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Internalizing negative externalities in vehicle routing problems through green taxes and green tolls

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Abstract

Road freight transportation includes various internal and external costs that need to be accounted for in the construction of efficient routing plans. Typically, the resulting optimization problem is formulated as a vehicle routing problem in any of its variants. While the traditional focus of the vehicle routing problem was the minimization of internal routing costs such as travel distance or duration, numerous approaches to include external factors related to environmental routing aspects have been recently discussed in the literature. However, internal and external routing costs are often treated as competing objectives. This paper discusses the internalization of external routing costs through the consideration of green taxes and green tolls. Numeric experiments with a biased-randomization savings algorithm, show benefits of combining internal and external costs in delivery route planning.

MSC: 90B06.

Keywords: Vehicle routing problem, biased randomization, green logistics, negative road externalities, internalization.

1. Introduction

Vehicle routing management is one of the most important operational activities in road freight transportation. Delivery routes are typically established by solving the NP-hard vehicle routing problem (VRP) in any of its variants (Caceres-Cruz et al., 2014; Toth and Vigo, 2014). However, the optimization of explicit operational costs is only one side of the coin. Delivery route planning has long focused on monetary aspects. Nevertheless, the negative externalities of road freight transportation related to air pollution, excessive noise levels, and traffic congestion are particularly noticeable in urban areas (European Union, 1999b; United Nations, 2016; United States Environmental Protection Agency, 2014; European Commission, 2009). In this context, different green

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logistics concepts aiming to reduce the negative impacts of road transportation have been presented (Bekta and Laporte, 2011; Gajanand and Narendran, 2013; Lin et al., 2014). Furthermore, the topic is still catching the interest of the academia as recent papers continue addressing the topic (Xiao et al., 2012; Kancharla and Ramadurai, 2018; Sawik, Faulin and Pérez-Bernabeu, 2017a, 2017b). In these papers, typically, some kind of emission estimation based on routing characteristics such as distance, load levels, vehicle type, road gradient, etc. are included in the optimization models. These estimations are then considered in the objective function in order to minimize the relevant variable.

By either focusing on monetary or environmental objectives, different factors are treated as competing variables, looking for either the cheapest solution or the least polluting option. Therefore, a way to internalize negative externalities into operational costs is of utmost interest. This paper proposes internalization through green taxes and green tolls, and evaluates the effects on company behaviours of such fiscal policies. Moreover, this paper reviews relevant literature about monetization of environmental costs and propose those values as taxation.

2. Literature review

Within the context of green logistics and road freight transportation, environmentally aware delivery route planning has received much attention in recent years (Helo and Ala-Harja, 2018). Next to new optimization problems arising from the use of new technologies such as electric vehicles (Juan et al., 2016) and the development of innovative supply chain strategies such as horizontal collaboration aimed at reducing routing related emissions (Serrano-Hernandez et al., 2017), especially the inclusion of green minimization objectives has been discussed. In this context, the green VRP (GVRP) focuses on minimizing fuel consumption instead of traditional cost- or distance based optimization targets (Erdogan and Miller-Hooks, 2012). The environmental routing impact is typically estimated with respect to the operating vehicle and some distinct criteria effecting predicted consumption/emission values. Especially travel speed, vehicle load levels, routing distances, and road gradients have been discussed (Bekta and Laporte, 2011; Demir, Bektas and Laporte, 2014; Lin et al., 2014).

Even though the GVRP is still a rather new topic, some optimization approaches have already been presented (Ubeda, Arcelus and Faulin, 2011). The energy minimizing VRP is defined by Kara, Kara and Kadri Yetis (2007), who propose a cost function for the VRP based on the product of vehicle load and travel distance. In Tavares et al. (2009), road gradient and vehicle weight is considered in optimizing fuel consumption in waste collection processes. The time dependent VRP is addressed by Kuo (2010). While the author considers different travel times and varying vehicle speed depending on the time of the day, the objective function is the minimization of fuel emissions considering vehicle loads and travel speed. The resulting model is solved with a simulated annealing metaheuristic, showing significant reductions of fuel consumption compared to objectives based on the minimization of travel time/distance. A fuel consumption rate based on vehicle load levels (similar to the approach applied in this paper) is proposed in the work of Xiao et al. (2012). The potential benefits of applying environmentally driven models compared to traditional VRPs is also shown using a simulated annealing approach. Even though not directly related to the GVRP, the load dependent vehicle routing problem is closer examined by Zachariadis, Tarantilis and Kiranoudis (2015). The authors consider cargo weight variations in routing activities in which transported cargo accounts for a significant amount of vehicle weight. Fuel consumption is, however, not directly addressed in their work. Regarding internalization in logistics activities, it is noticeable the Abdallah et al. (2012) work who presented a novel approach to greening the supply chain. They took into account a carbon trading mechanism for pricing emissions. Later, they formulated a mixed integer program that minimizes the sum of supply chain costs and carbon trading costs.

More recently, some papers from Sawik et al. (2017a, 2017b) consider multicriteria approaches to deal with economic and environmental criteria at the same time. Nevertheless, in those works there is not an explicit internalization of environmental costs (i.e. no pricing is performed). Likewise, Xiao et al. (2012) also propose a multiobjective model for the GVRP in which speed is a relevant variable to optimize. However, they focus on their suggested algorithm and show the advantages of the hybrid quantum immune heuristic. Finally, the driving behaviour is taken into consideration in Kancharla and Ramadurai (2018) paper as they address the effect of acceleration on fuel consumption and emissions. Similarly, there is a lack of explicit internalization of external costs derived from the emissions, although they consider a richer model for estimating such emissions.

