Environmental Issues in Vehicle Routing Problems

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Abstract In the last decade interest in environment preservation is increasing and environmental aspects play an important role in strategic and operational policies. Therefore, environmental targets are to be added to economic targets, to find the right balance between these two dimensions. Green logistics extend the traditional definition of logistics by explicitly considering external factors associated mainly with climate change, air pollution, noise, vibration and accidents. Among the logistical activities, the vehicle routing problem (VRP) is one of the most widely researched and has mainly focused on economic objectives, not considering explicitly environmental issues. In this chapter, a realistic variant of the VRP with heterogeneous vehicle fleets in which vehicles are characterized by different capacities and costs, has been considered and external costs have been estimated using international research projects, and have been included as part of a mixed-integer linear programming model to solve a realistic variant of the VRP. To solve medium to large-size VRP instances, heuristic approaches are necessary. An impressive number of heuristic have been proposed for the VRP in the literature. In this chapter, one heuristic is developed to find good solutions to the proposed eco-efficiency model: a savings heuristic when time windows are not considered. Since there are no instances for this problem variant, the algorithm is validated with benchmarking problems adapted from the literature, offering good solutions and quickness. The selection of eco-efficiency routes can help to reduce the emissions of air pollutants, noises and greenhouse gases, without losing competitiveness in transport companies.

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1 Introduction

Environmental issues can impact on numerous logistical decisions throughout the supply chain such as location, sourcing of raw material, modal selection, and transport planning, among others. Green logistics extends the traditional definition of logistics ("integrated management of all the activities required moving products through the supply chain at minimum cost") by explicitly considering other external factors associated mainly with climate change, air pollution, noise, vibration and accidents.

The logistical activities comprise freight transport, storage, inventory management, materials handling and all the related information processing. In this chapter, we study the design of routes in road freight transportation activities, which are significant sources of air pollution, noise and greenhouse gas emissions, with the former known to have harmful effects on human health and the latter, responsible for global warming. Thus, we analyze the well-known Vehicle Routing Problem (VRP) to estimate the effects of those environmental issues in this type of problems.

The VRP deals with founding the optimal routes of delivery or collection from one or several depots to a number of customers, while satisfying some constraints. The VRP plays a vital role in distribution and logistics. Huge research efforts have been devoted to studying the VRP since 1959 and thousands of papers have been written on several VRP variants. We refer to the survey by (Cordeau et al. 2007) for coverage of the state-of-the-art on models and solution algorithms.

The classical VRP tries to minimize the total distance travelled by a set of vehicles while satisfying the demand of a given set of customers and considering the assumption that each vehicle serves a single route during any planning period. This problem is a generalization of the well-known and widely studied Traveling Salesman Problem (TSP). The TSP is in mathematical terms a NP-hard combinatorial problem and therefore also the VRP is NP-hard. Different variations of the classical VRP have been proposed with the aim of approaching to real contexts, where some variables and constraints have been included.

When demand of all customers exceeds the vehicle capacity, two or more vehicles are needed. This implies that in the Capacitated Vehicle Routing Problem multiple Hamiltonian cycles have to be found such that each Hamiltonian cycle is not exceeding the vehicle capacity. Then the CVRP consists of designing a set of least-cost vehicle routes in such a way that: (1) each customer has a positive demand D_i which has to be fully satisfied once by exactly one vehicle; (2) all vehicle routes start and end at the depot, which has no demand; and (3) the vehicle fleet is homogeneous, i.e. each vehicle has an equal capacity of Q.

The Multi-Depot Vehicle Routing Problem (MD-VRP) is a generalization of the CVRP in which vehicles start from multiple depots and return to their original depots at the end of their assigned tours. If customers are dispersed around the depots, then the distribution problem can be modeled as several independent CVRP. However, if they are intermingled then a MD-VRP should be solved. Each depot is responsible for a number of customers who are served by the vehicles assigned to the depot.

The Vehicle Routing Problem with Time Windows (VRPTW) is the variant that has received the most attention in the literature by the practical importance of time windows. Time windows occur when customers require pick-up or delivery within a pre-specified service times, characterized by an early time and a late time. In addition to time windows for customers, it may be included also a limit on the total driving time, that is, the maximum time allowed for any vehicle due to contract regulations for drivers. In the literature a distinction is made between soft time windows that can be violated against a penalty-cost and hard time windows that cannot be violated. The VRPTW has been the subject of intensive research efforts for both heuristic and exact optimization approaches. An overview of the early published papers is given by (Solomon 1987).

The Vehicle Routing Problem with Pick-up and Delivering (VRPPD) considers that besides the deliveries to a set of customers, a second set of customers requires a pick-up, where deliveries and pickups can be made at any order. As a particularity of this problem, in the Vehicle Routing Problem with Backhauls (VRPB) it is assumed that each vehicle will first visit customers that require delivery (line-haul customers) before it visits the customers (suppliers) that require pick-up (backhaul customers). This arises from the fact that the vehicles are rear-loaded, and rearrangement of the loads on the tracks at the delivery points is not deemed economical or feasible (Toth and Vigo 2002).

The VRP with split deliveries (SD-VRP) is a variant where it is allowed that the same customer can be served by different vehicles if this will help to reduce the total route costs. It occurs when the sizes of the customer orders are as big as vehicle capacities.

In classical VRP, the planning period is a single day. In the case of the Period Vehicle Routing Problem (P-VRP), the classical VRP is generalized by extending the planning period to M days. For this variant, the following constraints must be considered: (a) each vehicle must have a defined capacity, (b) each customer has a known daily demand that must be completely satisfied in only one visit by exactly one vehicle, and (c) it is not necessary that the vehicle returns to the depot the same day it came out, but must return in a time period already defined.

In Stochastic VRP (S-VRP) is assumed that one or several components of the problem are random. There are three different kinds of S-VRP: (a) customers with a probability of presence or absence, (b) customers whose demand is a random variable, or (c) customers where the service time and travel time are random variables. In S-VRP, two stages are made for getting a solution. A first solution is determined before knowing the realizations of the random variables. In a second stage, a recourse or corrective action can be taken when the values of the random variables are known. When some data are random, it is no longer possible to require that all constraints be satisfied for all random variables, so the decision maker may either require the satisfaction of some constraints with a given probability or the incorporation into the model of corrective actions when a constraint is violated.

A variant of the VRP arises when a fleet of vehicles (limited or unlimited), characterized by different capacities, fixed costs and variable costs, is available for distribution activities. The problem is known as Heterogeneous Fleet VRP (HF-VRP). The HF-VRP with unlimited fleet, known as the Fleet Size and Mix VRP (FSM), was first proposed by (Golden et al. 1984) and it consists of determining, at the same time, the best fleet composition and the optimal routing of a fleet with an unlimited number of heterogeneous vehicles in order to serve a given set of customers with deterministic delivery demands, minimizing the total travel costs. The HF-VRP variant with a limited number of vehicles, called Heterogeneous VRP (HVRP), was proposed by (Taillard 1999) and it consists in optimizing the routes with the available fixed fleet. In both cases, fixed costs (F) and/or dependent routing costs (D) could be considered. As a result the following HF-VRP variants have been studied in the literature: (1) HVRPFD, (2) HVRPD, (3) FSMFD, (4) FSMF, and (5) FSMD. In Sect. 3, we present a survey on HF-VRP.

