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Effectiveness of carbon pricing policies for promoting urban freight electrification: analysis of last mile delivery in Madrid

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Abstract
This research analyzes the effect of carbon pricing policies in transport electrification. It combines a heuristic algorithm to solve the Green Vehicle Routing Problem with Multiple Technologies and Partial Recharges with an economic Total Cost of Ownership model. The paper compares the performance of battery electric (BEV) and internal combustion vehicles (ICEV) for last mile delivery, using real data of Madrid (Spain). The results show that carbon pricing is scarcely effective when daily mileage is low (precisely when BEVs require incentives), and its effectivity increases as mileage increases (precisely when it is not so necessary to incentivize BEVs). Hence, carbon pricing is not an effective tool for promoting electric vehicles in the short term, and as a result, any political decision to fix CO_2 prices must be adopted with a long-term view in mind. Specifically for the case of Spain, this research shows that current aids to BEVs are insufficient, with the exception of some regions like Madrid, which complement national subsidies with regional ones.

Keywords Carbon pricing · Electric vehicle · Transportation · Optimization

1 Introduction

Decarbonization of road transportation is currently a relevant research topic, due to the fact that the transport sector is the second largest emitter of CO_2. It is responsible of 24% of CO_2 emissions from fuel combustion (IEA 2017: 12), and the 68% increase in transport emissions since 1990 was led by the road sector, which represents three quarters of transport emissions (IEA 2017: 14). Recent work analyses the impact of carbon pricing in the road transport at regional level (typically at country level), such as the work of Johnston (2017) in Australia, Han et al. (2017) in China, or Liu

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and Santos (2015) in the US. However, given that there are significant differences between different cities and applications of the BEVs (Battery Electric Vehicles), general conclusions are difficult to translate into specific local policies, especially when it comes to establishing economic incentives. For this reason, it is of interest to analyze in detail more specific cases, such as the one we are considering in this work, which allows us to draw very concrete conclusions.

In this respect, the main objective of this paper is to analyze the effect of carbon pricing policies in transport decarbonization using real data for a specific case, the city of Madrid, and a concrete application, last mile delivery. The research focus is the impact of potential carbon pricing policies, which would influence energy costs and subsidies to purchase price. Therefore, our starting point is aligned with the conclusions of Braz da Silva and Moura (2016) for the Portuguese market. They precisely pointed out the purchase price and the oil price, modified by taxes, to be the most effective way to boost BEVs penetration. The first issue to be considered is the different applications of road vehicles, from private to freight transportation. We have selected last mile delivery for the following reasons:

First of all, considering current market maturity, this application allows a more factual comparison of TCO (Total Cost of Ownership) between BEVs and ICEVs (Internal Combustion Engine Vehicles) than other applications. For example, in private transport there are several subjective factors with a strong impact in purchase decision, which can distort a pure economic comparison based on TCO. Jensen et al. (2013) concluded that German drivers were reluctant to electric vehicles due to misconceptions about driving range, battery life and other factors, which can change after experiencing an electric vehicle for a few months. DeShazoa et al. (2017) analyzed the California rebate program, showing that sensibility to rebates depends on income level of potential buyers. Traut et al. (2013) studied the substantial impact of charging infrastructure availability in BEVs penetration in the USA, something that is not as relevant for last mile delivery as we will see below. In line with all these remarks, Deloitte (2017: 61) concludes that the TCO of a BEV must be significantly lower than that of an equivalent ICEV to be chosen by a potential buyer. As a consequence, a pure TCO analysis is not the best choice to determine the competitiveness of BEVs in private transportation. On the contrary, freight transportation in general and last mile delivery, in particular, are areas where a more rigorous cost analysis will be made, as the base to purchase decisions.

On the other hand, in respect of freight transportation, several studies conclude that BEVs are especially suited for last mile delivery (Pelletier et al. 2016; Laugesen et al. 2013: 294). A possible intuitive explanation is the BEVs paradox (see for example Lebeau et al. 2015): "On one hand, they have to drive a high number of kilometers to be competitive with conventional vehicles. On the other hand, range is limited due to the battery capacity. As a result, BEVs fit in a specific niche". For this reason, by analyzing last mile delivery, which is the most favorable application for BEVs, we can determine the minimum level of support that makes it competitive. Additionally, electrification of last mile delivery is interesting on its own, since it plays a relevant role in the reduction of Greenhouse Gases (GHG) and other negative externalities in the cities (Saenz-Esteruelas et al. 2016; Juan et al. 2016).

Table 1 Features of the vehicles. *Source*: Prepared by the authors from manufacturer information

	BEV	ICEV
Capacity of the battery (kWh)/fuel tank (l)	33 kWh	60 l
Power (CV)	60 CV	75 CV
Autonomy (km)	200 km	950 km
Energy consumption (Wh/km or l/km)	165 Wh/km	0.063 l/km
Load capacity (kg)	650 kg	630 kg
CO_2 emissions (g/km)	Depends on the mix	165 g/km

The main contribution of this paper is to integrate, from a carbon pricing perspective, an optimization model, which is a technique not commonly used in the study of electric vehicle costs, with real data of a specific city. Our approach is aimed at analyzing in detail the effect of carbon pricing policies in the BEV penetration in a concrete case, which allows the obtaining of specific and focused conclusions. Nevertheless, in light of our results, our methodological proposal could be applicable to other real cases, which we believe is another relevant contribution of our work.

2 Materials and methods

2.1 Data

Our starting point is a very concrete case study, the city of Madrid, for the purpose of using the most accurate data possible: the proposed analysis requires a considerable number of parameters, from the acquisition price to the insurance cost or the average speed, which are impossible to estimate in a general case. The main data that we will use in this work, together with a discussion about how they were determined, are described in detail in what follows.

2.1.1 Vehicle typology

We have considered two vehicles from the N1 category that the European classification for vehicle category defines as vehicles used for the carriage of goods, having a maximum mass not exceeding 3.5 tons. The selected BEV corresponds to the vehicle with the highest sales in the period 2012–2016, both in Spain and the rest of the world, according to the European Alternative Fuels Observatory (EAFO). As an ICEV, we have selected one with the same brand and the most similar performance. Table 1 shows the features for both vehicles. Please note that, instead of considering the NEDC (New European Driving Cycle) range, we have used the range estimated by the manufacturer under real conditions, which requires the modification of other magnitudes such as the emissions per kilometer.