2.1. Routing externalities and internalization

Considering the definition by Laffont (2008), externalities are (...) indirect effects of consumption or production activity, that is, effects on agents other than the originator of such activity which do not work through the price system. Thus, it becomes clear that not only environmental aspects related to emission factors have to be included in routing optimization. According to Ranaiefar and Amelia (2011), negative routing externalities can be classified into four different impact areas: (*i*) economy, which include congestion, road damage and longer travel times; (*ii*) society, comprising accidents, visual intrusion and noise pollution; (*iii*) ecology, encompassing biodiversity destruction and climate change; and (*iv*) the environment, including waste, air, and water pollution. Many works have tried to physically measure such externalities. To this respect, Demir et al. (2015) give an extensive review on externalities modeling in which they accounted for several different methodologies to deal with emissions, noise, congestion and accidents. The same paper also includes a pricing section, concluding that further research should be made in that direction.

In order to incorporate such externalities in delivery route planning, monetary values have to be considered to be able to price these factors. Different approaches were carried out by Litman (2006) and Delucchi and McCubbin (2010) reports. In the extensive Litman (2006) one, it is reviewed plenty of prior works regarding transportation costs (internal and external). Noise and air pollution are visited listing various circumstances to estimate the external cost. For instance, noise costs depend on the type of vehicle, density of the area, type of road and daytime. According to their revision, the 34 tonne-truck noise costs range from USD(2007) cents 0.0088 to USD(2007) cents 0.235294 per tonne and mile whereas the Delucchi and McCubbin (2010) one estimates in USD(2006) cents 0.0-5.3. On the other hand, air pollution cost is usually analysed from the "damage function" approach described by Adamowicz (2003). It consists of valuating the relationship in welfare due to a change in the emissions, mainly divided into different types of harmful emissions: CO_2, CO, PM_{10}, CH_4, and so on. Later, a price is assigned to each based on health care costs. Then, physical emissions are calculated and translated into monetary units using the previous prices. In the report, Litman (2006) concluded the automobile air pollution costs range from USD(2007) cents 0.0032 to 0.7352 per tonne and mile similarly to Delucchi and McCubbin (2010) who estimated such costs in USD(2006) cents 0.1-18.7. Note that the high variation between these reports is due to the different characteristics in the vehicle, road and weather conditions, thus being one of the main drawbacks.

3. Internalization of green taxes and green tolls

The capacitated VRP can be formulated on a graph $G = (V, E)$. Vertex set $V = L \cup 0$ describes a subset $L = 1, 2, \ldots, l$ of l customer nodes with demand $d_i \geq 0$ for all $i \in L$ and the central depot 0, at which a homogeneous fleet of vehicles with maximum capacity Q is located. Set $E = (i, j) : i, j \in V, i \neq j$ describes the connections between any two nodes i and j, whereas the travel distance $dist_{ij}$ to traverse any edge are assumed to be known. The objective of the (traditional) VRP is to minimize a distance-based costs function driven by a fleet of vehicles to serve a set of customers, subject to the following constraints: (*i*) vehicle routes start and end at the same depot, (*ii*) no customer node is visited twice, and (*iii*) vehicle capacities need to be adhered to.

Naturally, the objective of minimizing overall travel distance can be enhanced. Our approach introduces external costs $extCost_{ij}$ for each edge $(i, j) \in E$ that are made of green taxes t_{ij} and green tolls v_{ij}. Therefore, the full cost $fullCost_{ij}$ associated to each edge is described in Equation 1:

$$fullCost_{ij} = intCost_{ij} + extCost_{ij} = intCost_{ij} + t_{ij} + v_{ij} \tag{1}$$

The green taxes are charged on fuels so they will depend on fuel consumption whereas green toll costs are charged as tolls if the vehicle enters in high quality environmental areas that may be somehow protected. Note that now we deal with a directed graph since $fullCost_{ij}$ may not be equal to $fullCost_{ji}$. A real example of a green toll is functioning in some European countries. Known as Eurovignette (European Union, 1999a), it is a road user charge for heavy vehicles to account for external costs of air and noise pollution, among other costs. Therefore, the objective function consists of two components: the traditional distance-based (internal) costs and the external costs, compounded by the green taxes and the green tolls.

1. Internal costs. These costs comprise driver wage, asset depreciation and fuel cost and can be summarized as shown in Equation 2 where C_d is a cost parameter per unit of distance for any edge.

$$intCost_{ij} = C_d \, dist_{ij} \tag{2}$$

2. External costs. Green tax costs are charged to fuel. Therefore, the amount of green tax paid is described in Equation 3, where C_t is a cost parameter per unit of fuel consumed φ_{ij}. On the other hand, the green toll is paid according to the environmental category of the area as described in Equation 4.

$$t_{ij} = C_t \, \varphi_{ij} \tag{3}$$

$$v_{ij} = \begin{cases} C_v^l, & \text{if node } j \text{ belongs to a low environmental} \\ & \text{value area and node } i \text{ does not} \\ C_v^m, & \text{if node } j \text{ belongs to a medium environmental} \\ & \text{value area and node } i \text{ does not} \\ C_v^h, & \text{if node } j \text{ belongs to a high environmental} \\ & \text{value area and node } i \text{ does not} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

Being $C_v^l \leq C_v^m \leq C_v^h$ Note that we distinguish three different quality areas in order to give more flexibility for policymaking. In this sense, consider a high quality environmental area those places that could be significantly affected by the transportation activity, i.e. national parks, biosphere reserves, world heritage sites, etc. The medium quality area is devoted for a lower level of protection such particular landscapes proposed by local/regional authorities. The rest of places could be categorized as low environmental quality area.