The classical objective function in VRP is minimizing the total distance travelled by all the vehicles of the fleet or minimizing the overall travel cost, usually a linear function of distance. This objective is widely used by researchers with homogeneous fleet and when vehicles are not allowed to remain at the depot.

The main objective of companies with a heterogeneous fleet and with less demand than capacity consists of determining the fleet composition minimizing the fixed and the variant costs. Some authors (Sniezek and Bodin 2002) argue that only considering total travel time or total travel distance in the objective function is not enough in evaluating VRP solutions, especially for heterogeneous fleets. Instead, they determine a Measure of Goodness, which is a weighted linear combination of many factors such as capital cost of a vehicle, salary cost of the driver, overtime cost and mileage cost. These costs are considered as internal or economic costs for transportation companies.

In this chapter, the VRP with realistic assumptions and a new objective function that accounts environmental issues is considered. Thus, an eco-efficiency model of the VRP with Heterogeneous Fleet and Time Windows (HF-VRPTW) is presented with a broader objective function that accounts not just for the internal costs (driver, fuel, maintenance,…), but also for external costs (greenhouse emissions, air pollution, noise,…). This model is solved using a heuristic algorithm. With this approach, transportation companies can have positive environmental effects by making some operational changes in their logistics system, selecting 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 remainder of this chapter is organized as follows. In Sect. 2 the environmental impacts of transportation activities and the cost estimation of these externalities are analyzed. Section 3 reviews the literature on the HF-VRPTW and on incorporating environmental issues in VRP. Section 4 presents the proposed approach, a mixed-integer linear programming model and a heuristic algorithm to solve it. A numerical example will be explained in Sect. 5 and a real case application is presented in Sect. 6. Section 7 presents the results and discussion. The conclusions and recommendations for further work are given in Sect. 8.

2 Externalities in Transport

In the last decade interest in environment preservation is increasing and environmental aspects play an important role in strategic and operational policies. Therefore, environmental targets are to be added to economic targets, to find the right balance between these two dimensions (Dyckhoff et al. 2004).

Transport activities give rise to environmental impacts, accidents and congestion. In contrast to the benefits, the costs of these effects of transport are generally not borne by the transport users. Without policy intervention, these so called external costs are not taken into account by the transport users when they make a transport decision. Transport users are thus faced with incorrect incentives, leading to welfare losses.

The internalisation of external costs means making such effects part of the decision making process of transport users. According to the welfare theory approach, internalisation of external costs by market-based instruments may lead to a more efficient use of infrastructure, reduce the negative side effects of transport activity and improve the fairness between transport users.

Internalization of external cost of transport has been an important issue for transport research and policy development for many years in Europe and worldwide. Some authors (Bickel et al. 2006) focus their research on evaluating the external effects of transport to internalize them through taxation. As a result, decisions such as the selection of vehicle types, the scheduling of deliveries, consolidation of freight flows and selection of type of fuel, considering internal and external costs can help to reduce the environmental impact without losing competitiveness in transport companies.

In this chapter, we focus our attention on external costs associated with: greenhouse emissions, atmospheric pollutant emissions, noise emissions and accidents. These four components reflect 88 % of the total average external cost freight in the European Union, excluding congestion costs (INFRAS/IWW 2004). 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 global warming impacts of transport are mainly caused by emissions of the greenhouse gases: carbon dioxide (CO_2), nitrous oxide (N_2O) and methane (CH_4). The main cost drivers for marginal climate cost of transport are the fuel consumption and carbon content of the fuel. For internalization purposes the estimated external costs of CO_2 emissions can be factored into the total well-to-wheel greenhouse gas emissions per litre of fuel used by multiplying the grams of CO_2 per litre with the external costs per gram of CO_2 emitted.

The recommended value for the external costs of climate change for year 2010, expressed as a central estimate is 25€/ton.CO_2. 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 litre of diesel.

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). Emissions of a road vehicle depend on vehicle speed, fuel type and the related combustion technology, the load factor, vehicle size, the driving pattern and the geographical location of the road. For internalization purposes the estimated external costs of each pollutant emissions can be obtained by multiplying the grams of the pollutant per kilometer travelled with the external costs per gram of pollutant emitted.

The recommended air pollution costs for each pollutant in Spain (emissions 2010, in €2000/ton of pollutant) are: $NO_x = 2{,}600$; $NMVOC = 400$; $PM_{2.5} = 41{,}200$; $PM_{10} = 16{,}500$, using PM in outside built-up areas. The ratio €2010/€2000 is fixed to 1.323. The estimation of pollutant emissions from road transport are based on the Tier 2 methodology (EMEP/EEA 2010). This approach considers the fuel used for different vehicle categories and technologies according to emission-control legislation.

Noise costs consist of costs for annoyance and health. For the estimation of noise costs data on the number of exposed people is needed. In road transport the sound emitted is mainly made up by the sound of the propulsion system and the sound of rolling. The ratio of both sources depends on the speed of the vehicle, the vehicle type, the kind of tyres, the vehicle's state of maintenance, the slope of the road and the kind of surface.

The recommended noise costs based on (INFRAS/IWW 2004) for Heavy-Duty Vehicles are in a range from 0.25 to 32 (in €2000/ton-km) considering different vehicle categories, countries and traffic situations, with a mean value of 4.9.

External accident costs are those social costs of traffic accidents which are not covered by risk oriented insurance premiums. The most important costs in road transport are besides vehicle kilometers, vehicle speed, type of road, drivers' characteristics, traffic speed and volume, time of day (day/night) and interaction with weather conditions.

The recommended accident costs also based on (INFRAS/IWW 2004) for Heavy-Duty Vehicles are in a range from 0.7 to 11.8 (in €2000/ton-km), with a mean value of 4.75.

In this chapter, the designed routes will employ all of these average costs and emission factors, multiplying these parameters by the respective distance travelled, load carried or fuel consumed in each route.

3 Literature Review

3.1 VRP with Heterogeneous Fleet

As mentioned in Sect. 1, several variants on VRP inspired by real world applications were proposed over the years. Our interest in this chapter relies on the heterogeneous fleet VRP (HF-VRP), instead of the homogeneous fleets. In industry, fleets are rarely homogeneous and companies are incorporated vehicles with different features over the time (Hoff et al. 2010). As a result, standing and running costs depend on each vehicle according to depreciation level or usage time of the fleet.

The first HF-VRP variants were the FSM problems, proposed by (Golden et al. 1984). These authors suggested two heuristics where the first one is based on the savings algorithm of (Clarke and Wright 1964), and the second one use a giant tour schema. They proposed 20 instances with 12–100 customers and 3–6 vehicle types with an unlimited number of each one. Instances 1–12 have 12 or 30 customers. Instances 13–20 are larger, with 50–100 customers. This second set of instances is considered as benchmark in FSM problems.