2.1.2 Costs of energy

The average diesel price, including taxes, for 2016, has been considered. This price, provided by the "Confederación Española de Transporte de Mercancías" (CETM—Spanish Confederation for the Transportation of Merchandise), is 1.0151 €/l, which is unusually low if compared to the average prices in 2013, 2014 and 2015, (1.36, 1.30 and 1.11 €/l, respectively). During the first months of 2017, the diesel price was around 1.13 €/l. In the case of BEVs, the calculation of energy cost is substantially more complex, due to hourly pricing, the existence of different tariffs for each supplier, the type of use and the type of client, the different components of the electricity price, etc. For this reason, the PVPC ("Precio Voluntario para el Pequeño Consumidor"—Voluntary Price for the Small Consumer) data for BEVs in 2016 have been used as an approximation, by calculating the average price in each time zone during the 365 days of the year. In this way, we would have the price for the billing term of the active energy, which would be 0.053 €/kWh for the night-time recharge. In this study, we will assume that the fleets are small, and therefore PVPC is applicable (less than 10 kW of installed power). In relation to the en-route recharge, and given that it would be carried out on a third-party charger, it is not reasonable to take on only the energy cost: the price is unavoidably going to include not only the cost associated to the power term, but also the supplier's profit margin. Our best estimate, based on data from Deloitte (2017: 56), is approximately 0.65 €/kWh. Thus, the energy costs used in this study are 0.053 €/kWh and 0.65 €/kWh for the night-time recharge and the en-route recharge, respectively. The energy price considered, both per kWh and per liter of diesel, during the different simulations performed, varies according to a normal distribution with the indicated mean value as the mean, and a standard deviation of 5% of the mean value.

A critical aspect of the design of this study is determining the way in which carbon pricing is set, and which is the pass-through rate that the oil and gas companies would apply. In relation to the way of articulating the carbon pricing, we will talk about carbon tax, being aware that the conclusions would not be different in a cap and trade system. Concerning the pass-through rate, a recent analysis on pass-through rates of carbon costs in electricity that was developed for the Australian National Electricity Market concluded that "carbon costs would indeed be fully passed on to wholesale electricity spot prices, resulting in higher electricity prices for consumers" (Nazifi 2016), a consistent result with other studies in that same market, which propose high pass-throughs (Maryniak et al. 2016). Similar results have been reached for other markets such as Germany (Hintermann 2016) or Spain (Fabra and Reguant 2014). Based on these articles, we will assume that, before a particular CO_2 price, it will be totally charged to the final electricity consumers. Logically, this increase in cost will depend on the intensity of carbon within the electricity mix. In this respect, according to data from the Spanish transport system operator (REE 2017), the CO_2 emission factor in national generation during 2016 was 0.242 tCO_2/MWh.

In fact, in marginalist markets such as Spain, in which the latest technology to enter the market sets the price of the MWh, it is the emissions factor of this technology that determines the carbon cost. This cost will be charged to the final consumers, regardless of the emissions factor of the global mix. Nevertheless, by introducing a carbon pricing policy, the current generation structure would be severely altered. For these reasons, and against the impossibility of achieving a better estimate without the availability of a complete model of the Spanish electric market, we have opted to work with an emissions factor of 0.242 tCO_2/MWh (the average of the mix) as a base scenario, and execute a sensibility analysis on it. As for diesel, we concur on the same pass-through rate for its emissions.

2.1.3 Other costs

The sale prices provided by the manufacturer have been evaluated excluding economic aid and subsidies. According to the current regulation of the Spanish Tax Agency, this type of vehicles could be amortized in a minimum period of 6.25 years, and for this reason we have considered 6 years, with a business calendar of 250 working days per year. From a fiscal point of view, there are three different taxes that have to be taken into account: Registration Fee, which does not apply to industrial vehicles like the ones we are analyzing as they are exempt, "Impuesto sobre Vehículos de Tracción Mecánica" (IVTM—Tax on Motor Vehicles), applied to the analyzed vehicles in Madrid at a rate of 73 €/year, although in the case of BEVs there is an exemption of 75%, and Value Added Tax (VAT), which is 100% deductible in the case of commercial vehicles. In respect of the vehicle purchase loan, following Hagman et al. (2016), we have considered that buyers finance 80% of the purchase of their vehicle with a 36-month loan at a 6% annual interest rate.

The calculation of the residual value is significantly complex. Due to the different stages of technological maturity of BEVs and ICEVs, different residual values could be argued for each of them. A BEV will be obsolete in 6 years for sure, as a result of its technological evolution, while the same cannot be said for ICEVs, which will improve progressively. On the other hand, more restrictive emission policies, such as the ones that are being proposed in many EU countries, would make the sale of a second-hand ICEV much more difficult than the sale of a free emission vehicle, which would produce the opposite effect than technological evolution. After different tests, we have verified that the impact of residual value on the results is limited; therefore, we have opted to consider a null residual value in both cases. The considered BEV price does not include the rental of a battery, which varies depending on the annual mileage and on the period of subscription complicating its valuation. Nevertheless, according to the available information and assuming a 12-month subscription, it is possible to estimate a monthly cost of 100 €.

Regarding the maintenance cost, the shortage of historical data if compared with ICEV makes the estimation for BEV more difficult. According to data provided by different sources, a yearly maintenance cost of 400 €/year is assumed for the BEV, and 800 €/year for the ICEV. Another cost to consider is the insurance premium. Again, it is very complex to estimate this cost, as it depends on many different variables (type of insurance, mileage, driver characteristics, parking area features, type of use of the vehicle, etc.). After consulting different online insurance companies, we conclude that the insurance premium could be estimated at around 900 €/year, which is approximately 20–30% higher than the equivalent insurance for a diesel vehicle (675 €/year). Finally, one driver per vehicle has been considered, with a company cost of 25.000 €/year, and a workday of 8 h.

2.1.4 Speeds and geographical area

According to data from the Madrid City Council (Ayuntamiento de Madrid 2014: 30), average road speeds inside M-30[1] and between M-30 and M-40[2] have remained very stable for years. Last available data are 19.03 km/h (speeds inside M-30) and 24.49 km/h (speed between M-30 and M-40). Average road speed on the M-30 has experienced more volatility, although it is also relatively stable, and the last available estimation is 64.62 km/h. These speeds are substantially lower than the maximum speed range of both vehicles, and as a consequence, circumscribing the analysis to the M-40 perimeter (the model considers a 20 km × 20 km grid), it is possible to consider an average speed of 36 km/h.

2.1.5 Additional parameters

The distribution of parking time for offloading vehicles in Madrid follows a distribution that is highly dependent on the time of the day (Ponce-Cueto and González 2016). Nevertheless, considering mainly morning deliveries, we can assume a parking time between 8 and 12 min, modeled as a uniform distribution. Lastly, a 2% inflation rate has been used to increase the different costs of the vehicles.