3.1. Measuring fuel consumption

Estimating properly the fuel consumption is of utmost interest in our work since most pollutants are released to the environment when fuel is burnt. Thus, we have used for this purpose the methodology proposed in Knörr et al. (2011) since it is updated, well documented, and takes into account upstream energy consumption (generation and distribution of energy), also known as well to tank (WTT). Note that this approach considers also the final pipeline energy consumption made in the transportation activity (the tank to wheel – TTW). As a combination of both, the WTT and the TTW, we get the well to wheel (WTW).

In such methodology, energy consumption is measured in megajoules and it depends on distance, payload, road slope, speed, and vehicle characteristics. All in all, for any given distance, the fuel consumption ϕ can be represented as a function of load weight as shown in Equation 5 where ϕ_e is the fuel consumption when empty, ϕ_f is the fuel consumption when fully loaded, P is the payload and Q is the vehicle capacity.

$$\phi = \phi_e + (\phi_f - \phi_e)P/Q \tag{5}$$

3.2. Pricing air pollution and GHG emissions- Estimating C_t

Air pollution is caused by emission of air pollutants like NOx, CO_2, non-methane volatile organic compounds ($NMVOC$), and particulate matters (PM) that affect people, vegetation, materials, and global climate. Climate change or global warming impacts of road transport are, mainly, generated by emissions of greenhouse gases (GHG): carbon dioxide (CO_2), nitrous oxide (N_2O) and methane (CH_4). Nevertheless, CO_2 is the dominant anthropogenic GHG, and the remaining GHG can be expressed as CO_2 equivalent (CO_{2e}) as described in Equation 6[1]:

$$CO_{2e} = CO_2 + 25CH_4 + 298N_2O \tag{6}$$

Table 1, based on Korzhenevych et al. (2014) shows average EU prices for 1 kg of pollutant component, in EUR(2010). On one hand, air pollution components are priced, generally, attending to the related health costs and crop losses. Later they are computed based on the average exposure. On the other hand, GHG, i.e CO_{2e}, are priced attending to prevention costs to reduce risk of climate change and the damage costs of increasing global temperature.

Table 1: *Prices for 1 kg of emitted component in EUR(2010), based on Korzhenevych et al. (2014).*

Component	Harmful effects	EUR(2010)/Kg
NOx	Smog, soil acidification	12.81
$NMVOC$	Smog, damage to health	1.89
SO_2	Soil acidification, damage to health	12.35
PM	Damage to health	47.73
CO_{2e}	Climate change	0.11

1. CO_{2e} is computed using the Global Warning Power (GWP) of the GHG relatively to the CO_2. To this respect, it is assumed that CO_2 GWP is 1, CH_4 GWP is 25 times the CO_2 GWP, and N_2O GWP is 298 times the CO_2 GWP. Further information can by found in the didactic document written by Brander (2012).

4. Solving approach

The vehicle routing problem (VRP) is one of the most studied problems in combinatorial optimization, with many real-world applications as well as logistics and transportation (Toth and Vigo, 2014). Since its appearance in 1959 by Dantzig and Ramser (1959), who made for the first time a formulation of the problem for a fuel distribution application, the study of the VRP problem has generated numerous research works and thousands of articles have been written about many variants of the classical problem (Caceres-Cruz et al., 2014). VRP is known to be a NP-hard problem and its exact solution can be only achieved for very small instances. Therefore, heuristics algorithms are widely used for solving the VRP. To this respect, the savings heuristic proposed by Clarke and Wright (1964) is still widely used because it is simple to implement and it returns relatively good and extremely fast solutions. Nevertheless, many improvements can be made to this classical heuristics in order to obtain better solutions.

A biased randomization of the classical savings heuristic is proposed in this paper following the ideas described in Grasas et al. (2017), Juan et al.(2015) and Juan et al. (2010) who showed the competitiveness of the proposed algorithm. This randomization is performed in the constructive phase using a probability distribution for selecting the nodes to merge. By doing so, every time the heuristic is executed, a different solution is returned that may outperform the best solution obtained so far. Therefore, the main difference of the randomized version of the savings heuristic is that it does not always pick the first position in the savings lists. Moreover, the biased adjective is added in such a way that the probability of selecting the nodes is not uniformly distributed but biased, contrary to greedy proposals. These biased randomized processes rely on the use of the geometric probability distribution, which is characterized by a single and bounded parameter (p). Actually, when p becomes closer to 1, the greedy behaviour of the heuristic is retrieved. Being an approach with few parameters, the algorithm does not require fine-tuning processes, which tend to be time consuming. The Figure 1 shows the flowchart of the proposed algorithm.