The another HF-VRP variants were the HVRP problems, first introduced by (Taillard 1999) who presented a heuristic column generation method. This method starts by solving the homogeneous vehicle routing problem for each vehicle type using a tabu search algorithm. The routes obtained are stored in a set of possible final routes and then, through a process of successive iterations, these routes are extracted and combined into a partial solution to the criterion of non-repetition of customers. The final set of routes is obtained by solving a SP problem minimizing the total costs and ensuring that each customer is served by only one route. This method is tested for the FSMF and FSMD on the second set of instances of (Golden et al. 1984), and also for the HVRPD adding a limited number for each type of vehicle. This set of 8 instances is considered as benchmark in HVRP problems.

As the HF-VRP is a special case of the classical VRP, these problems are NP-Hard and therefore heuristic algorithms are suitable approaches to obtain high-quality solutions in an acceptable computing time. To the best of our knowledge, no exact algorithms have been developed for any variant of HF-VRP.

Some mathematical formulations have been presented in the literature. Gheysens et al. (1984) formulated the FSMF using a three-index binary variables x_{ij}^k to represent if a vehicle of type k travels directly from customer i to customer j. Golden et al. (1984) proposed a similar formulation for the FSMF but using the Miller-Tucker-Zemlin constraints for the TSP to avoid sub-tours (Miller et al. 1960). Yaman (2006) also described six different formulations for the FSMF using these binary variables. Another type of formulations for FSMF is based on the Set Partitioning (SP) model of the VRP and associates a binary variable with each feasible route (Balinski and Quandt 1964). Mathematical formulations for the FSM with Time Windows were described in (Dell'Amico et al. 2006) and (Bräysy et al. 2008).

Although no exact algorithms have been proposed for the FSM, some lower bounds were presented. Golden et al. (1984) proposed some lower bounds for the FSMF problem when there are symmetric distances and triangle inequality between customers. Yaman (2006) also proposed lower bounds for the FSMF based on cutting-plane techniques applied to the six mathematical formulations. Choi and Tcha (2007) extended the lower bounds to all the variants of FSM problems (FSMFD, FSMD and FSMF) based on a SP formulation and using a column generation technique. Pessoa et al. (2009) developed a Branch-Cut-and-Price algorithm to obtain lower and upper bounds for the three FSM variants. Baldacci and Mingozzi (2009) proposed a SP algorithm with bounding procedures based on linear and Lagrangian relaxation to solve the five variants of HF-VRP mentioned in Sect. 1.

All solutions approaches presented in the literature are heuristic algorithms, and they usually are adaptations or extensions of heuristics applied to classical VRP variants. In this way, since the late 90s, metaheuristic approaches are applied to find high-quality solutions of HF-VRP as well.

After (Golden et al. 1984) developed two constructive heuristics to adapt the savings and giant-tour for solving the FSMF problem, some other authors also proposed constructive heuristics (Gheysens et al. 1984; Salhi and Rand 1993). Renaud and Boctor (2002) proposed an extension of the sweep algorithm for classical VRP, to solve the FSMF problem.

Considering metaheuristic approaches, some authors implemented heuristic procedures based on Genetic Algorithms (GA). Ochi et al. (1998) developed a hybrid algorithm that combines GA and Scatter Search to solve the FSMF. Also, (Liu et al. 2009) proposed a GA with a local search to solve the FSMF and FSMD. Lima (2004) solved the FSMF using a Memetic Algorithm (MA). Prins (2009) developed two heuristic procedures based on a MA for all the variants of the FSM problem and for the HVRPD.

Tabu Search (TS) is one of the most extended metaheuristics applied to VRP. Some TS approaches were proposed for solving FSMF and FSMD. Gendreau et al. (1999) developed a TS algorithm based on the GENIUS neighborhoods and an adaptive memory procedure. Lee et al. (2008) proposed a TS algorithm combined with a SP approach. Brandao (2009) proposed a deterministic TS with different procedures to generate the initial solutions.

Recently, new metaheuristics have been applied to FSM. Imran et al. (2009) developed a Variable Neighborhood Search (VNS) algorithm for all FSM variants. Penna et al. (2011) presented a hybrid heuristic based on the Iterated Local Search metaheuristic which uses a VNS procedure in the local search phase.

Prins (2002) developed a heuristic for solving the HVRPD by extending a series of VRP classical heuristics and incorporating a local search procedure based on the Steepest Descent Local Search and TS.

Tarantilis et al. (2003) and later Tarantilis et al. (2004) developed a list-based threshold accepting algorithm (denoted by LBTA) and a backtracking adaptive threshold accepting algorithm (denoted by BATA) for solving the HVRPD. The idea of this class of algorithms is to allow moves toward solutions with higher objective function values (uphill moves) in order to escape from local minimums.

Both methods start with an initial solution generated by a constructive heuristic. The algorithms seek feasible solutions in the neighborhood (local search) and are compared to a list storing the T best threshold values. In LBTA, the list of T values is used during the search, while in BATA the list of T values is allowed to increase during the search.

Two years later, (Li et al. 2006) developed a similar algorithm called HRTR to solve HVRPD and HVRPFD problems, based on the algorithm Record-To-Record (RTR), a deterministic variant of the Simulated Annealing metaheuristic. The algorithm accepts neighbor solution with less objective function value than actual ones plus a deviation, avoiding a local minimum. Then, using a local search (downhill moves), the algorithm looks for new global minimums.

Finally, some heuristics were developed for the heterogeneous fleet VRP with Time Windows. Liu and Shen (1999) proposed a two-phase algorithm to solve the FSMFTW problem. In the first phase, a savings algorithm evaluates the insertion of complete routes in all the possible insertion places of the other routes, taking into account the time windows. In the second phase, intra-route and inter-route exchanges are performed to improve the best solutions found during the first phase. Computational results were performed on a set of 168 test instances derived from the (Solomon 1987) VRPTW test set. This set of 168 instances is considered as benchmark in FSM-TW problems.

Dullaert et al. (2002) extended to FSMFTW the sequential insertion algorithm proposed by (Solomon 1987) incorporating the (Golden et al. 1984) modified saving expressions. Dell'Amico et al. (2006) proposed a ruin-and-recreate metaheuristic approach using a parallel insertion procedure. Bräysy et al. (2008) proposed a deterministic annealing metaheuristic in three phases. These three heuristics has been tested on the 168 instances for solving the FSMFTW problems.

A HF-VRP survey with all the five variants mentioned in this chapter can be found in (Baldacci et al. 2008). Also a survey on industrial aspects of combined fleet composition and routing in maritime and road-based transportation heterogeneous fleet was performed by (Hoff et al. 2010).

As a result of this literature review, we consider that the HVRP is less studied than the FSM, and there are no benchmarking tests on HVRP-TW.

3.2 VRP and Sustainability

VRP studies have been benefiting green logistics from its origin, as early as their introduction by (Dantzig and Ramser 1959). This contribution has always been completely implicit and researchers have often been totally unaware of the beneficial connotations of their works on the environment.

While VRP aims at minimizing distances and total assigned vehicles, it is satisfying green transportation requirements by reducing the amount of fuel and consequently reducing the CO_2 emissions from road transportation.

