed neighborhood structures is compared within a computational study. Then, additional experiments are introduced to evaluate and compare the effectiveness of the VNTS, VNS and TS algorithms.

6.3.1 Local search with different sets of neighborhoods

This experiment is motivated by the observation that the defined neighborhood structures may be inefficient or they may provide minimal improvements. Therefore, in order to choose the best strategies, computational experiments are performed to analyze the results obtained by testing different sets of neighborhoods on the Taillard (1999) benchmark problems. As the possible combinations that can be made with the neighborhood operators become too large for a complete study, a selection has been made by the authors, where only a specific neighborhood operator is removed in order to measure its contribution to the final solution. Thus, considering the list of operators described in Section 5.2.2, eight different sets of neighborhood structures are defined in which the order of the operators is maintained. Then, for every set of neighborhood structures and every problem instance, the VNTS is run with the same parameter values, which are shown in Table 3, and a solution is obtained. In order to evaluate the solution quality achieved by a specific set of neighborhood structures, we measure, for every instance, the percentage deviation with respect to the solution obtained by the VNTS when all neighborhood operators are included.

Table 6 shows the results obtained by the application of different sets of neighborhood structures to the VNTS algorithm. The first line of the table shows the set of neighborhood structures, designated by the removed operator, while the first column of the table shows the instance category. Then, the values of the VNTS, when all neighborhood operators are included, are presented. Next, for each set of neighborhood structures, the best found solution (BFS) and the percentage deviation (% Dev.) are provided. Finally, the last row indicates the average obtained values.

The results show that the neighborhood operators that have minor improvements in the final solution are Double Insertion, Exchange-1 and Relocate-1 with average deviations of 0.03, 0.14 and 0.25% respectively. It is observed that these operators have influence in instances with a long scheduling horizon and large vehicle capacities (instances 18, 19 and 20). As the WCVRP is characterized by designing vehicles routes with a large number of CPs, the non-consideration of these operators would lead to obtaining lower quality solutions. On the other hand, CROSS and GENI operators are capable of exploring the solution space in an effective way with average deviations of 1.94 and 1.89% respectively. These moves affect the VNTS in different aspects; The GENI operator causes more intensification effect since it alters the solution just once, while CROSS moves causes more diversification effect since it interchanges two segments of CPs between two different circuits. In our opinion, the results show how well these neighborhood structures complement each other. When a neighborhood structure transforms one solution to another, the optimization process can continue from other regions of the solution space. Thus, if a neighborhood structure is dismissed, the optimization process may finish at a local minimum obtaining a lower quality solution. For this reason all neighborhood operators have been considered in this work.

6.3.2 VNTS versus basic VNS or TS

This section compares the VNTS hybrid algorithm with other metaheuristic approaches, which consist of the basic VNS proposed by Mladenović and Hansen (1997) and a TS algorithm. The basic VNS follows the same scheme of the VNTS based on the three phases: *shaking*, *local search* and *move*. However, a steepest descent procedure (known also as best improvement local search) is considered for the local search. The TS algorithm is implemented following the scheme described in section 5.2.1 with the described neighborhood structures. Table 7 provides the BFS, the percentage deviation in relation to the solutions obtained by VNTS (% Dev.) and the CPU time in seconds. The last row of the table indicates the average obtained values.

Table 6. Comparison between different sets of neighborhoods for Taillard (1999) instances