2.2 Study design

All the data introduced in the previous section related to energy and other costs, the specifications of the vehicles and the geographical characteristics of the area under consideration are real, allowing us to perform a deep analysis of the particular case of Madrid. However, in order to develop a realistic TCO comparison between BEVs and ICEVs, using real data about daily covered distances, partial recharges and fleet sizes has a key problem: most probably, real routing designs are conditioned by the restrictions on the range of BEVs. Abidi et al. (2015) explained that "in some [real] cases, due to the dependence on the battery capacity of the electric vehicle, the dispatch planner has reduced the tour of delivery 10–12 customers per day using diesel engine vehicle to 5–6 customers per day using electric vehicle". Therefore, in our opinion, using real data of these elements does not allow a fair comparison between BEVs and ICEVs. Alternatively, our approach relies on estimating the ranges in which the daily covered distance, the number of en-route partial recharges required and the size of the fleet vary by solving a mathematical problem called the Green Vehicle Routing Problem with Multiple Technologies and Partial Recharges (GVRP-MTPR), as defined by the real data introduced in the previous section. Once the range of daily covered distances is obtained, we perform a series of simulations inside that range that do not incorporate any bias in favor of electric vehicles, and use them to obtain our results. This approach has already been employed in previous research by using algorithms to solve the vehicle routing problem (VRP) for urban freight transport (see, for example:

[1] Ring road around the very center of Madrid, with an average radius of 5.17 km.

[2] Ring road around the center of Madrid, with an average radius of 10.07 km.

Van Duin et al. 2013; Lebeau et al. 2015; Davis and Figliozzi 2013), and we believe it is the most appropriate in this case.

3 Methods

The first step of our methodology is to calculate the distances covered by each vehicle. As stated earlier, the mathematical problem that we are solving to obtain the routing plan of the given fleet is the GVRP-MTPR, that was introduced by Felipe et al. (2014). This problem consists in finding an optimal set of routes for the m available vehicles serving N customers (each with demand q_i and service time s_i) while minimizing the overall energy cost. In particular, one vehicle route is feasible if it starts and ends at the depot, the vehicle capacity (Q) and the driving time limit (T) are not exceeded and the energy level of the vehicle is always between 0 and B. A set of feasible routes is a viable solution if all customers are visited exactly once and the number of routes is less than or equal to m.

The mathematical model that represents this problem is a mixed integer linear program, defined on a directed network containing m copies of the depot (D), the customer locations (N) and several copies of the recharge stations (F_0) as nodes, and the available roads as arcs (A'). For each arc (i,j) the distance (d_{ij}) and travel time (tt_{ij}) are known. For each technology t we assume a given recharge speed ρ_t and a given recharge unit cost γ_t (the recharge cost at the depot is denoted by γ*). The energy consumption is considered proportional to the distance traveled through a coefficient π. The recharge time at the stations has a fixed component (f_i) and a variable one depending on the partial recharge performed.

In order to model the problem properly, the following groups of variables are defined: *Decision variables*:

x_{ij} Binary variable with value 1 if a vehicle travels from i to j

y_j^A Amount of energy available when arriving at node j

y_j^L Amount of energy available when leaving node j

l_j Amount of load left in the vehicle after visiting node j

z_{jt} Amount of energy recharged at node j using technology t

g_v Amount of energy recharged by vehicle v at the depot

τ_j Departure time from node j

As a result, the following mathematical program is obtained:

$$\min \sum_{v \in D} \gamma^* g_v + \sum_{j \in F_0} \sum_{t \in \mathcal{T}_j} \gamma_t z_{jt} + \vartheta \sum_{i \in V', j \in F_0 \cup D} x_{ij} \tag{1}$$

$$\sum_{j \in V'} x_{ij} = 1, \quad \forall i \in \mathcal{N} \tag{2}$$

$$\sum_{j \in V'} x_{ij} \leq 1, \quad \forall i \in F_0 \tag{3}$$

$$\sum_{j \in V'} x_{ji} - \sum_{j \in V', j \neq i} x_{ji} = 0, \quad \forall i \in V' \tag{4}$$

$$\sum_{j \in V'} x_{vj} = \sum_{j \in V'} x_{jv} \leq 1, \quad \forall v \in D \tag{5}$$

$$y_v^L \leq g_v, \quad \forall v \in D \tag{6}$$

$$\tau_j \geq \tau_i + tt_{ij} + s_i - M_1(1 - x_{ij}), \quad \forall i \in \mathcal{N}, \ \forall j \in V', \ i \neq j \tag{7}$$

$$\tau_j \geq \tau_i + tt_{ij} + \sum_{t \in \tau_j} \frac{1}{\rho_t} z_{jt} + f_j - M_1(1 - x_{ij}), \quad \forall i \in F_0, \ \forall j \in V', \ i \neq j \tag{8}$$

$$\tau_j \geq tt_{vj} - M_1(1 - x_{vj}), \quad \forall v \in D, \ \forall j \in V', \ v \neq j \tag{9}$$

$$0 \leq \tau_v \leq T, \quad \forall v \in D \tag{10}$$

$$y_j^A \leq y_i^L - \pi d_{ij} x_{ij} + B(1 - x_{ij}), \quad \forall (i, j) \in A' \tag{11}$$

$$y_j^L \leq B, \quad \forall j \in F_0 \tag{12}$$

$$g_v \leq B, \quad \forall v \in D \tag{13}$$

$$y_j^L = y_j^A, \quad \forall j \in \mathcal{N} \tag{14}$$

$$y_j^L = y_j^A + \sum_{t \in T_j} z_{jt}, \quad \forall j \in F_0 \tag{15}$$

$$l_j \geq l_i + q_j - M_2(1 - x_{ij}), \quad \forall i \in V', \ j \in \mathcal{N}, \ i \neq j \tag{16}$$

$$l_j \geq l_i - M_2(1 - x_{ij}), \quad \forall i \in V', \ j \in F_0, \ i \neq j \tag{17}$$

$$l_j \leq Q, \quad \forall j \in V' \tag{18}$$

$$x_{ij} \in \{0, 1\}; y_j^L, y_j^A, l_j, z_{jk}, p_j, g_v, \tau_j \geq 0, \quad \forall i, j, k, v \tag{19}$$

The objective function (1) of the optimization model (in euros) comprises several terms associated with some of the costs mentioned earlier (variable energy costs plus a fixed cost ϑ for each recharge). The conditions that must be verified to ensure feasibility are defined through different sets of constraints, related with one another. They are the following: (2) all customers are visited exactly once; (3) each recharge station copy is visited at most once; (4) vehicle and load flows are conserved at each node; (5) each vehicle leaves and returns to the depot exactly once; (6) the energy level is always above zero and compatible with the recharges performed; (7)–(9), (11)–(15) travel, recharge and service times are consistent; (10), (16)–(18) the vehicle capacity and the driving limit are not exceeded. Note that M_1 and M_2 are just appropriate big-M bounds to make the corresponding constraints trivially verified when $x_{ij} = 0$. See Felipe et al. (2014) for further details on the model.