The influence of VRP is not limited to minimizing travel distance and vehicle numbers, there are green transportation factors that could be considered in a VRP model and have been studied during the past few years.

The contribution of VRP to green logistics has its origins in studies of (Sbihi and Eglese 2007) and PhD dissertation of (Palmer 2007).

In a working paper for Lancaster University Management School, Sbihi and Eglese (2007) reviewed the literature related to vehicle routing in order to find the relationship between vehicle routing and scheduling problems (VRSP) and green logistics. They couldn't find much literature that links VRP models with the Green Logistics issues, but they argued that reduction in total distance would provide environmental benefits due to the reduction in fuel consumption and the consequent air pollutants.

Palmer (2007) suggested an integration of elements from transportation planning and environmental modeling combined with logistics based vehicle routing techniques for freight vehicles and investigated the role of speed in reducing CO_2 emissions under various scenarios and time windows settings. They developed a computer based vehicle routing model that calculates the overall amount of CO_2 emitted from road journeys, as well as time and distance.

Following in this emerging area, a number of studies taking account environmental considerations in their objective functions were published. The first important paper is the "Pollution Routing Problem (PRP)" by (Bektas and Laporte 2011). They defined the PRP as a variant of the VRP, with or without time windows, using a comprehensive objective function which measures and minimizes the cost of GHG emissions along with operational costs of drivers and fuel consumption. They also analyzed and compared between various performance measures of vehicle routing, such as distance, load, emissions and costs evaluated through a variety of objective functions.

Xiao et al. (2012) contemplated the Fuel Consumption Rate (FCR) as a load dependant function, and added it to the classical VRP to extend it with the objective of minimizing fuel consumption. They presented a mathematical optimization model to formally characterize the FCR considered CVRP (FCVRP) as well as a string based version for calculation. The results of the experiments showed that the FCVRP model can reduce fuel consumption by 5 % on average compared to the CVRP model.

Erdogan and Miller-Hooks (2012) introduced the Green Vehicle Routing Problem (G-VRP) as a mixed-integer linear program. They developed techniques to aid organizations with alternative fuel-powered vehicle fleets in overcoming difficulties that exist as a result of limited vehicle driving range in conjunction with limited refueling infrastructure. These techniques seek a set of vehicle tours that minimize total distance traveled to serve a set of customers while incorporating stops at Alternative Fueling Stations (AFSs) in route plans so as to eliminate the risk of running out of fuel. Given a complete graph consisting of vertices representing customer locations, AFSs, and a depot, the G-VRP seeks a set of vehicle tours with minimum distance each of which starts at the depot, visits a set of customers within a pre-specified time limit, and returns to the depot without exceeding the vehicle's driving range that depends on fuel tank capacity. Each tour may include a stop at one or more AFSs to allow the vehicle to refuel en route.

Ubeda et al. (2011) presented a case study to show how the introduction of green practices into the daily decision-making process in a transportation company can simultaneously meet efficiency and environmental objectives. They incorporated the CO_2 emissions in the objective function of the CVRP with backhauls and maximum allowable driving time.

Figliozzi (2010) introduced a different problem: the minimization of emissions and fuel consumption as the primary or secondary objective, creating the Emissions VRP (EVRP). He considered time windows and capacity constraints as well as time-dependent travel time. The chapter deals with a static problem, and the dispatcher is assumed to know the impact of congestion on travel speeds. The amount of emissions is a function of travel speed and it will depend of the departure time in each node.

Maden et al. (2010) considered a VRSP with time Windows in which Speedy depends on the time of the travel. They described a heuristic algorithm to solve the problem. Jabali et al. (2009) considered a similar problem but estimated the amount of emissions based on a nonlinear function of speed and other factors, finding the optimal speed with respect to emissions. Kara et al. (2007) introduced the Energy-Minimizing VRP, an extension of the VRP where a weighted load function is minimized, trying to minimize the energy consumed.

The above-discussed studies have been published recently. This shows that the topic is at its beginning and is still too attractive and demanding.

4 A Sustainable VPR Approach

4.1 An Eco-efficiency Model for HVRPTWB

The problem presented in this chapter is an extension of the classical Capacitated Vehicle Routing Problem, including Time Windows and Backhauls, and a Heterogeneous Fleet with different vehicles and fuel types (HVRPTWB). 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, (g) maximum driving time, and (h) backhaul nodes. The main contributions of this chapter deal with formulating a mathematical model of the HVRPTWB and with considering external and social impacts as part of the internal costs of the company. Then the overall objective is to minimize the total cost that is composed of internal costs (cost of drivers, energy costs, fixed cost of vehicles–depreciation, inspection, insurance-, maintenance costs and toll costs) and external costs (climate change, air pollution, noise and accidents).

The HVRPTWB is defined on a graph $G = \{N, A\}$ with $N = \{0,1,\ldots,t, t+1,\ldots,n\}$ as a set of nodes, where node 0 represents the depot, nodes numbered

1 to t represent delivery points and nodes numbered $t + 1$ to n represent supply points (backhauls), and A is a set of arcs defined between each pair of nodes. A set of m heterogeneous vehicles denote by $Z = \{1, 2,\ldots,m\}$ is available to deliver the desired demand of all customers from the depot node and then to pick-up the inbound products from the supply and return to the depot node. The constructing routes of each vehicle must meet the following constraints: no vehicle carries load more than its capacity, each customer and supplier is visited within its respective time window, customers are not visited after any suppliers and no vehicle exceeds the maximum allowable driving time per day.

We adopt the following notation:

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

Our formulation of the problem uses de following decision variables:

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

Constraints of the model are as follows:

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

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

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

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

$$\sum_{i=t+1}^{n} D_i \sum_{\substack{j=0 \\ j\neq i}}^{n} x_{ij}^k \leq q^k \quad (k = 1,\ldots,m) \tag{5}$$

$$\sum_{k=1}^{m}\sum_{i=t+1}^{n}\sum_{j=1}^{t}x_{ij}^{k}=0 \tag{6}$$

$$\sum_{k=1}^{m}\sum_{j=t+1}^{n}x_{0j}^{k}=0 \tag{7}$$

$$\begin{aligned}&y_i^k+s_i^k+t_{ij}\leq y_j^k+T^k(1-x_{ij}^k)\\&(i=1,\ldots,n;\quad j=0,\ldots,n;\quad j\neq i;\quad k=1,\ldots,m)\end{aligned} \tag{8}$$

$$t_{0j}\leq y_j^k+T^k(1-x_{0j}^k)\quad (j=1,\ldots,n;\quad k=1,\ldots,m) \tag{9}$$

$$e_i\leq y_i^k\leq l_i\quad (i=1,\ldots,n;\quad k=1,\ldots,m) \tag{10}$$

$$y_0^k\leq T^k\quad (k=1,\ldots,m) \tag{11}$$

$$\sum_{k=1}^{m}\sum_{\substack{j=0\\j\neq i}}^{n}f_{ji}^{k}-\sum_{k=1}^{m}\sum_{\substack{j=0\\j\neq i}}^{n}f_{ij}^{k}=D_i\quad (i=1,\ldots,t) \tag{12}$$