		CROSS		**Double Insertion**		**Exchange-1**		**Relocate-1**		**2-OPT**		**GENI**		**Exchange-2**		**Relocate-2**	
Instance	**VNTS**	BFS	% Dev.	BFS	% Dev.	BFS	% Dev.	BFS	% Dev.	BFS	% Dev.	BFS	% Dev.	BFS	% Dev.	BFS	% Dev.
13	1517.84	1549.59	2.09	1517.84	0.00	1517.84	0.00	1517.84	0.00	1517.84	0.00	1548.09	1.99	1517.84	0.00	1517.84	0.00
14	607.53	607.53	0.00	607.53	0.00	607.53	0.00	607.53	0.00	607.53	0.00	622.05	2.39	618.57	1.82	622.48	2.46
15	1015.29	1031.07	1.55	1015.29	0.00	1015.29	0.00	1015.29	0.00	1019.55	0.42	1041.38	2.57	1016.86	0.15	1019.55	0.42
16	1144.94	1163.82	1.65	1144.94	0.00	1144.94	0.00	1144.94	0.00	1144.94	0.00	1148.87	0.34	1144.94	0.00	1146.38	0.13
17	1066.40	1111.35	4.22	1066.4	0.00	1066.4	0.00	1066.4	0.00	1086.64	1.90	1093.82	2.57	1084.41	1.69	1094.75	2.66
18	1843.26	1843.42	0.01	1843.26	0.00	1843.26	0.00	1869.09	1.40	1871.00	1.51	1910.52	3.65	1843.26	0.00	1843.26	0.00
19	1144.47	1185.63	3.60	1144.47	0.00	1157.36	1.13	1144.47	0.00	1157.36	1.13	1151.29	0.60	1144.47	0.00	1144.47	0.00
20	1557.15	1594.95	2.43	1560.83	0.24	1557.15	0.00	1565.87	0.56	1557.15	0.00	1572.92	1.01	1557.15	0.00	1575.346	1.17
Avg.	1237.11	1260.92	1.94	1237.57	0.03	1238.72	0.14	1241.43	0.25	1245.25	0.62	1261.12	1.89	1240.94	0.46	1245.51	0.85

Table 7. Comparison between different approaches for Taillard (1999) instances

		VNTS		*VNS*			*TS*		
Instance	Nodes	*BFS*	Time(s)	*BFS*	% Dev.	Time(s)	*BFS*	% Dev.	Time(s)
13	50	1517.84	112	1559.29	2.73	54	1545.17	1.80	86
14	50	607.53	108	607.53	0.00	58	612.44	0.81	62
15	50	1015.29	122	1027.57	1.21	71	1029.41	1.39	95
16	50	1144.94	188	1158.99	1.23	68	1156.38	1.00	89
17	75	1066.40	359	1095.32	2.71	199	1094.01	2.59	254
18	75	1843.26	391	1855.89	0.69	210	1891.19	2.60	229
19	100	1144.47	545	1178.66	2.99	302	1175.19	2.68	408
20	100	1557.15	598	1614.04	3.65	326	1586.96	1.91	451
Avg.		1237.11	302.88	1262.16	1.90	161.00	1261.34	1.85	209.25

The results in Table 7 show that the VNTS efficiently improves the performance of the VNS and TS algorithm, obtaining equal or higher quality solutions for all instances. In comparison with VNS algorithm, VNTS produces better solutions for seven out of eight instances and matched one, with an average percentage deviation of 1.90%. When comparing with TS, the VNTS outperforms all the obtained solutions with an average percentage deviation of 1.85%. This may be attributed to the combination of the qualities of the two algorithms; a VNS scheme, which can diversify the search exploring new solution space, and a TS mechanism that prevents the algorithm from trapping in local optimization. However, while the hybrid algorithm improves the obtained solutions, it also increases the computation time. It can be observed from Table 7 that the computational effort required by VNTS is greater than in the other two algorithms. The average computing time taken by VNTS was about 302.88 seconds while VNS and TS spent 161 and 209.25 seconds respectively. Nevertheless, the increase in computational time experimented by the VNTS when compared with VNS and TS is considered relatively reasonable to obtain improvements in the final solutions.

6.4 Real case study provided by the company

The municipality of Alcalá de Guadaíra was selected as the case study for the present research. Integrated within the Los Alcores district, the municipality belongs to the province of Seville, located in the western part of the autonomous community of Andalusia, in the south of Spain. The collection of organic waste is this area is daily performed by a public company. The waste is collected from trash bins and transported to a landfill which is 30.94 kilometers away from the depot. The population of Alcalá de Guadaíra is estimated to be around 72,800 with an average amount of waste collected per year of 33,905 tons. Although five vehicle routes are presently available for the collection of urban waste in Alcalá de Guadaíra, the routes are not fixed at an operational level and may vary according to the distribution of CPs in a daily or weekly scheduling. In addition, the waste collection of each CP does not only depend on the capacities of the trash bins, but also on the quantity of residues outside the trash bins, usually known by drivers based on their experience performing the service. Another very important aspect is the poor general condition of the municipal solid waste (MSW) vehicles. The fleet is more than eight years old and vehicles often present mechanical problems; both these facts have an influence on the route planning, making it difficult to reach good results in terms of energy consumption and pollutant emissions.