Given that we have to decide on the value of the aforementioned parameter (p), a learning mechanism for dynamically setting the value is implemented. Initially, we set the value at 0.2 as it is shown values belong to the (0.05, 0.25) interval provide a good performance of the algorithm (Juan et al., 2010). However, instead of using the same parameter value for all iterations we update it according to the results we are obtaining. We set the threshold for updating p at 5%. It means that if the current iteration gives a solution at least 5% worse than the best solution achieved so far, then the parameter value p is updated in the same proportion. For instance, consider the Table 2 in which we have a best solution of 100 obtained with parameter value of 0.2 and a current solution of 110 at iteration k. As our new solution is 10% worse than the best one, we will change the parameter value to 0.22 and 0.18 ($\pm$ 10%) for our next two iterations ($k+1$ and $k+2$). We now look into those two new solutions and three different outcomes are possible.

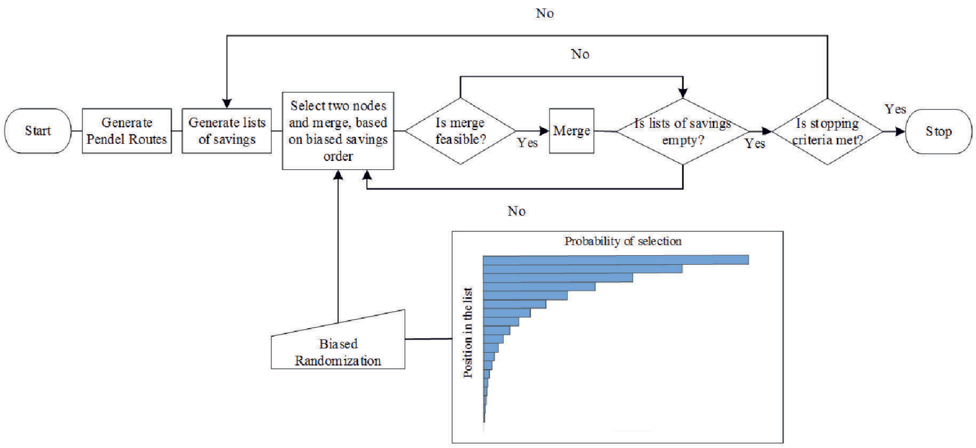

Figure 1: *Biased-randomized savings algorithm.*

Table 2: *Numerical example on the application of the learning mechanism.*

	Before iteration k Best solution= 100 $p = 0.2$	
	Iteration k Current solution= 110 $p = 0.2$	
Case A	**Case B**	**Case C**
Iteration $k+1$ Current solution= 115 $p = 0.22$	Iteration $k+1$ Current solution= 102 $p = 0.22$	Iteration $k+1$ Current solution= 115 $p = 0.22$
Iteration $k+2$ Current solution= 98 $p = 0.18$	Iteration $k+2$ Current solution= 104 $p = 0.18$	Iteration k+2 Current solution= 120 $p = 0.18$
Before Iteration k+3 Best solution= 98 $p = 0.18$	Before iteration k+3 Best solution= 100 $p = 0.2$	Before iteration k+3 Best solution= 100 $p = 0.253 \rightarrow p = 0.25$
		Before iteration $k+4$ Best solution= 100 $p = 0.187$

- Case A: a new best solution is achieved from one or both of those two iterations. Then for the next iteration it is considered the parameter value associated to the best solution obtained so far.
- Case B: no improvements are made and threshold is not exceeded. Then consider the previous solution and the initial parameter value.

- Case C: no improvements are made and threshold is exceeded. Then take the solution closest to the best solution (i.e. 150) and update the parameter value properly (± 15%). Additionally, if the value of the parameter lays out of the previous interval (0.05, 0.25), then it is used the closest value in the interval. Later, the process continues.

5. Experimental results

5.1. Parameter setting

Augerat et al. (1995) set A instances are used as database because its wide implementation in which coordinates are random points in a [100, 100] grid and demands are generated from a uniform distribution $U(1,30)$ (Uchoa et al., 2017; Faulin et al., 2011). Vehicles are defined as a standard EURO V 26-40 truck, i.e. $Q = 26$ and curb weight = 14; for parameter setting, based on Ecotransit estimations (Knörr et al., 2011). Since upstream energy consumption is taken into account, conversion factors referring to WTW are used as shown in Table 3. A standard desktop with an Intel® Core™ i5- 3570 CPU @ 3.40 GHz and 8GB RAM was used to run all the experiments with a time limit set at 120 seconds.

Table 3: *Conversion factors for tank to wheel (TTW) and considering upstream energy consumption- well to wheel (WTW).*

	TTW	WTW
$MJ/l\,diesel$	35.86	42.68
$gr\,NOx/l\,diesel$	6.79	8.25
$gr\,NMVCO/l\,diesel$	0.12	0.93
$gr\,SO_2/l\,diesel$	0.01	1.08
$gr\,PM/l\,diesel$	0.11	0.16
$kg\,CO_{2e}/l\,diesel$	2.67	3.24

With the following estimated diesel fuel (liters) consumption function per kilometer based on payload, where parameters ϕ_e and ϕ_f have been replaced by their real values according to the aforementioned vehicle.

$$\phi = 0.2364 + 0.15P/26; 0 \leq P \leq 26 \tag{7}$$

The green tax is set through the economic valuation of air pollution and GHG described in the Table 1 of Section 3. The computation is shown in Table 4.