$$\sum_{k=1}^{m}\sum_{\substack{j=0\\j\neq i}}^{n}f_{ij}^{k}-\sum_{k=1}^{m}\sum_{\substack{j=0\\j\neq i}}^{n}f_{ji}^{k}=D_i\quad (i=t+1,\ldots,n) \tag{13}$$

$$\begin{aligned}&f_{ij}^k\leq(q^k-D_i)x_{ij}^k\\&(i=0,\ldots,t;\quad j=0,\ldots,n;\quad j\neq i;\quad k=1,\ldots,m)\end{aligned} \tag{14}$$

$$\begin{aligned}&D_jx_{ij}^k\leq f_{ij}^k\\&(j=1,\ldots,t;\quad i=0,\ldots,n;\quad i\neq j;\quad k=1,\ldots,m)\end{aligned} \tag{15}$$

$$\begin{aligned}&D_ix_{ij}^k\leq f_{ij}^k\\&(i=t+1,\ldots,n;\quad j=0,\ldots,n;\quad j\neq i;\quad k=1,\ldots,m)\end{aligned} \tag{16}$$

$$\begin{aligned}&f_{ij}^k\leq(q^k-D_j)x_{ij}^k\\&(j=t+1,\ldots,n;\quad i=0,\ldots,n;\quad i\neq j;\quad k=1,\ldots,m)\end{aligned} \tag{17}$$

Constraints (1) mean that 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) and (5) ensure that no vehicle can be overloaded. Constraint (6) guarantees that customers are not visited after any suppliers (backhauls), while constraint (7) avoids empty running on the way out. Starting service times are calculated in constraints (8) and (9). These constraints also avoid subtours. Time windows are imposed by constraints (10). Constraints (11) avoid exceeding the maximum allowable driving time. Balance of flow is described through constraints (12) and (13). Constraints (14)–(17) are used to restrict the total load a vehicle carries.

The goal of the problem is to construct several routes minimizing the sum of internal and external costs. The internal costs (IC) associated with a given route is composed of five major items: costs of driver (DRC), energy costs (ENC), fixed cost of vehicles–investment, inspection, insurance- (FXC), maintenance costs (MNC) and toll costs (TLC). In addition, the external costs (EC) and social effects of transportation activities are considered. They are composed of: climate change costs (CCC), air pollution costs (APC), noise costs (NSC) and accidents costs (ACC).

$$\begin{aligned} Minimize\ IC + EC = & (DRC + ENC + FXC + MNC + TLC) \\ & + (CCC + APC + NSC + ACC) \end{aligned} \tag{18}$$

The mathematical forms of the aforementioned components shown in Eq. (18) are presented below.

$$DRC = \sum_{k=1}^{m} p^k y_0^k \tag{19}$$

$$ENC = \sum_{i=0}^{n} \sum_{\substack{j=0 \\ j \neq i}}^{n} \sum_{k=1}^{m} \sum_{r=1}^{R} fc^r \delta^{kr} d_{ij} (fe^k x_{ij}^k + feu^k f_{ij}^k) \tag{20}$$

$$FXC = \sum_{i=1}^{n} \sum_{k=1}^{m} fx^k x_{0i}^k \tag{21}$$

$$MNC = \sum_{i=0}^{n} \sum_{\substack{j=0 \\ j \neq i}}^{n} \sum_{k=1}^{m} mn^k d_{ij} x_{ij}^k \tag{22}$$

$$TLC = \sum_{i=0}^{n} \sum_{\substack{j=0 \\ j \neq i}}^{n} \sum_{k=1}^{m} tl_{ij} x_{ij}^k \tag{23}$$

$$CCC = \sum_{i=0}^{n} \sum_{\substack{j=0 \\ j \neq i}}^{n} \sum_{k=1}^{m} \sum_{r=1}^{R} pe^{CO2} \delta^{kr} ef^{CO2,r} d_{ij} (fe^k x_{ij}^k + feu^k f_{ij}^k) \tag{24}$$

$$APC = \sum_{i=0}^{n} \sum_{\substack{j=0 \\ j \neq i}}^{n} \sum_{k=1}^{m} \sum_{r=1}^{R} \sum_{t=1}^{T} \sum_{p=1}^{P} pe^p \delta^{kr} \gamma^{kt} ef^{p,t} d_{ij} x_{ij}^k \tag{25}$$

$$NSC = \sum_{i=0}^{n} \sum_{\substack{j=0 \\ j \neq i}}^{n} \sum_{k=1}^{m} ne\ d_{ij} f_{ij}^k \tag{26}$$

$$ACC = \sum_{i=0}^{n} \sum_{\substack{j=0 \\ j \neq i}}^{n} \sum_{k=1}^{m} ae \; d_{ij} f_{ij}^{k} \tag{27}$$

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
δ^{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)
pe^{CO2}	unit price per ton of CO_2 emitted
$ef^{CO2,r}$	emission factor, amount of CO_2 emitted per unit of fuel r consumed
pe^p	the unit price per ton of the pollutant p emitted
$ef^{p,t}$	amount of pollutant p emitted from technology vehicle t per km travelled
γ^{kt}	equal to 1 if vehicle k belongs to technology t
ne	costs of noise emissions per ton of load carried and per km travelled
ae	costs of accidents per ton of load carried and per km travelled

4.2 A Heuristic Algorithm to Solve the HVRP

Our approach to solving HVRP is based on the savings heuristic originally proposed for the routing problem by (Clarke and Wright 1964). Because Clarke and Wright heuristic was not designed for heterogeneous fleet with capacity constraints, an extension that evaluates the benefit of merging two routes and then assigns a vehicle with feasible capacity to satisfy the demand has been incorporated.

The extended algorithm includes the ability to perform with a heterogeneous fleet. Thus, the route costs are calculated for all vehicles, regardless of meeting with the capacity condition, and then the saving costs for all vehicles can be obtained. Finally, the candidate routes to be fused can be selected based on several criteria, a highest saving or a highest average saving. When two routes are, fused an assignment problem is solved to get the best assignment of vehicles to routes (based on cost criteria).

In the initial iteration process, any generated solution has a high probability to be unfeasible, because the number of routes may exceed the number of available vehicles. Also in the last algorithm iterations, routes cannot be fused because demands exceed the vehicle capacity. Therefore, the heuristic has to select the best solution that will be acceptable compared with the solutions in subsequent iterations.