A set of four experiments are carried out to show and compare the different solutions obtained by the algorithm when different MSW vehicle types are taken into consideration for a vehicle replacement. Clearly, there is a strong dependency between the choice of a vehicle type and the routing of the vehicle in the fleet. In order to show the differences in the use of different objective functions, each case study has been run three times, by minimizing the total distance traveled (1), the total fuel consumption (2) and the total external costs (3). Case study (a) obtains the current waste collection route from the company and improves the route with the algorithm proposed. Case studies (b) and (c) analyze the situation when the vehicle that currently performs the route is replaced by another less polluting vehicle. Particularly, in case study (b) the capacity of the new vehicle is not changed while case study (c) considers acquiring a vehicle with a lower capacity. Finally, case study (d) introduces a compressed natural gas (CNG) vehicle of the same capacity with an enhanced environmentally friendly vehicle (EEV) engine technology. The objective is to account for the total external costs when implementing a vehicle replacement and compare the amounts of the different types of pollutant emissions obtained in each case study. Moreover the routes provided by the VNTS are compared to the current solution to evaluate the reduction of pollutant emissions in the waste collection route.

The vehicle fleet for the cases studies includes four MSW vehicles (A, B, C and D). Vehicle A is defined by the vehicle that currently performs the real route. Vehicles B, C and D are the three options for the vehicle acquisition. In this study, MSW vehicles are comparable to those of heavy duty vehicles of the same weight because the same engines are used for both; their characteristics can be found in Table 8.

The COPERT model (Ntziachristos and Samaras, 2012) is used for the determination of average emission factors for diesel-engine vehicles A, B and C. However, the experimentation on CNG vehicles is poor. Only emissions and fuel consumption factors are provided for CNG buses.

Nevertheless, as a result of the lack of experimental data from CNG fuelled MSW vehicles in the scientific literature, the authors decided to use the Tier 2 emission factors based on the COPERT model of CNG buses. This decision is based on the observation that buses have weights and driving cycles similar to MSW vehicles, are characterized by stop and go traffic situations and low average speeds (Pastorello et al., 2011).

Table 8 Fleet parameters

Vehicle	Vehicle type	Capacity (Tons)	Type of fuel
A	RT >20-26t (Euro-3)	22.5	Diesel
B	RT >20-26t (Euro-5)	22.5	Diesel
C	RT >14-20t (Euro-5)	18	Diesel
D	RT >20-26t (EEV)	22.5	CNG

The defined route is performed in the north district of Alcalá de Guadaíra and collects waste from 81 CPs completing two circuits to the landfill. A constant demand of 0.5 tons on each CP is assumed. The characteristics and total emissions of the current route are shown in Tables 9 and 10 respectively. The application Open Street Maps was used for obtaining the real distances in kilometers between each pair of CPs belonging to one existing route for organic waste collection. Regarding the external costs parameters, the external costs of climate change, NO_x, NMVOC and PM were established as 25, 3,600, 800 and 79,800 (€/ton of pollutant) respectively.

Table 9 Characteristics of the existing route for organic waste collection

Route Name	Number of CPs	Vehicle	Nº Circuits per vehicle	Stage I speed (Km/h)	Stage II speed (Km/h)	Stage III speed (Km/h)	Stage IV speed (Km/h)
Alcalá Norte	81	A	2	50	7	40	50

Table 10 Total emissions of the existing route for organic waste collection

Route Name	Dist (Km)	Fuel Cons.(l)	Ext. Costs(€)	CO_2 Emis.(Kg)	NO_x Emis.(g)	NMVOC Emis.(g)	PM Emis.(g)
Alcalá Norte	127.81	47.60	10.26	127.11	1209.82	85.43	33.40

In order to compare the results obtained by the proposed algorithm for the different cases with those currently existing in Alcalá de Guadaíra, the travelled distance, fuel consumption, external costs and pollutant emissions amounts were computed for each instance and are shown in Table 11. The first column of the table indicates the case study. Next, the second and third columns indicate the vehicle type and number of circuits respectively. The fourth column shows the objective function (O.F.) considered. Then, the total distance traveled (Dist.) the total fuel consumption (F. Cons.) and the external costs (Ext. C.) are shown. The value of the O.F. to be minimized is represented in bold. Finally, CO_2 and pollutant emissions are also indicated.