For an instance of the problem with n customers, m vehicles, r stations and t recharge technologies, the model has $O(n^2)$ binary variables, $O(rt + 4n + m)$ continuous variables and $O(3n^2 + 2nr + mn + 4n + 3r + 3m)$ constraints. In most cases, it holds that $m < n$, $t < 3$ and $r < n$, in which case the number of continuous variables is simply $O(n)$ and the number of constraints $O(n^2)$. The GVRP-MTPR is proven to be NP-hard, and only very small instances can be solved to optimality within reasonable computing times.

Then, in order to solve realistic instances of the problem, we will use the 48A heuristic algorithm proposed by Felipe et al. (2014). It is based on a constructive phase used to generate an initial feasible solution, followed by a deterministic local search, aimed at improving the initial solution. The constructive phase is a greedy generation method, which starts from an empty solution and extends it iteratively by adding a customer location or refueling station to the current route until a complete feasible solution is obtained. The selection of the next element to be added to the solution is based on the distance from the customers that remain to be visited (only the k closest unvisited nodes are considered) and the closest stations to the current route (a recharge stop is added whenever required). A random component is included to diversify the generation of initial solutions: the next node is chosen randomly among the k selected nodes, and it may not be the closest one.

The deterministic local search (see, for example, Aarts et al. 2003) takes any solution built by the constructive algorithm and tries to improve it by performing small changes, each of which makes the solution get better after each iteration. Three different local search operators, allowing the introduction of different types of changes into the solution, are considered: Recharge Relocation, 2-Opt and Reinsertion. The Recharge Relocation operator removes all recharge stops of a certain route and, if it exists, finds the optimal location of a single recharge stop, calculating the optimal amount of energy to be recharged in order to ensure the route feasibility. It is illustrated in Fig. 1: firstly, the two recharge stops at stations rA and rC (solution S1) are removed, leading to a partial infeasible solution (solution S2); then, a visit to station rB is optimally inserted between nodes v2 and v3, recovering feasibility and leading to a new solution which is cheaper than the initial one (solution S3).

The 2-Opt operator has been used largely in the literature (see, for example, Englert et al. 2014). It is applied to each leg of the routes, determined by two consecutive recharges. A 2-interchange consists in removing two arcs and reconnecting the solution without reusing them (there is only one way to do it). It is illustrated in Fig. 2: the starting point is S1, which represents a leg connecting stations rA and rB; if arcs (v2, v3) and (v4, v5) are removed, the partial solution S2 is obtained; when reconnected by adding arcs (v2, v4) and (v3, v5), a shorter leg is obtained (S3), leading to energy savings.

The Reinsertion operator moves one node from one route to another, with the aim of saving energy by removing recharge stops or by reducing the overall distance travelled by the vehicles. Similar operators have been used in the literature for other

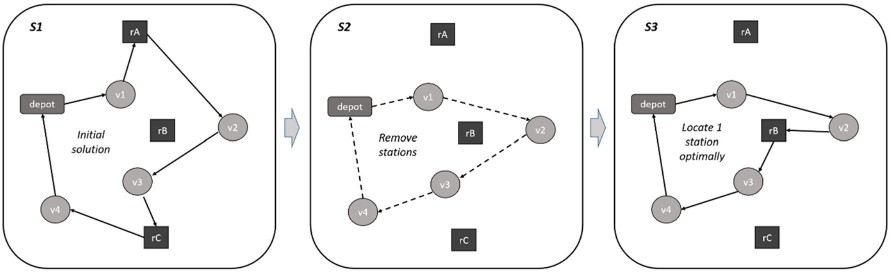

Fig. 1 Illustration of the recharge relocation operator

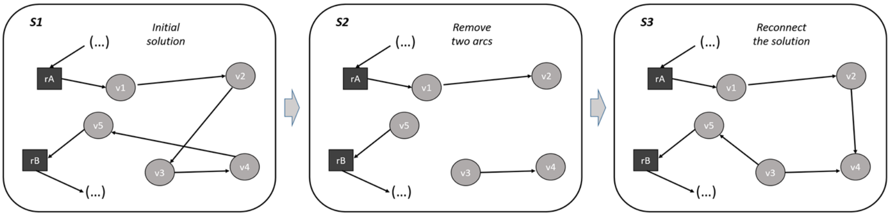

Fig. 2 Illustration of the 2-Opt operator

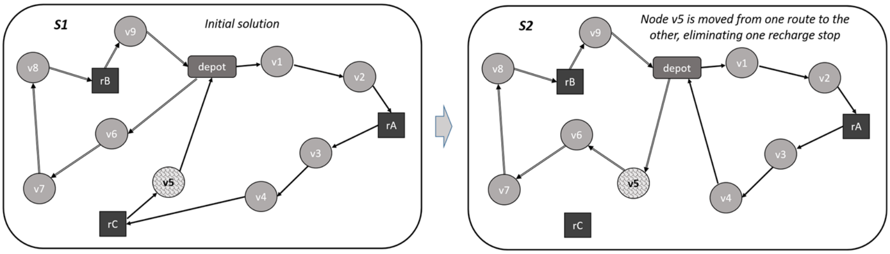

Fig. 3 Illustration of the reinsertion operator

routing problems, as in Felipe et al. (2009). The Reinsertion operator is illustrated in Fig. 3: the initial solution (S1) comprises two routes: v1–v2–rA–v3–v4–rC–v5 (route 1) and v6–v7–v8–rB–v9 (route 2); the operator moves node v5 from route 1 to route 2, allowing the removal of the recharge stop at station rC, which is no longer necessary, and providing an overall energy saving.

At each iteration, the 48A algorithm applies one of the three operators, finding the move leading to the highest energy saving, and implements it. This process is iterated until the current solution cannot be improved any further,[3] providing a local optimum. Since the local search processes associated to each operator are quite fast, the algorithm is able to consider all of their possible combinations.

Regarding the instances to be solved by the algorithm, we have considered eight possible scenarios for each type of vehicle, serving 100 or 200 customers with four different geographical configurations: depot located in the center or in a corner of the

[3] For additional details regarding the mathematical model of the problem and the algorithm to solve it we refer the reader to Felipe et al. (2014).

considered 20 km × 20 km grid, and random uniformly distributed clients or grouped in random clusters. The distribution of charging stations is not relevant for this particular problem, as will be explained later. Lastly, we have considered packages whose weight follows a uniform distribution between 15 and 20 kg. The results obtained by solving the GVRP-MTPR in all the considered scenarios show that daily average distances covered by each vehicle are in the range of 45–70 km. This is consistent, especially in the most realistic scenarios with random clients, with the real data obtained by the FREVUE project (Validating Freight Electric Vehicles in Urban Europe) of the 7th Framework Program of the European Union, that measured a daily average distance in Madrid of 75 km (Fernández-Balaguer 2016). As a conclusion, the GVRP-MTPR heuristic allowed us to determine three key elements: daily average covered distances (45–70 km); confirm that BEV's range is not a problem and en-route recharges are not required; and lastly, confirm that the small load capacity differences between both vehicles do not affect the sizing of the fleets.