Table 4: *Details of computation of parameter C_t.*

Pollutant	kg emitted per liter	Price per kg (EUR)	Total
NOx	0.00825	12.61	0.1040
$NMVCO$	0.00093	1.73	0.0016
SO_2	0.00108	12.03	0.0130
PM	0.00016	47.43	0.0076
CO_{2e}	3.24000	0.11	0.3564
Total (C_t)			**0.4826**

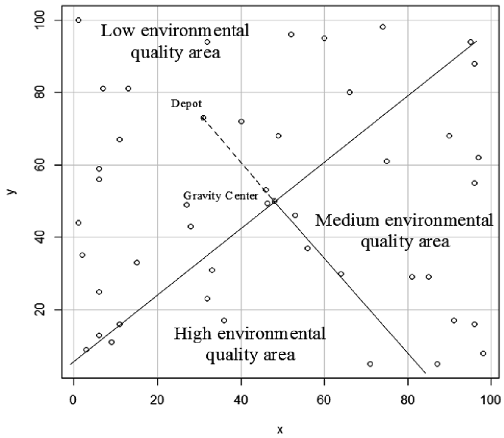

Figure 2: *Example of area allocation corresponding to the instance A-n45-k6.*

With respect to the cost parameter related to the internal costs, (C_d), it corresponds to the traditional distance-based VRP in which a cost parameter of 1.15 EUR/km has been applied. This value is considered appropriate for an average articulated truck that operates in Spain (Spanish Ministry of Transportation, 2016). Green tolls are set at 0, 10 and 30 for C_v^l, C_v^m, and C_v^h respectively. We consider those values appropriate in order to significantly influence driver behaviours. Nevertheless they are in line to those proposed in the EU for the Eurovignette (European Union, 1999a). Moreover, for our experiments, the nodes have to be assigned to one of the proposed environmental area: low, medium, and high. That process is executed for all instances in such a way that it guarantees that (i) the depot is always in the low environmental quality area, (ii) low environmental quality area represents 50% of the total area, (iii) medium environmental quality area represents 25% of the total area and, (iv) high environmental quality area represents 25% of the total area. The detailed description of the process is as follows. Firstly, the centre of gravity is computed with all the customers. Secondly, the perpendicular line at centre of gravity resulting from linking the depot to the centre of gravity is set as the border for the low environmental quality area that the depot belongs to. Thirdly, the other region is also divided into two subregions, following the line from linking the depot to the centre of gravity. Finally, the region with fewer customers is set as high environmental quality area and the other is set as medium environmental quality area. If there is a tie in customers, areas are randomly assigned. As an illustrative example, the Figure 2 shows the area allocation corresponding to the instance A-n45-k6.

5.2. Results

Detailed results are depicted in the Tables 5-8 considering the implementation of the green taxes (Table 5), green tolls (Tables 6 and 7) and both at the same time (Table 8). The structure of the instances is A-nX-kY where X is the number of nodes and Y is the number of vehicles available, i.e. maximum routes (Augerat et al., 1995). All tables have same structure. The first block contains the values corresponding to the traditional approach, i.e. the objective function is minimizing the internal costs (IC). Information about external costs (EC) was also saved when solving and it is shown in that approach. Finally, FC accounts for the full costs of operation; that is, including internal and external costs. The second block corresponds to the approach which includes EC; that is, objective function is minimizing the FC. Finally, a difference block is reported to compare the approaches.

Table 5 details the results when EC are included as green taxes. On average, including green taxes would lead to a reduction of 26.34% of external costs paid. That fact is achieved by increasing 1.57% the internal costs invoice. All in all, a reduction of 1.62% in FC is reached. Reasons behind such a reduction have to do with a much better utilization of vehicle load as well as a smarter way to do the deliveries. This is achieved by delivering high loads sooner in order to drive higher distances with a lighter vehicle. Particularly interesting is the case of instance A-n54-k7 where a huge reduction in EC is achieved by slightly increasing the IC. That suggest that in some cases there exist strong possibilities of reducing EC with simply taking them into account when optimizing. In general, those opportunities arise in bigger instances.

Table 6 depicts the results when implementing EC as green tolls. In that case a reduction of 14.38% in EC can be achieved, again slightly increasing the IC. Nevertheless, the effect on FC is lower than in the case of green taxes. Highly interesting is the information referred in the Table 7 in which H, M, L state for the fuel consumed on the areas of high, medium and low environmental quality. A last column (T) is the total fuel consumption within the three areas. Those results suggest the application of green tolls would lead to a reduction in the fuel consumed, i.e. emissions, in the high environmental quality area and an increase in the other two areas. On average, it is obtained a fuel consumption reduction of 2.84% in the high quality area and 0.37% in the medium quality area against an increase of 17.99% in the low environmental quality area. However, that also means that an increase in the fuel consumption is requested. Note that the behaviour of the medium quality area is irregular and it is not guaranteed a reduction in fuel consumption in that area as a consequence of implementing green tolls.