Finally, it's possible that the problem will be not feasible (for example with high demands in delivery points and few vehicles with low capacity). Given this case, the algorithm has a feasible verification process. The algorithm diagram is represented in Fig. 1

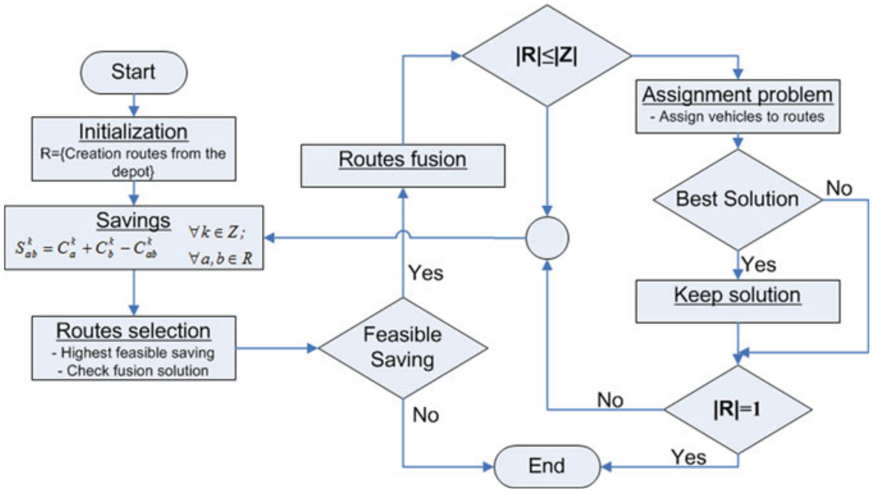

Fig. 1 Savings algorithm diagram

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

4.2.1 Savings Calculation

After each fusion route process, the algorithm calculates for each vehicle, the savings cost between each pair of routes from set R (28), obtaining a savings matrix for each vehicle. Vehicle availabilities and capacities conditions are not taken into account in savings calculation.

$$S_{ab}^k = C_a^k + C_b^k - C_{ab}^k \quad \forall k \in Z; \quad \forall a, b \in R \tag{28}$$

where:

S_{ab}^k is the saving between routes a and b when performed with a vehicle k

C_{ab}^k is the total cost of fusion routes a and b when performed with a vehicle k.

Once the savings matrix for each vehicle is obtained, average values (29) are calculated. The highest value of this matrix designates the two candidate routes to be joined.

$$S_{ab} = \frac{\sum_{\forall k} S_{ab}^k}{m} \quad \forall k \in Z; \quad \forall a, b \in R \tag{29}$$

4.2.2 Check Fusion Routes

To guarantee feasibility, a fusion route check procedure is considered. It orders the routes from higher to lower demand and sequentially routes are assigned to the smaller capacity feasible vehicle. If all routes demands are linked into vehicles, the solution is feasible and routes are joined; otherwise the next largest saving value is chosen and the check procedure is repeated.

4.2.3 Keep the Best Solution

Every time the number of routes in R is less or equal to the number of available vehicles, it is possible to obtain a new feasible solution for the problem. For this purpose, the Hungarian Algorithm is used. It is a combinatorial optimization algorithm which solves the assignment problem in polynomial computing time.

When two routes have been joined and the condition to obtain a solution is satisfied, the algorithm evaluates the assignment problem and keeps the solution if it is better than a previous found.

4.2.4 Lambda OPT Framework

Savings Algorithm ends with 2-optimal and 3-optimal procedures applied to each of the found routes from the feasible solution to improve them.

5 A Numerical Example

In this section, we use a four-node illustrative example to show the differences between using three objective functions: minimizing the total distance travelled (1), minimizing the total internal costs (2) and minimizing the total internal and external costs (3). We also study the traditional CVRP with Heterogeneous Fleet (a), versus the effect of adding Backhaul (b), adding also maximum allowable driving Time (c), and adding also Time Window (d). Thus, 12 instances from the HVRPTWB are solved using optimization software.

We consider the four node network of Fig. 2, with 3 different vehicles at node 0 to serve customers 1, 2 and 3. We consider an average speed of 50 km/h on each arc. Then the driving times t_{ij} between nodes are 1, 2 and 2.24 h, depending on the length of the arc. We assume a homogeneous load demanded by each node as $D_i = 8$ ton. Service times are set to $S_i^k = 1$ h in all nodes by all vehicles, and there are no toll costs.

Table 1 shows the parameters associated to each vehicle of the fleet. Table 2 shows the parameters associated to fuel unit costs, external unit costs and emission factors of vehicle types used. As mentioned above, 12 instances are modeled using the MILP problem. In case (b) we consider a backhaul in node 2 with a demand of

Fig. 2 Four node example

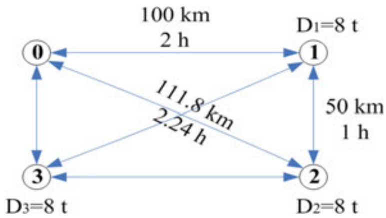

Table 1 Fleet parameters

Vehicles (k)	1	2	3
q^k (tons)	9.5	18	9.5
p^k (€/h)	19.89	21.40	19.89
Type of fuel (r)	Diesel	Diesel	Diesel
fe^k (l/100 km)	17.50	19.80	17.50
feu^k (l/ton·100 km)	1.05	0.75	1.05
fx^k (€/day)	42.65	54.60	42.65
mn^k (€/km)	0.0590	0.0787	0.0590
Technology (t)	Rigid; 12–14_t; Euro_IV t = 2	Rigid; 20–26_t; Euro_IV t = 3	Rigid; 12–14_t; Euro_II t = 1

Table 2 Unit costs

fc^{diesel} (2010€/l)	0.9009		
pe^{CO2} (2010€/ton)	25		
$ef^{CO2,diesel}$ (kg/l)	2.67		
Pollutant (p)	NOx	NMVOC	PM
pe^p (2010€/ton)	3439.8	529.2	76337.1
$ef^{p,1}$ (g/km)	5.50	0.207	0.1040
$ef^{p,2}$ (g/km)	2.65	0.008	0.0161
$ef^{p,3}$ (g/km)	3.83	0.010	0.0239
ne (2010€/ton-km)	0.00648		
ae (2010€/ton-km)	0.00635		

$D_2 = -8$ ton. In case (c) we also assume a maximum driving time for each vehicle of 8 h. And finally in case (d) we also set a time window in node 1 of [3, 5 h]. We have used CPLEX 11.1 with its default settings to solve the 12 MILP instances. Eight different solutions have been found (Table 3). The solutions associated to each instance and the objective functions are illustrated in Table 4.

Some implications of the results presented in Table 4 are as follows.

Optimal solutions which consider the traditional objective function of minimizing total distance travelled (Sol#1 to Sol#4) are not optimal in some cases when the objective function includes costs parameters. But optimal solutions which consider internal and external costs in the objective function (Sol#5, #2, #6 and #8) are also optimal minimizing distances or internal costs. The reason is that minimizing internal costs is quite similar to minimizing distances.