In summary, we have used the GVRP-MTPR model to calculate the range of daily average covered distances (45–70 km). Then, we have calculated the total cost of ownership (TCO), a financial estimate to determine all the direct and indirect costs of a product over its lifetime. In order to calculate TCO, we have considered 14 variables, including purchase price, all taxes and fees, financing, insurance, cost of the recharge system, fuel/energy cost, driver costs and CO_2 taxes (see Sect. 2.1). Additionally, TCO has been calculated according to the mid-year net present value criterion with a discount rate of 4%, in line with the rate used by Hagman et al. (2016). In the TCO calculation, the distance travelled is the most critical variable, so using the range obtained by the GVRP-MTPR model (45–70 km), we have performed 5000 Monte Carlo simulation runs in the TCO model, considering that distances follow a uniform distribution in this range, and varying also the other variables as indicated in Sect. 2.1.

However, in order to incentive sustainable mobility, BEVs have purchase subsidies, so that users who buy this type of vehicles receive a refund of the purchase price. Therefore, we have repeated the 5000 Monte Carlo simulation runs for different subsidy levels, from 0 € (no subsidy) to 11,000 €, at intervals of 1000 €. Finally, for each simulation, we have calculated the CO_2 tax required to ensure that the TCO of BEVs and ICEVs is exactly the same. This value, which we have called critical CO_2 price, is precisely the object of analysis of this paper, as our objective is to determine the price of CO_2 that would make BEVs competitive.

4 Results

Once we have obtained the distribution of the critical price of the CO_2 over all the considered cases, we have performed a descriptive analysis of it. We considered all subsidy levels up to 8000 €, as for larger levels, the BEV starts being competitive in some cases without a carbon price (see Table 2). For each case, we systematically searched for the best fit among sixty-one density functions, from the most common ones, such as Normal, Gamma, Weibull or Beta, to more sophisticated alternatives, such as Nakagami or Fréchet distributions. This study showed that the distribution providing the best fit (in fact, the only one providing a reasonable fit for all tested values of the subsidy to purchase price) is, the Johnson SB model. Random variable SB is one of the three distribution families introduced by Johnson (Johnson 1949). They are transformations of a Standard Normal distribution. Specifically, if random variable Y follows a Standard Normal distribution, $Y \equiv N(0,1)$, then a random variable X defined as

$$\mathrm{X} = \xi + \frac{\lambda \exp\left(\frac{\mathrm{Y}-\gamma}{\delta}\right)}{1+\exp\left(\frac{\mathrm{Y}-\gamma}{\delta}\right)}$$

follows a Johnson distribution $SB(\xi, \lambda, \gamma, \delta)$, where ξ is the location parameter, λ is the scale parameter and γ, δ are the shape parameters. Its probability density function, $f(x)$, and its cumulative distribution functions, $F(x)$, are, respectively:

$$f(x) = \frac{\delta}{\sqrt{2\pi}} \frac{\lambda}{(x-\xi)(\lambda+\xi-x)} \exp\left\{-\frac{1}{2}\left(\gamma + \delta \ln \frac{x-\xi}{\lambda+\xi-x}\right)^2\right\}, \quad x \in (\xi, \xi+\lambda)$$

$$F(x) = \Phi\left(\gamma + \delta \ln \frac{x-\xi}{\lambda+\xi-x}\right)$$

$$\Phi(y) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{y} \exp\left(-\frac{1}{2}t^2\right) dt.$$

where $\Phi(.)$ is the cumulative distribution function of a Standard Normal distribution. The parameters $(\xi, \lambda, \gamma, \delta)$ of the SB Johnson distribution can be estimated by different methods. The maximum likelihood estimation method is used in practice frequently due to its good properties, but it becomes quite involved when dealing with the SB Johnson distribution (Kamziah et al. 1999). Other widely used methodologies are the method of moments, which is usually easier to apply, the methods based on quantiles (Slifker and Shapiro 1980) and the combination of maximum likelihood and least squares methods (George and Ramachandran 2011). Once the parameter estimation is performed, a usual goodness of fit hypothesis test is the one associated to the Kolmogorov–Smirnov D_n statistic, which can also be used as an optimization criterion for parameter estimation (see Felipe 1988; Weber et al. 2006).

In particular, when dealing with a Johnson $SB(\xi, \lambda, \gamma, \delta)$ distribution, the goodness of fit Kolmogorov–Smirnov statistic is $D_n(\xi, \lambda, \gamma, \delta) = \sup_{x \in \mathbb{R}} \left| F_n^*(x) - F_0(x) \right|$, where $F_n^*(x)$ is the sample cumulative distribution function and $F_0(x)$ is the cumulative distribution function of $X \equiv SB(\xi, \lambda, \gamma, \delta)$. Thus, the min D_n estimators are

$$(\hat{\xi}, \hat{\lambda}, \hat{\gamma}, \hat{\delta}) = \underset{(\xi,\lambda,\gamma,\delta)}{\arg\min}\{D_n(\xi, \lambda, \gamma, \delta) | \gamma > 0, \delta > 0\}.$$

In our particular application, we will estimate the $(\hat{\xi}, \hat{\lambda}, \hat{\gamma}, \hat{\delta})$ parameters of the Johnson SB distribution in two phases. First, the method of moments will be used to obtain an initial estimation of the parameters. Then, this initial estimation will be

Table 2 Main metrics and fit of Johnson SB distribution

	Subsidy to purchase price (€)											
	0	1000	2000	3000	4000	5000	6000	7000	8000	9000	10,000	11,000
Mean	975.95	875.00	768.39	675.28	571.02	468.77	368.55	267.68	166.21	71.30	11.05	0.00
Standard deviation	182.40	172.73	155.67	144.56	131.64	119.76	107.71	94.85	83.07	63.60	22.28	0.26
Asymmetry	0.30	0.32	0.33	0.28	0.29	0.31	0.29	0.30	0.26	0.54	2.19	70.31
kurtosis	− 1.03	− 1.05	− 1.00	− 1.02	− 1.00	− 0.98	− 0.96	− 0.90	− 0.89	− 0.84	4.26	4960.90
50% (Median)	955.29	849.57	747.68	659.51	556.22	452.03	356.86	255.33	157.40	59.58	0.00	0.00
Parameters—Johnson SB										–	–	–
γ	0.30	0.31	0.33	0.29	0.30	0.35	0.33	0.38	0.35			
δ	0.69	0.68	0.71	0.73	0.73	0.74	0.77	0.83	0.84			
λ	700.45	648.68	602.01	566.17	522.35	477.89	440.42	405.01	360.18			
ξ	680.11	602.70	518.33	433.65	349.56	271.44	183.20	100.15	15.27			
P value	1.00	0.87	0.87	1.00	0.94	0.34	0.91	0.44	0.72	–	–	–