Finally, Table 8 combines the result of applying green taxes and green tolls as EC. As can be observed, an increase in IC of 1.23% is borne for reducing a 17.56% and a 7.52% the green taxes and green tolls costs, respectively. This finally led to a reduction of

Table 5: *Detailed results when green taxes are implemented.*

	Traditional Approach			Green Taxes					
Instance	IC	EC	FC	IC	EC	FC	Dif IC	Dif EC	Dif FC
A-n32-k5	905.05	118.77	1023.82	924.70	95.90	1020.60	2.17%	−19.26%	−0.31%
A-n33-k5	761.30	96.08	857.38	779.50	72.29	851.79	2.39%	−24.75%	−0.65%
A-n33-k6	853.30	109.11	962.41	872.25	87.24	959.49	2.22%	−20.05%	−0.30%
A-n34-k5	898.15	115.87	1014.02	916.36	87.64	1004.00	2.03%	−24.36%	−0.99%
A-n36-k5	922.30	120.21	1042.51	940.86	83.29	1024.16	2.01%	−30.71%	−1.76%
A-n37-k5	772.80	95.59	868.39	787.47	68.16	855.63	1.90%	−28.70%	−1.47%
A-n37-k6	1092.50	140.49	1232.99	1116.90	90.98	1207.89	2.23%	−35.24%	−2.04%
A-n38-k5	841.80	110.08	951.88	861.33	72.25	933.58	2.32%	−34.36%	−1.92%
A-n39-k5	955.65	122.63	1078.28	973.35	89.56	1062.91	1.85%	−26.97%	−1.43%
A-n39-k6	957.95	126.49	1084.44	970.61	94.75	1065.36	1.32%	−25.09%	−1.76%
A-n44-k7	1089.05	141.94	1230.99	1104.89	94.54	1199.43	1.45%	−33.40%	−2.56%
A-n45-k6	1097.10	140.97	1238.07	1114.84	105.63	1220.48	1.62%	−25.07%	−1.42%
A-n45-k7	1320.20	169.46	1489.66	1338.24	137.21	1475.45	1.37%	−19.03%	−0.95%
A-n46-k7	1054.55	137.60	1192.15	1069.46	91.78	1161.25	1.41%	−33.29%	−2.59%
A-n48-k7	1290.30	162.70	1453.00	1300.66	130.06	1430.72	0.80%	−20.06%	−1.53%
A-n53-k7	1173.00	150.63	1323.63	1185.15	118.21	1303.36	1.04%	−21.52%	−1.53%
A-n54-k7	1346.65	176.70	1523.35	1357.27	118.73	1476.00	0.79%	−32.81%	−3.11%
A-n55-k9	1239.70	159.80	1399.50	1249.74	104.87	1354.61	0.81%	−34.37%	−3.21%
A-n61-k9	1197.15	155.94	1353.09	1210.09	127.24	1337.33	1.08%	−18.40%	−1.16%
A-n65-k9	1373.10	177.67	1550.77	1382.27	143.37	1525.64	0.67%	−19.30%	−1.62%
Average	**1057.08**	**136.44**	**1193.52**	**1072.80**	**100.69**	**1173.48**	**1.57%**	**–26.34%**	**–1.62%**

Table 6: *Detailed results when green tolls are implemented.*

Instance	Traditional Approach			Green Tolls					
	IC	EC	FC	IC	EC	FC	Dif IC	Dif EC	Dif FC
A-n32-k5	905.05	60.00	965.05	905.05	60.00	965.05	0.00%	0.00%	0.00%
A-n33-k5	761.30	60.00	821.30	761.30	60.00	821.30	0.00%	0.00%	0.00%
A-n33-k6	853.30	70.00	923.30	861.38	60.00	921.38	0.95%	−14.29%	−0.21%
A-n34-k5	898.15	60.00	958.15	898.15	60.00	958.15	0.00%	0.00%	0.00%
A-n36-k5	922.30	60.00	982.30	922.30	60.00	982.30	0.00%	0.00%	0.00%
A-n37-k5	772.80	60.00	832.80	772.80	60.00	832.80	0.00%	0.00%	0.00%
A-n37-k6	1092.50	60.00	1152.50	1092.50	60.00	1152.50	0.00%	0.00%	0.00%
A-n38-k5	841.80	80.00	921.80	857.20	60.00	917.20	1.83%	−25.00%	−0.50%
A-n39-k5	955.65	60.00	1015.65	955.65	60.00	1015.65	0.00%	0.00%	0.00%
A-n39-k6	957.95	80.00	1037.95	959.02	60.00	1019.02	0.11%	−25.00%	−1.82%
A-n44-k7	1089.05	110.00	1199.05	1101.19	80.00	1181.19	1.11%	−27.27%	−1.49%
A-n45-k6	1097.10	90.00	1187.10	1113.83	60.00	1173.83	1.52%	−33.33%	−1.12%
A-n45-k7	1320.20	100.00	1420.20	1333.64	80.00	1413.64	1.02%	−20.00%	−0.46%
A-n46-k7	1054.55	120.00	1174.55	1063.81	90.00	1153.81	0.88%	−25.00%	−1.77%
A-n48-k7	1290.30	100.00	1390.30	1293.42	90.00	1383.42	0.24%	−10.00%	−0.50%
A-n53-k7	1173.00	110.00	1283.00	1185.64	90.00	1275.64	1.08%	−18.18%	−0.57%
A-n54-k7	1346.65	110.00	1456.65	1352.35	90.00	1442.35	0.42%	−18.18%	−0.98%
A-n55-k9	1239.70	140.00	1379.70	1250.93	110.00	1360.93	0.91%	−21.43%	−1.36%
A-n61-k9	1197.15	160.00	1357.15	1210.53	120.00	1330.53	1.12%	−25.00%	−1.96%
A-n65-k9	1373.10	160.00	1533.10	1388.13	120.00	1508.13	1.09%	−25.00%	−1.63%
Average	**1057.08**	**92.50**	**1149.58**	**1063.94**	**76.50**	**1140.44**	**0.61%**	**–14.38%**	**–0.72%**