Table 11 Comparison of results for the case studies

Case Study	Veh.	Circ.	O.F.	Dist. (Km)	F. Cons	Ext. C. (€)	CO_2 Emis.(Kg)	NO_x Emis.(g)	NMVOC Emis.(g)	PM Emis.(g)
a	A	2	Dist.	**118.47**	41.75 l	8.85	111.49	1048.33	71.12	28.07
			F. Cons.	118.47	**41.75 l**	8.85	111.49	1048.33	71.12	28.07
			Ext. C.	121.57	41.92 l	**8.84**	111.93	1050.27	70.31	27.74
b	B	2	Dist.	**118.47**	39.94 l	4.43	106.65	363.65	3.82	5.75
			F. Cons.	119.24	**39.53 l**	4.38	105.55	359.41	3.70	5.58
			Ext. C.	119.24	39.53 l	**4.38**	105.55	359.41	3.70	5.58
c	C	3	Dist.	**164.44**	42.03 l	4.64	112.24	381.75	3.87	5.84
			F. Cons.	165.98	**41.82 l**	4.61	111.67	379.33	3.80	5.73
			Ext. C.	165.98	41.82 l	**4.61**	111.67	379.33	3.80	5.73
d	D	2	Dist.	**118.47**	69.28 m^3	3.80	107.17	296.19	5.33	0.59
			F. Cons.	118.47	**69.28 m^3**	3.80	107.17	296.19	5.33	0.59
			Ext. C.	118.47	69.28 m^3	**3.80**	107.17	296.19	5.33	0.59

In general, minimizing distances is not the best alternative for reducing pollutant emissions as it does not consider load factors, travel speeds and vehicle categories, which are of special importance in the specified objective function. As observed in case studies (b) and (c) the solution obtained by the algorithm when minimizing the total travel distance, presents higher amounts of pollutant emission than minimizing the total fuel consumption or the total external costs. On the other hand, minimizing the total fuel consumption leads us to take into account distances, load factors, travel speeds and vehicle categories in the problem resolution, but exclusively for the reduction of CO_2 emissions. The minimization of other pollutant emissions such as NO_x, NMVOC or PM is not considered in this alternative. Finally, minimizing the total external costs not only considers distances, load factors, travel speeds and vehicle categories, but also incorporates pollutant emissions factors in the objective function of the problem (see Equation 26). Therefore, the solutions obtained by this objective function are very close or equal to the solutions obtained by minimizing the total fuel consumption but with lower external costs. Consequently, these solutions may present lower amounts of other types of pollutants such as NO_x, NMVOC or PM, which have a relevant importance in urban areas. This fact can be observed in the solutions obtained for all case studies.

Looking at the results obtained for case study (a), substantial reductions can be obtained just by applying the VNTS to redesign the current route performed by the vehicle. Specifically, the solution obtained by the algorithm outperforms the current route with significant reductions in the CO_2 (11.94%), NO_x (13.19%), NMVOC (17.71%) and PM (16.95%) emissions (see Tables 10 and 11).

The solution obtained by the VNTS for case study (b) further reduces the current pollutant emissions. The effect of replacing the current vehicle A by vehicle B results in reductions of 21.56 Kg of CO_2 (16.96%), 850.41 g of NO_x (70.29%), 81.73 g of NMVOC (95.67%) and 27.82 g of PM (83.29%) each time the route is performed.

As can be seen from the results obtained for case study (c), replacing the current vehicle A with vehicle C implies the execution of three circuits for the waste collection. Although this fact involves an increment in the length of the route of 38.17 kilometers (29.87%) when it is compared with the real case, the amounts of the different pollutant emissions are actually reduced. However, they do not improve the results obtained in case study (b).

The solution with the lowest external costs is obtained in case study (d) where the routes are performed by a CNG vehicle with an EEV engine technology. The reductions obtained in this case study are 19.94 Kg of CO_2 (15.69%), 913.63 g of NO_x (75.52%), 80.10 g of NMVOC (93.76%) and 32.81 g of PM (98.23%). Figure 2 shows the pollutant emissions for the current (vehicle A) and optimized routes in case studies (b) and (d) with vehicles B and D respectively.