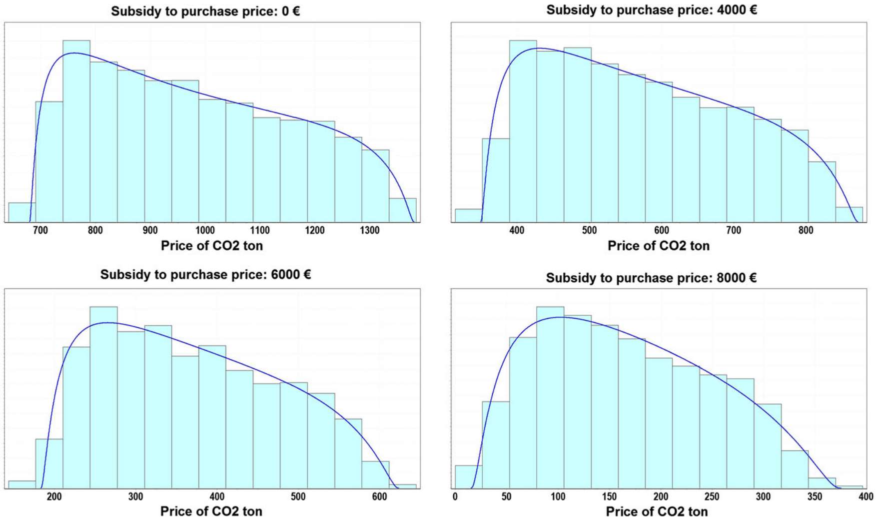

Fig. 4 Real and adjusted distribution of CO_2 price for different subsidy levels

used as the starting point of a quasi-Newton method, which will provide the min D_n estimators. Table 2 shows the values of the parameters obtained for each case by following this 2-phase method.

For each subsidy to purchase price level considered, Fig. 4 shows the proportion of simulations in which the different critical prices of CO_2 are obtained. For the base scenario, which does not include any subsidy to purchase price for the BEV, we get a very high price of CO_2 (in the range of 642–1385 €/tCO_2). Nevertheless, as the World Bank (2016: 23) points out, several studies propose a CO_2 price in the range of US$80/t$CO_2$e to US$120/tCO_2e in 2030, and three quarters of the existing carbon pricing initiatives worldwide use a price below US$10/t$CO_2$e. Obviously, the range obtained in the simulation substantially exceeds all these prices, which implies that currently, in the absence of direct subsidies to purchase price, reasonable carbon pricing policies are not going to contribute significantly to the adoption of BEVs. In addition, we observe that as the subsidy level decreases, distributions become more platykurtic: in order to cover a larger number of possible instances, it would be necessary to further increase the price with respect to the average value.

Thus, a key aspect that must be solved is the subsidy level required to allow for a CO_2 price in the range of 9–10 €/tCO_2 to be effective. Table 3 summarizes the theoretical cumulative distribution function of the carbon price, expressed as a percentage, for different subsidy levels. Based on this, Fig. 5 shows the average carbon price (solid line) and the price interval that contains the 90 and 50 percentile values required to make BEV competitive for different subsidy levels. To this effect, results show that, in order to make BEV competitive, it would be necessary to have a difference in purchase price between BEV and ICEV of 4000–5000 € in favor of BEVs, which implies a purchase subsidy in the range of 9000–10,000 €.

Table 3 Theoretical cumulative distribution function (in percentage) of the carbon price for different subsidy levels

	Subsidy to purchase price (€)								
	0	1000	2000	3000	4000	5000	6000	7000	8000
F(x)									
0.5	691.020	611.653	527.988	444.166	359.709	280.518	193.270	111.422	26.143
2.5	706.067	624.525	540.930	457.694	372.496	291.745	204.948	123.098	37.143
5.0	720.161	636.809	552.915	469.985	384.008	301.793	215.110	132.823	46.209
25.0	818.443	725.404	635.229	551.373	459.128	367.143	278.012	189.249	97.795
50.0	956.436	854.124	750.223	660.273	558.445	454.478	357.805	257.443	158.697
75.0	1123.504	1012.634	891.356	789.890	676.486	561.104	452.434	338.458	229.813
95.0	1293.001	1172.435	1039.439	924.303	800.247	677.801	556.101	432.766	311.802
97.5	1322.341	1199.502	1065.938	948.574	822.947	699.971	576.285	452.648	329.102
99.5	1355.397	1229.478	1096.344	976.768	849.593	726.450	600.951	478.308	351.535

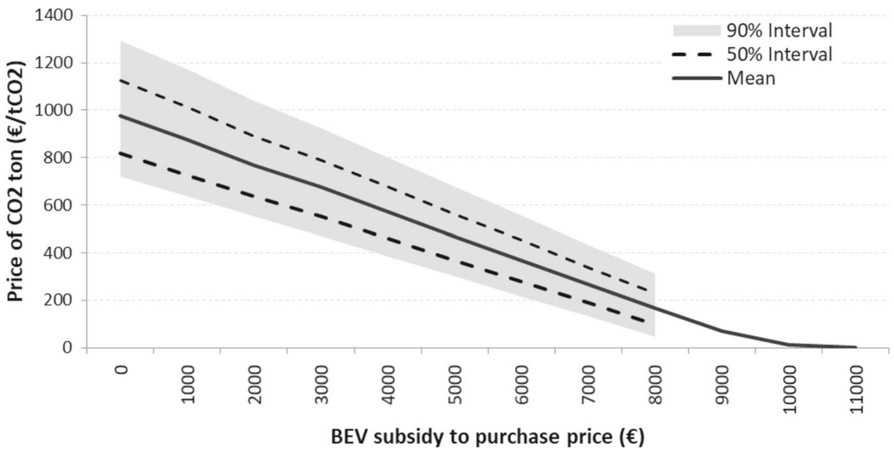

Fig. 5 CO_2 price that makes BEVs competitive for different subsidy levels

MOVEA 2017 Plan from Central Administration of Spain (BOE-A-2017-7165 2017) provides a subsidy to purchase price of 8000 € to N1 type BEVs. Nevertheless, subsidies to private companies are lower than this amount. Our results conclude that this subsidy is insufficient and would require an additional carbon tax of over 150 €/tCO_2, just to make BEVs competitive in 50% of the instances. This, at least partially, explains the reason why BEVs penetration in Spain is relatively low compared with other countries with more aggressive supporting policies to electric vehicles (Deloitte 2017: 60). In the case of Madrid, there are additional subsidies that can be added to the ones provided by the central administration, adding up to 6000 € (BOCM 2014). Both subsidies combined make BEVs competitive, even in the absence of a carbon tax. This is probably one of the reasons why this region is a leader in new