Table 7: *Fuel consumption allocation within the three areas when green tolls are implemented.*

	Traditional Approach				Green Tolls							
Instance	H	M	L	T	H	M	L	T	Dif H	Dif M	Dif L	Dif T
A-n32-k5	62.90	71.50	111.72	246.12	62.03	71.48	135.65	269.16	−1.40%	−0.02%	21.43%	9.36%
A-n33-k5	56.23	57.71	85.27	199.20	53.62	56.58	111.61	221.82	−4.63%	−1.95%	30.90%	11.36%
A-n33-k6	22.92	66.18	137.04	226.14	22.13	64.94	166.11	253.18	−3.45%	−1.88%	21.21%	11.96%
A-n34-k5	46.33	60.09	134.26	240.68	45.72	59.05	149.92	254.69	−1.32%	−1.74%	11.67%	5.82%
A-n36-k5	51.59	61.24	137.08	249.91	49.79	60.71	155.80	266.30	−3.49%	−0.86%	13.65%	6.56%
A-n37-k5	55.12	50.60	92.63	198.36	53.94	50.97	108.72	213.63	−2.14%	0.72%	17.36%	7.70%
A-n37-k6	93.24	54.74	143.13	291.12	91.49	55.45	165.07	312.01	−1.88%	1.30%	15.32%	7.18%
A-n38-k5	53.32	59.96	115.24	228.52	52.66	59.84	138.29	250.78	−1.25%	−0.20%	20.00%	9.74%
A-n39-k5	76.84	51.15	126.40	254.39	73.75	50.52	145.14	269.41	−4.01%	−1.23%	14.82%	5.91%
A-n39-k6	78.89	64.09	119.33	262.31	77.16	63.40	137.93	278.49	−2.19%	−1.08%	15.59%	6.17%
A-n44-k7	92.37	79.68	122.20	294.25	88.78	80.65	150.02	319.44	−3.89%	1.22%	22.76%	8.56%
A-n45-k6	82.01	60.87	149.28	292.16	80.65	61.24	174.06	315.94	−1.67%	0.61%	16.60%	8.14%
A-n45-k7	106.29	87.68	157.41	351.37	101.85	88.70	175.05	365.60	−4.17%	1.16%	11.21%	4.05%
A-n46-k7	63.26	74.75	147.76	285.77	60.38	75.02	165.54	300.95	−4.54%	0.36%	12.03%	5.31%
A-n48-k7	127.47	68.63	141.09	337.19	124.75	68.46	180.44	373.64	−2.14%	−0.26%	27.89%	10.81%
A-n53-k7	48.96	99.92	163.28	312.16	47.33	101.87	184.50	333.71	−3.33%	1.96%	13.00%	6.90%
A-n54-k7	113.87	54.26	198.38	366.51	109.53	53.19	240.14	402.86	−3.81%	−1.97%	21.05%	9.92%
A-n55-k9	69.38	97.97	163.68	331.03	68.40	96.31	196.34	361.06	−1.41%	−1.69%	19.96%	9.07%
A-n61-k9	100.69	52.82	169.91	323.43	96.31	52.52	189.42	338.25	−4.35%	−0.57%	11.48%	4.58%
A-n65-k9	89.22	86.45	193.17	368.84	87.70	85.38	235.60	408.68	−1.70%	−1.24%	21.96%	10.80%
Average	**74.55**	**68.01**	**140.41**	**282.97**	**72.40**	**67.81**	**165.27**	**305.48**	**−2.84%**	**−0.37%**	**17.99%**	**7.95%**