Table 3 Different optimal solutions

Solution	Vehicle	Optimal route	Load (ton)	Arrival time (h)
#1	1	0-3-0	8-0	3
	2	0-2-1-0	16-8-0	7.24
#2	2	0-3-1-2-0	16-8-0-8	9.48
#3	1	0-3-0	8-0	3
	3	0-1-2-0	8-0-8	7.24
#4	1	0-1-0	8-0	6
	2	0-3-2-0	8-0-8	7.24
#5	1	0-3-0	8-0	3
	2	0-1-2-0	16-8-0	7.24
#6	1	0-1-2-0	8-0-8	7.24
	3	0-3-0	8-0	3
#7	1	0-1-0	8-0	6
	3	0-3-2-0	8-0-8	7.24
#8	1	0-3-2-0	8-0-8	7.24
	3	0-1-0	8-0	6

Table 4 Solutions and values of the three objective functions for all the instances

Instance	Solution	Objective function 1 Total distances	Objective function 2 Total inernal costs	Objective function 3 Total costs
1a	#1	361.8[a]	419.5	463.9
1b	#2	323.6[a]	358.3[a]	402.0[a]
1c	#3	361.8[a]	387.2[a]	428.1
1d	#4	461.8[a]	498.6	538.6
2a	#5	361.8[a]	418.2[a]	460.0[a]
2b	#2	323.6[a]	358.3[a]	402.0[a]
2c	#6	361.8[a]	387.2[a]	425.2[a]
2d	#7	461.8[a]	468.6[a]	511.6
3a	#5	361.8[a]	418.2[a]	460.0[a]
3b	#2	323.6[a]	358.3[a]	402.0[a]
3c	#6	361.8[a]	387.2[a]	425.2[a]
3d	#8	461.8[a]	468.6[a]	510.5[a]

[a] Optimal solution with that objective function

When a heterogeneous fleet is considered, adding external costs implies the selection of the less pollutant vehicles or the assignment of longer routes to those vehicles (Sol#7 vs. Sol#8), maintaining minimum total internal costs.

Depending on the type of VRP, the analysis of performance measures must be different. Solutions including backhauls reduce all the costs [see Table 4, Inst. (b) vs. Inst. (a)]. But adding time constraints increase the costs [see Table 4, Inst. (d) or Inst. (c) vs. Inst. (b)]. Using the total costs allows comparing different solutions and selecting the most appropriate. For example, Sol#8 is better than Sol#7 for the external cost, and also Sol#7 is better than Sol#4 for the internal and external costs.

6 A Real Case Application

This section shows the results obtained by analyzing the delivery activity of a Spanish leading supermarket chain in the region of Huelva, a southern Spanish province.

In this region, the network consists of 17 supermarkets or delivery points, which are spread throughout the province (See Fig. 3) served directly from a central distribution center (Depot). Service times are set to $S_i^k = 1$ h in all nodes by all vehicles, and there are no toll costs.

The optimal resolution of the model has been made with CPLEX 11.1 with default parameters in a 3, 30 GHz Intel(R) Core(TM) i5-2400 CPU.

As in the above example, it is used the same heterogeneous fleet to show differences in the use of three different objective functions: minimizing the total distance traveled (1), minimizing internal costs (2) and minimizing internal and external costs (3), taking into account the capacity constraints on each one. The number of vehicles of each class is doubled, to guarantee a feasible solution to the problem.

It is also compared this problem (type *a*), to the inclusion of a maximum driving time of 8 h (type *c*) and limitations of time windows in nodes (type *d*). In problems type *a*, *c* and *d*, a maximum computing time of one, two and four hours has been established respectively and a gap value is obtained. This gap value indicates the percentage of the search space that still remains to be processed with a tolerance of 10^{-4}.

Data concerning the location in geographic coordinates of the distribution and delivery points are summarized in Table 5.

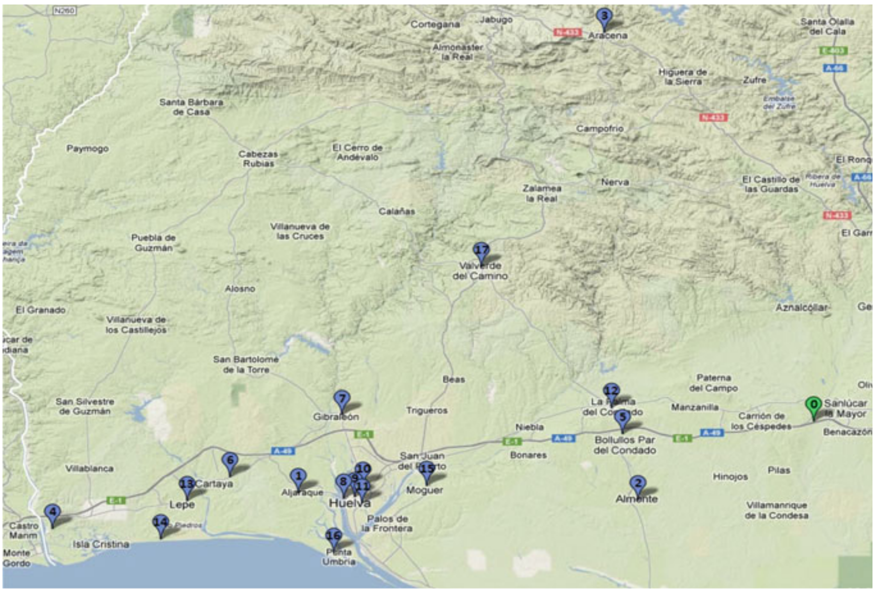

Fig. 3 Distribution and delivery point's locations

Table 5 Distribution and delivery points location

Node	Denomination	Geographic coordinates
0	Depot	37.36777, −6.251307
1	Aljaraque	37.269481, −7.028072
2	Almonte	37.2602, −6.515853
3	Aracena	37.897758, −6.56756
4	Ayamonte	37.22076, −7.399118
5	Bollullos Par del Condado	37.350237, −6.540298
6	Cartaya	37.291339, −7.131093
7	Gibraleón	37.376795, −6.963138
8	Huelva 1	37.262245, −6.959466
9	Huelva 2	37.264112, −6.942893
10	Huelva 3	37.278407, −6.930155
11	Huelva 4	37.25542, −6.932226
12	La Palma del Condado	37.385996, −6.556054
13	Lepe 1	37.258957, −7.196568
14	Lepe 2	37.206551, −7.235068
15	Moguer	37.279747, −6.834899
16	Punta Umbría	37.187369, −6.975337
17	Valverde del Camino	37.578435, −6.752129

The costs of travelling between each two customers, the distances and the travelling time, have been obtained using the Google Maps application.

It is assumed a homogeneous load demanded by each node as $D_i = 1$ ton. In this problem, it has been chosen the same heterogeneous fleet of case 2 (Table 1) but the number of vehicles of each class is doubled to guarantee a solution, being vehicles number 4, 5, 6 the same than 1, 2 and 3 respectively.

Table 6 shows the nodes chosen for this problem with their demands and time windows, while Tables 7 and 8 show the results obtained.

As Table 8 shows, the solutions to the problems, do not ensure that they are optimal, since the gap value obtained indicates that the search space has not been totally explored. This can be tested in the solutions found for every type of problem of minimizing total costs, which have smaller internal costs than the solution found to minimizing those costs.

These results suggest that heuristics approaches are necessary to find high quality solutions to the environmental model.

7 Experimental Results

To analyze the behavior of the heuristics described above, it has been programmed in C++. Computational tests have been performed on the real case of study described in Sect. 6, and also on eight HVRP large instances, well-known as Taillard problems.