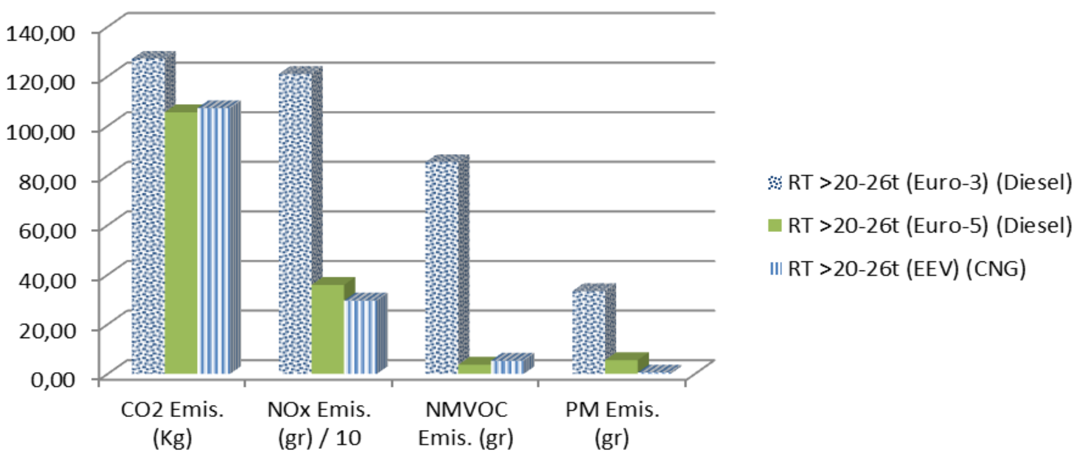

Figure.-2 Pollutant emissions for current and optimized route in cases studies (b) and (d).

Table 12 Emission reductions of pollutants per year for the current route

Case Study	Veh.	CO_2 Emis. (tons)	NO_x Emis. (Kg)	NMVOC Emis. (Kg)	PM Emis.(Kg)
a	A	5.54	58.24	5.52	2.07
b	B	7.87	310.40	29.83	10.15
c	C	5.64	303.13	29.80	10.10
d	D	7.28	333.48	29.24	11.98

These results confirm the importance of taking into account external costs in the objective function of the problem. Although the differences are relatively small for a given route, it is important to note that these reduction percentages must be applied to the total amount of each pollutant emitted per year. Table 12 presents the estimated savings in the total amount of each type of pollutant emissions emitted per year in the studied route. Moreover, these savings may be even greater if the methodology is extended to the other four waste collection routes in the municipality.

7. Conclusions

In this paper, the Eco-WCVRP is introduced. The problem is a variant of the well-known WCVRP where external costs derived from freight transport (climate change and air pollution) are considered in the objective function of the problem to be part of the planning and operational process in companies. The problem considers a heterogeneous fleet and allows vehicles performing more than one circuit for the waste collection, identifying four activity stages in the route which are characterized by different travel speeds for the calculation of the emissions. The equations provided by the COPERT methodology are used for estimating CO_2 and pollutant emissions (NO_x, NMVOC and PM); they depend on the vehicle category, the vehicle assigned speeds and the total load carried. To our knowledge, this is the first paper that considers pollutant emissions in a WCVRP with a heterogeneous fleet.

The Eco-WCVRP is modeled with linear programming techniques. In order to obtain high quality solutions, an algorithm based on a semi-parallel insertion heuristic and a VNTS post-processing method is implemented. The algorithm is validated for a real problem in the municipality of Alcalá de Guadaíra, within the metropolitan area of Seville (Spain) where experimental results are obtained on a set of case studies. Solutions show that the effect of replacing the current vehicle with another of the same capacity and low-emission vehicle technology results in significant reductions on the emissions of CO_2 (15.69%), NO_x (75.52%), NMVOC (93.76%) and PM (98.23%).

In summary, the proposed methodology can not only optimize the current route in terms of distance traveled or fuel consumption but also reduce other transport-associated impacts such as pollutant emissions, which are of special importance in urban areas. The consideration of the external costs into the objective function provides ecological solutions very close to those that minimize fuel consumption but with lower amounts of pollutant emissions. The designed tool efficiently analyzes the differences between scenarios and can provide decision making support for cities when designing their waste collection routes by taking into account environmental issues.

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