Table 8: *Detailed results when green taxes and green tolls are implemented.*

	Traditional Approach				Green Taxes and Green Tolls							
Instance	IC	Tax	Toll	FC	IC	Tax	Toll	FC	Dif IC	Dif Tax	Dif Toll	Dif FC
A-n32-k5	905.05	118.77	60.00	1083.82	906.72	103.56	60.00	1070.28	0.18%	−12.81%	0.00%	−1.25%
A-n33-k5	761.30	96.08	60.00	917.38	766.91	82.04	60.00	908.95	0.74%	−14.61%	0.00%	−0.92%
A-n33-k6	853.30	109.11	70.00	1032.41	860.07	91.19	70.00	1021.25	0.79%	−16.43%	0.00%	−1.08%
A-n34-k5	898.15	115.87	60.00	1074.02	915.00	91.70	60.00	1066.70	1.88%	−20.86%	0.00%	−0.68%
A-n36-k5	922.30	120.21	60.00	1102.51	934.22	96.10	60.00	1090.32	1.29%	−20.05%	0.00%	−1.11%
A-n37-k5	772.80	95.59	60.00	928.39	781.03	78.49	60.00	919.52	1.06%	−17.89%	0.00%	−0.96%
A-n37-k6	1092.50	140.49	60.00	1292.99	1108.09	115.40	60.00	1283.49	1.43%	−17.86%	0.00%	−0.73%
A-n38-k5	841.80	110.08	80.00	1031.88	853.42	93.54	60.00	1006.96	1.38%	−15.03%	−25.00%	−2.42%
A-n39-k5	955.65	122.63	60.00	1138.28	973.14	97.84	60.00	1130.97	1.83%	−20.22%	0.00%	−0.64%
A-n39-k6	957.95	126.49	80.00	1164.44	960.86	102.88	70.00	1133.75	0.30%	−18.66%	−12.50%	−2.64%
A-n44-k7	1089.05	141.94	110.00	1340.99	1103.08	116.75	90.00	1309.83	1.29%	−17.75%	−18.18%	−2.32%
A-n45-k6	1097.10	140.97	90.00	1328.07	1115.89	113.17	90.00	1319.06	1.71%	−19.72%	0.00%	−0.68%
A-n45-k7	1320.20	169.46	100.00	1589.66	1339.97	133.07	90.00	1563.04	1.50%	−21.47%	−10.00%	−1.67%
A-n46-k7	1054.55	137.60	120.00	1312.15	1064.80	110.98	100.00	1275.78	0.97%	−19.34%	−16.67%	−2.77%
A-n48-k7	1290.30	162.70	100.00	1553.00	1310.75	133.01	100.00	1543.76	1.58%	−18.25%	0.00%	−0.60%
A-n53-k7	1173.00	150.63	110.00	1433.63	1191.74	122.81	100.00	1414.55	1.60%	−18.47%	−9.09%	−1.33%
A-n54-k7	1346.65	176.70	110.00	1633.35	1369.31	146.61	110.00	1625.92	1.68%	−17.03%	0.00%	−0.45%
A-n55-k9	1239.70	159.80	140.00	1539.50	1251.76	137.62	110.00	1499.38	0.97%	−13.88%	−21.43%	−2.61%
A-n61-k9	1197.15	155.94	160.00	1513.09	1209.60	133.47	130.00	1473.07	1.04%	−14.41%	−18.75%	−2.64%
A-n65-k9	1373.10	177.67	160.00	1710.77	1392.19	148.37	130.00	1670.56	1.39%	−16.49%	−18.75%	−2.35%
Average	**1057.08**	**136.44**	**92.50**	**1286.02**	**1070.43**	**112.43**	**83.50**	**1266.36**	**1.23%**	**–17.56%**	**–7.52%**	**–1.49%**

1.49% in the FC. Note that those figures are intermediate values to the one obtained when individually implemented the green taxes and the tolls. However the effect on FC is not so penalized and a reduction on fuel consumption (i.e. emissions) is obtained, contrarily to the implementation of just green tolls. At the same time, given the reduction of the green tolls, it is also gained a redistribution of fuel consumption from the highest environmental quality area to poorer ones.

6. Conclusions and future research

The consideration of external cost of routing is of utmost interest in present-day society that is increasingly suffering from air pollution, among other externalities. In this sense, literature about transportation externalities has mainly focused on achieving the greenest solution, usually omitting the economic implications of those approaches. However, they are both sides of the same coin and the treatment of environmental and economic objectives as competing variables would lead to a myopic solutions. For that reason, this article considers the internalization of external costs within the economic structure of the company. Thus, not only the traditional approach of distance-based internal costs of routing is taken into account but also the external costs are used as the objective function: that is, minimization of the full costs. Two protocols of internalizing are further analysed and discussed: green taxes and green tolls.

The effect of implementing green taxes is doubtless. In one hand, behaviour of companies when internalize their external costs through a green taxes significantly changes. That means that they plan a different route in order to minimize their full costs. On the other hand, this change allows for a noticeable reduction on fuel consumption, i.e. emissions. Green tolls effects are rather limited. Even though it also contributes to a change in the behaviour of the companies, it is not achievable a reduction in emissions. Instead, an increase and a redistribution of emissions within different environmental areas are obtained. However, those insights are pretty interesting from the policy maker's point of view since it is possible to transfer emissions from cherished environmental areas to a valueless ones. This is particularly applicable to protected areas such as national parks or high value landscapes. Through combining both mechanisms, an intermediate point is reached. That is, it is possible to change the delivery planning routes in order to make them greener, in the sense that a reduction of fuel consumption is achieved. Moreover, it is possible to obtain fairer scenarios, in the sense that emissions are transferred from high quality environmental areas to poorer ones; and economically supported, in the sense that a real cost function is minimized.

Many limitations arise as a consequence of the assumptions made, though. Firstly, the way fuel consumption is calculated can be fairly enriched with many other factors such as speed, road gradient, and so on. Secondly, parameters for the green taxes and green tolls can be also enchanted and plenty of sensitivity analysis can be performed in that direction. Finally, our results and conclusions are structured within a capacitated vehicle routing problem and may be not valid in any other variant. Therefore, those limitations make the base for the future research lines: richer variants of the VRP, more exhaustive fuel consumption estimation and deeper analysis in the parametrization.

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