Table 6 Demands and time windows for the 17 nodes problem

Node	Demand (ton)	Time window (h)
0	–	[0–8]
1	1	[4–8]
2	1	[4–8]
3	1	[0–4]
4	1	[0–4]
5	1	[4–8]
6	1	[0–4]
7	1	[0–4]
8	1	[0–4]
9	1	[0–4]
10	1	[0–4]
11	1	[4–8]
12	1	[4–8]
13	1	[4–8]
14	1	[0–4]
15	1	[0–4]
16	1	[0–4]
17	1	[0–4]

In the real case application, the *type a* problem (without time window constraints) has been solved using the savings heuristic proposed in Sect. 4. The solutions obtained for the three different objective functions (minimizing the total distance traveled, minimizing internal costs and minimizing internal and external costs) are compared respect to the best solution value obtained with CPLEX in the established computing time.

In order to validate the heuristic behavior for large problems, a set of 8 instances from the HVRP literature have been solved and compared respect to the best known solutions for each instance.

7.1 The Real Case Application

Type *a* problem does not have time windows (TW) constraints. Table 9 shows the results obtained and compare the heuristic and the better solution found with the optimization software.

With respect to solution quality, the heuristic savings algorithm obtained the same solution as CPLEX for minimizing the distance traveled. The deviation from the best solution found by CPLEX in the established computing time was quite small (less than 1 %).

Table 7 Route and travel time solutions for the 17 nodes problem

Problem	Objetive function	Vehicle	Route	Time (h)
Type a (no. max. driving time)	Distance	3	0-5-0	1.60
		5	0-12-17-3-7-4-14-13-6-1-16-8-9-11-10-15-2-0	23.86
	Internal costs	1	0-5-2-12-17-3-0	8.96
		2	0-15-7-10-11-9-8-16-1-6-13-14-4-0	16.61
	Internal + external costs	1	0-9-8-11-10-7-15-17-3-0	12.99
		4	0-5-2-4-14-13-6-1-16-12-0	13.43
Type c (max. driving time 8 hours)	Distance	2	0-5-12-17-3-0	7.44
		4	0-16-1-8-9-11-0	7.55
		5	0-15-10-7-2-0	6.45
		6	0-13-6-14-4-0	7.14
	Internal costs	1	0-6-13-4-14-0	7.01
		3	0-5-2-9-11-15-0	7.47
		5	0-7-1-16-8-10-0	7.57
		6	0-12-17-3-0	6.39
	Internal + external costs	1	0-6-13-14-4-0	6.84
		4	0-5-12-17-3-0	7.44
		5	0-15-7-16-1-0	6.79
		6	0-10-11-9-8-2-0	7.31
Type d (time windows)	Distance	1	0-7-10-15-2-0	6.48
		3	0-3-17-12-5-0	7.44
		5	0-9-8-16-1-11-0	7.59
		6	0-6-4-14-13-0	7.00
	Internal costs	1	0-15-10-7-12-0	6.22
		3	0-4-14-6-11-0	7.26
		4	0-3-17-5-2-0	7.95
		6	0-9-8-16-1-13-0	7.84
	Internal + external costs	1	0-9-16-10-12-2-0	7.94
		3	0-6-4-14-13-0	7.00
		4	0-15-7-8-11-1-0	7.74
		6	0-3-17-5-0	6.42

7.2 Taillard Problems

In this section we describe the performance of the heuristic algorithm on the set of 8 instances from Taillard problems (13–20) and compare the solutions to the results reported in the literature. Taillard problems do not have TW constraints.

As illustrated in Table 10, the heuristic savings algorithm seems to perform well, with an average percentage difference from the best known solution of 11.09 %. It is important to mention that the proposed heuristic has been developed to solve the HVRP with internal and external costs, and Taillard instances are prepared to solve the HVRP with Dependent routing costs.

Table 8 Solution values of the three objective functions for the 17 nodes problem

Problem	Objetive function	Distance (km)	Internal costs (€)	External costs (€)	Total costs (€)	Gap (%)	Run time (s)
Type a	Distance	520.80	801.97	75.55	877.52	8.61	3,600
	Internal costs	567.60	779.88	39.13	819.01	74.39	3,600
	Internal + external costs	628.60	768.51	44.65	813.15	70.91	3,600
Type c	Distance	859.10	1.000.41	47.59	1.048.01	45.70	7,200
	Internal costs	851.20	965.12	47.41	1.012.53	77.46	7,200
	Internal + external costs	852.20	963.09	42.21	1.005.30	73.82	7,200
Type d	Distance	849.40	970.32	55.15	1.025.47	29.70	14,400
	Internal costs	903.70	968.57	56.46	1.025.03	61.11	14,400
	Internal + external costs	888.40	960.91	54.86	1.015.77	62.31	14,400

Table 9 Comparison on the algorithm on type a problem

Problem	Obj func.pollution-routing problem	CPLEX (max 3,600 s)			Savings algorithm	
		Cost (€)	Time (s)	Solut. (%)	Cost (€)	Error (%)
17a	Distance	520.8	3,600	8.61	520.80	0.00
	Internal costs	779.88	3,600	74.39	786.78	0.88
	Internal + external costs	813.15	3,600	70.91	822.03	1.09

Table 10 Comparison on the algorithm on Taillard problems

Problem	Nodes	Best known solution	Savings algorithm	
			Cost (€)	Error (%)
13	50	1,517.84	1,720.57	13.36
14	50	607.53	661.02	8.80
15	50	1,015.29	1,110.21	9.35
16	50	1,144.94	1,248.78	9.07
17	75	1,061.96	1,159.59	9.19
18	75	1,823.58	1,990.70	9.16
19	100	1,117.51	1,327.57	18.80
20	100	1,534.17	1,702.80	10.99

8 Conclusions

Research in Vehicle Routing Problems still needs more extensive study in the areas of environmental issues and heterogeneous fleet with time windows constraints. There are few publications that address eco-efficiency objectives in vehicle routing and scheduling problems. The need for companies to incorporate these external factors as part of their planning and operational process is forcing traditional VRP studies to model the fuel consumption, the pollutants emissions and other external impacts within the objective function.

In this chapter, external factors were incorporated in a mixed integer linear programming model for solving the traditional VRP with realistic assumptions such as a limited number of heterogeneous vehicles, time windows constraints and backhauls (HVRPTWB). Before the model was suggested, literature reviews on VRP with heterogeneous fleet and on VRP and sustainability were presented. Due to the intrinsic difficulty of this type of routing problems, solution approaches in the literature are heuristic algorithms. In this chapter, a new heuristic algorithm that extends the savings algorithm of Clark and Wright was developed to solve the HVRP.

A numerical example was showing to illustrate and validate the model. A real case application for the HVRPTW was presented and solved using optimization software with a limited computing time and using the proposed heuristic in some cases. Finally the heuristic was tested on the set of 8 instances from Taillard for HVRPD. Computational results show good quality solutions and may be used to solve the new eco-efficiency model without time windows.

Further research may lead to the development of a new metaheuristic algorithm to incorporate time windows. Also further work on quantifying the congestion factor is in order. Finally, we are incorporating variations in speed as part of the model.

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