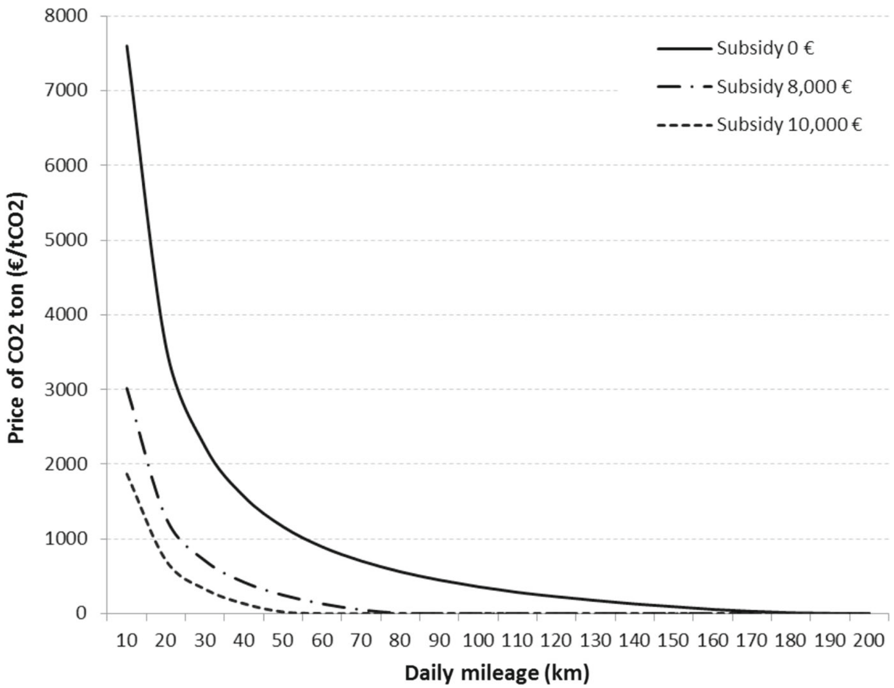

Fig. 6 CO_2 price required to make BEVs competitive as a function of daily mileage, calculated for different subsidy levels

BEVs registrations in the country: 37% of all national van registrations in 2016 and 41% until April 2017 (DGT 2017).

It is also interesting to analyze the effect of subsidies and carbon tax in daily mileage required to make BEVs competitive (Fig. 6). In the most extreme case (non-existent subsidy and absence of carbon tax), the equilibrium point is reached for 190–200 km per day, which is consistent with the vehicle range. Hence, we conclude that the BEV would be hardly competitive in this scenario. Considering a 8000 € subsidy, this distance decreases to 80 km a day. In any case, this mileage is superior to what we have estimated using the GVRP-MTPR heuristic.

5 Discussion

Our results are consistent with the main part of the academic literature, which points out that, currently, BEVs are not economically viable for urban freight without subsidies or other types of incentives. This is mainly due to its high purchase price (Nesterova and Quak 2015: 34; Taefi et al. 2014; Laugesen et al. 2013: 293). Similar conclusions have been obtained for freight in general (Quak et al. 2016; Van Duin et al. 2013). In fact, Feng and Figliozzi (2013) analyzed the USA market and concluded that an annual mileage of 22,000 miles (close to 35,500 km) is required to reach the equilibrium point in all scenarios. Regarding the concrete application of last mile delivery, it is worth mentioning that the paper by Abidi et al. (2015) has an opposing view. The main reason seems to be that the authors consider an annual mileage of 40,000 km, which implies, according to the parameters of our model, a daily mileage of 160 km. Our results are also consistent with the observed behavior of several logistic companies in Spain which, even though are developing pilot tests with BEVs, still perform last mile delivery with ICEVs. In this regard, the main reason behind these BEV pilot tests is probably related to gaining practical experience with BEVs, that will likely be competitive in the future due to the reduction of costs or to more restrictive environmental regulations.

5.1 Importance of the recharging infrastructure and BEVs performance

Even though the analyzed literature agreed that the current recharging infrastructure and vehicle performance are not the main limiting factors to the BEVs adoption process, there were two key factors that we wanted to explore. The first one was related to the manufacturer's decision of not incorporating a fast recharging system in the BEV vehicle considered in our research, which could be thought as a mistake, due to the considerable reduction of the vehicle's flexibility. Nevertheless, our results show that this feature is not necessary, at least for last mile transportation: routes are completed with a considerable security margin that allows for slow recharging during night-time hours. In fact, the current range is enough even to allow double daily shifts.

The second issue, closely linked to the previous one, was regarding the recharging infrastructure. At the time of writing this paper, there were less than 200 recharging points on the public streets of Madrid, which would be rather small if the BEVs fleet was considerable. Nevertheless, our results show that the most critical factor is the availability of recharging points in parking zones, not on the streets. This is consistent, because the main part of recharging operations will be developed during night-time hours, and en-route recharging will be more the exception than the rule. The future transportation model will not require as many electro-stations as current gas-stations, even though an important increase of parking charging points is a must.

5.2 The carbon pricing paradox in transportation

As mentioned above, BEVs are especially suitable for last mile delivery. However, even in this type of use, a positive business case cannot be achieved without government support. Lévay et al. (2017), in their study of eight European countries, concluded that the key for BEVs penetration is the reduction of their purchase price. In addition, McKerracher et al. (2016: 16) estimate that, for private vehicles, BEVs are likely to reach the same TCO as ICEVs in the mid-2020s, while for taxis and freight vehicles this will happen a bit earlier. In fact, the meta-analysis developed by Coffman et al. (2016) over 50 peer-reviewed studies about factors that affect EV adoption, concludes that "the literature on EV adoption suggests that high purchase price is a major impediment to EV uptake". Hence, carbon pricing will not have a significant effect in the short term. This result is consistent with the analysis made by Davis and Figliozzi (2013), whereby they stated that it is not currently a critical factor for the competitiveness of the electric trucks. Our analysis proposes an explanation about this phenomenon. Figure 6 shows that carbon pricing is hardly effective when daily mileage is low (precisely when BEVs need to be incentivized), and that it becomes more effective with the increase of mileage (precisely when BEVs do not need as many incentives), as a small increase in CO_2 price can vary the required mileage substantially. As a consequence, carbon pricing is not going to be an effective measure, in the short term, in any realistic scenario (Table 4).

