A Multicriteria Methodology for Estimating Consumer Acceptance of Alternative Powertrain Technologies

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Abstract

A multicriteria methodology for estimating consumer acceptance of vehicles with alternative powertrain technologies is presented. The approach is based on the non-compensatory ELECTRE TRI method and compares hybrid, plug-in hybrid, and electric vehicles to conventional models. Criteria considered are ownership costs and restrictions to vehicle use, which apply mainly to electric vehicles. The methodology is applied to a case study of 94 vehicles of different market segments and alternative powertrains. The analysis is carried out per segment and considers two driver profiles, city and all-purpose, and a baseline scenario for all cases. Output is tested for statistical significance, with powertrain technology as disaggregating factor, and a sensitivity analysis on the base scenario is also carried out, as well as a comparison with results derived by a compensatory multicriteria method (TOPSIS). Results show that conventional vehicles are the top choice for the small vehicles segment, due to lower purchase prices and higher use flexibility. For medium sized vehicles, all powertrain technologies are competitive for city drivers, whereas for all-purpose drivers, use restrictions for electric vehicles make these less attractive. The baseline scenario and sensitivity analysis highlight that opting for an electric vehicle depends strongly on the driver's use flexibility needs. As such, an electric vehicle can be either very attractive or outright unusable, regardless of financial considerations. It is also seen that plug-in hybrids do not present any significant advantage, as compared to other, non-electric choices, due to their higher purchase prices.

Keywords: alternative powertrain technologies; alternative fuel vehicles; consumer acceptance; multicriteria decision-making; ELECTRE TRI; TOPSIS.

1 Introduction

Transportation is responsible for over a quarter of the world's greenhouse gas emissions (IEA, 2017a), with road traffic being the biggest emitter, having accounted for circa 70% of all transport-related greenhouse gas emissions in the EU in 2014 (EC, 2017a). The road traffic sector represented 47.5% of EU oil consumption, being thus responsible for a high fraction of Europe’s energy dependence (Eurostat, 2018). Consequently, several strategies have emerged to further accelerate the diffusion of alternative powertrain vehicles, sometimes also referred to as “alternative fuel vehicles” (EVI, 2016). However, the rate of market penetration of them is still low, even though consumers already have multiple models of each kind available for purchase (IEA, 2017b). Psychological factors, such as the fear to embrace unseasoned expensive technology, may partly explain slow adoption but other factors also play a part. In particular, alternative powertrain vehicles tend to have higher purchase prices (see e.g. Lévay et al., 2017) and, in the case of battery electric vehicles, possible restrictions to their use also influence sales. The question then arises of determining to what degree quantifiable factors, such as costs and use restrictions, can influence consumer choice for these types of vehicles. This article proposes a new methodology to answer this question, based on multicriteria decision-making methods, which complements other existing approaches in the literature. It is tested in a case study which uses as data the vehicles available for purchase in Portugal as of 2017 and the country’s fiscal and financial context.

When considering a vehicle for purchase, consumers intuitively consider multiple aspects, so it is natural to try and explain consumer acceptance of alternative powertrain vehicles using analysis tools that consider multiple dimensions of reality, especially those that can be objectively quantified, such as costs and use restrictions. Several studies have shown that, when considering electrically chargeable vehicles, ownership costs, driving range, charging availability, and charging time are the factors that most influence their adoption (see e.g. Coffman et al., 2017; Liao et al., 2017). This research follows those findings and adopts the aforementioned criteria in its analysis, plus, in a particular scenario, CO2 emissions.

In this research four main powertrain technologies were considered, namely internal combustion engine vehicles (ICEV), hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV) and battery electric vehicles (BEV). These represented almost all of the 2016 sales in Portugal, with market shares of respectively 97%, 1.6% and 0.9% (PHEV + BEV) (ACEA, 2017). Alternative fuel vehicles, such as liquefied petroleum gas (LPG), natural gas or gasoline-ethanol blend (E85), were not included because they represented a combined share of less than 0.5% of the market and are not truly alternative powertrains, but merely ICEV running on different fuels. Vehicles of conventional powertrain technology (ICEV) were included to serve as comparison term, since it is against this status-quo technology, which represents the vast majority of sales, that alternatives are compared to. In addition, as vehicle segment and mobility patterns can influence vehicle characteristics and choice, the analysis was segregated into three vehicle sizes: small, medium and large vehicles; and two driver profiles, namely city and all-purpose driver profiles, for a total of six different sets of analysis. Segregation of analysis by vehicle size was also done in the analysis of Sharma et al. (2012).