Nevertheless, it is important to point out that, even though carbon pricing policies are not going to have a significant impact in BEVs penetration in the short term, according to some previous research papers they could have positive effects in the long term. Carbon pricing incentivizes disruptive innovation in clean technologies in a significant way (Clancy and Moschini 2015), including the automotive sector (Aghion et al. 2016). Additionally, they will promote more efficient charging strategies once the BEV achieves a high penetration level (Hoehne and Chester 2016).

5.3 Limitations

All the data introduced in the model are based on real information, from average travel speeds to charge and recharge times, together with all the elements associated with the cost of the vehicle. The only exception is traveled distance and, as explained before, the use of real data could distort the comparison between vehicles, reason for which we think it is more convenient to use simulations performed inside the distance range provided by the mathematical model. This approach is different to many of the consulted studies that search for more general results by resorting upon acceptable estimates for different cases and geographies. This strength is, at the same time, the main limitation of this study, since it reduces its application range. Given that the highest fidelity has been searched for a specific case, namely the last mile delivery in Madrid, its conclusions only apply to this case or others with similar characteristics. However, in our opinion, and in view of the coincidence of these results with the conclusions reached by most of the consulted literature, we think that our methodology and our results, in what refers to carbon pricing, can be generalized to other cities and BEV applications, since, as pointed out in the introduction, last mile transport is the most favorable application for this type of vehicles.

On the other hand, there are qualitative variables that are very difficult to add to a purely quantitative model, even though they might be relevant. For example, the study from Taefi et al. (2014) on Freight Electric Vehicles in five European states concluded that one of the main limiting factors for the adoption of BEVs in this type of applications was, in all the analyzed countries, “the lack of quality in after sales services”. However, including this factor into a model such as the one proposed in this paper seems quite intricate. One last limitation of the study is the variation in fuel consumption depending on the load of the vehicle. As the different deliveries are performed, the consumption of the vehicle will reduce as a result of a lesser cargo weight. Even though this effect may not be significant in most cases, it might be relevant from an operation cost perspective. The inclusion of this effect in the model would require real consumption data for different cargo loads.

Table 4 CO_2 price (€/tCO_2) required to make BEVs competitive for different subsidy levels and daily mileage

Subsidy (€)	Daily mileage (km)																			
	10	20	30	40	50	60	70	80	90	100	110	120	130	140	150	160	170	180	190	200
0	7598	3576	2235	1567	1162	894	705	560	449	359	285	227	176	130	92	56	30	11	3	0
4000	5306	2431	1472	991	708	513	376	275	195	130	79	36	8	1	0	0	0	0	0	0
8000	3014	1284	709	419	247	131	51	5	0	0	0	0	0	0	0	0	0	0	0	0
10,000	1869	712	326	132	22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11,000	1295	427	135	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12,500	436	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

5.4 Implications for research and policy

From an academic perspective, it would be necessary to extend these conclusions to different geographies and BEV applications. It is well known that the main objective of carbon pricing policies is to reduce the level of emissions from electricity and heat generation, which are responsible for 42% of the carbon emissions from burning of fossil fuels (International Energy Agency 2017: 12). However, the transport sector is in the second place in carbon emission levels, with a 23%. It is necessary to determine in what measure and in what timeframe, establishing a carbon price will contribute to the substitution of ICEVs by BEVs. In that same way, it would also be very useful to extend this study to Plug-in Hybrids Electric Vehicles (PHEVs).

It would also be of interest integrating our model with an electric market model, so that for every CO_2 price level the exact generation structure could be known and, therefore, the marginal technology which determines the pass-through to the final consumer, depending on its emission factor. Another future line of investigation which would be interesting, from our point of view, is expanding the scope of this study with Liu and Lin's (2017) proposal of using Monte Carlo simulations in several variables of the model. In this investigation, Monte Carlo has only been applied to energy prices and mileage. Nevertheless, it would actually be viable to use it on all other variables, increasing the applicability of this study to other more general scenarios. Finally, in order to improve the measure of the impact of the carbon price on the substitution of ICEVs by BEVs, the interaction between energy, carbon and BEVs prices could be analyzed in more detail.

From a political perspective, there are two especially relevant conclusions. The first one is that, in the short term, the most effective way of backing the BEV for last mile transportation is by obtaining support applied directly to the business case. Subsidies, in particular, are the most evident way but not the only one. A regulation that favors activities of this type of vehicles over ICEVs does not necessarily imply direct economic support. Nevertheless, this can be clearly applied to the income statement of those logistic companies that bet on clean vehicles (see, for example, European Environment Agency 2016: 62–63). The second conclusion is that carbon pricing mechanisms may help BEV penetration, but its effects are not going to materialize in the short term.

6 Conclusions

This article's main contribution is a model to analyze the impact of carbon pricing in transport decarbonization that combines real and detailed data of a specific city (in our particular case, Madrid) with simulated data obtained by solving a mathematical optimization model (the GVRP-MTPR). The latter, which is intended for avoiding biases observed in real data of daily covered distances that could favor electric vehicles, is a rather innovative approach in this context. Furthermore, analyzing the effects of BEVs being supported by a carbon pricing policy is also something relatively new in this type of research. Most existing studies do not include the effect of a carbon tax, or if they do, it is only included as a secondary element without an in-depth analysis of very relevant aspects such as the electric mix or the pass-through rates. Given the consistency of our results with other previous works, our methodological proposal could be applicable to different cities, which in fact we consider is another relevant contribution of this research.

The most important conclusion of this research is that, even though carbon pricing policies could have a positive effect in the long term, they are not an effective tool to promote BEVs/penalize ICEs in the short term, at least for the case of Madrid. In relatively clean electric mixes, carbon pricing is shown to be hardly effective when daily mileage is low (precisely when BEV requires incentives), while its effectivity increases as mileage increases (precisely when it is not so necessary to incentivize BEVs). Thus, this mechanism will not generate immediate effects and, as a result, any political decision must be adopted with a long-term view in mind. Our model explains this result for the particular case of last mile delivery, but taking into consideration that this application is the most favorable one for BEVs, we consider that it could be generalized to other BEV's applications, such as private transport.

There is an additional difficulty related to carbon pricing: the distribution of the required CO_2 price, which we showed to follow a Johnson SB distribution, is platykurtic and has a positive skewness value. As a consequence, in order to cover a wide variety of scenarios, it is necessary to substantially increase the CO_2 price from the average and mode values. On the contrary, direct subsidy to purchase price is an interesting alternative: although the implicit CO_2 price to make BEVs competitive is, logically, very high, and similar to the one necessary in a carbon pricing scheme, this implicit price only affects transportation, and as a consequence, it does not distort other sectors. Finally, and specifically for the case of Spain, we have shown that current aids to BEVs have been insufficient, with the exception of some regions like Madrid, which complement national subsidies with regional ones. This explains the low penetration of BEVs in Spain in comparison with other countries, whose bet for transport electrification has been more aggressive.

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