In order to estimate consumer acceptance of the various vehicles on offer for each set, the multicriteria decision analysis method ELECTRE TRI was used (see section 3.4 for a brief description of this method. See also Mousseau et al. [1999] or Appendix C for technical details). This method classifies vehicles, i.e. puts them into bins, or classes, ordered and labeled from "avoid" to "buy", and does so by comparing them one-by-one against pre-defined reference classes, in a non-compensatory way; the latter meaning that a very low performance on a given evaluation aspect (criterion) cannot be compensated by good scores on other criteria. Furthermore, ELECTRE TRI captures in a natural way the imprecision and uncertainty inherent to human decision processes. These characteristics make it therefore a sensible choice to approach the decision problem at hand. Classifying the vehicles into classes that reflect consumer appreciation then allows for the use of statistical methods to determine how this appreciation depends on powertrain technology. The proposed methodology considers a base scenario, consisting of current real-world market and financial conditions, and follows up with a sensitivity analysis to changes in technical (BEV use restrictions), financial and analysis parameters, as well as a scenario with CO2 emissions as extra criterion. The outcome is thoroughly examined with statistical testing to draw significant conclusions concerning present and future consumer acceptance.

2 Literature review

Several studies on alternative powertrain technologies have been carried out over the last years. Many of these studies focus on financial aspects, such as e.g. estimating total cost of ownership (TCO) for different powertrain options. Bubeck et al. (2016) present an overview of TCO studies between 2012 and 2014 and also carried out an analysis for the German market, having found that PHEV and BEV are not economically feasible without major government subsidies. A similar conclusion was reached by Letmathe and Suares (2017), who also did a TCO analysis on the same market. Another regional analysis is that of Sharma et al. (2012), which focused on the Australian market and used sensitivity analysis to find what TCO changes would be required for BEV to be favored. Rudolph (2016) analyzed the impact of financial incentives in the likelihood of purchase BEV using logit models, having found that a surge in fuel prices would be the biggest factor increasing BEV sales. Tamor et al. (2013) used statistical trip data in a US city and a payback model to estimate acceptance of BEV and PHEV on a financial level. More recently, Lévay et al. (2017) carried out TCO calculations in eight European countries to find out how costs and sales of BEV relate to each other and to examine the role of fiscal incentives in reducing TCO and increasing BEV sales.

Research which considers multiple aspects of reality to evaluate or compare consumer acceptance of powertrain technologies has resorted mainly to stated preference research. This methodology usually consists of applying statistical logit and probit models to survey data. The approach gained momentum with early work by Ewing and Sarigöllü (2000), whose set of explanatory variables included, among others, the same criteria proposed in the present article. Batley et al. (2004) considered multiple logit models with different sets of explanatory variables. Caulfield et al. (2010) considered financial aspects together with CO_2 emissions. More recently, Hackbarth and Madlener (2013) attempted to profile the consumer most likely to prefer an alternative fuel vehicle. Hoen and Koetse (2014) carried out a choice experiment via online survey for the Dutch context. These authors also recognized that if availability of actual models is low, stated preference research becomes a necessity to obtain insight into potential barriers to alternative powertrain vehicles adoption. Shin et al. (2015) considered the impact of behavioral, socio-economic and demographic aspects in consumer acceptance. Valeri and Danielis (2015) considered a small sample of alternative powertrain vehicles and used Monte-Carlo simulations based on consumer interviews to estimate vehicle market shares. They also presented an overview of methodologically similar research. All these studies generally converged in the conclusion that use restrictions are important deterrents to consumer acceptance of BEV and other alternative fuels, and that major financial incentives would be required to make those attractive.

Research on vehicle powertrain and fuel choice for fleets includes van Rijnsoever et al. (2013), who estimated local government powertrain choices for vehicle fleets with a logit model, Yavuz et al. (2015) who compared seven alternative fuel technologies using a hierarchical hesitant fuzzy linguistic model for healthcare fleet use, and Oztaysi et al. (2017) who used multicriteria fuzzy analysis to find the best alternative fuel for a utility company vehicle fleet in the USA. In the first and second studies BEV came out as preferred, and in the third, natural gas vehicles were found to be the best single-technology fit. All these analyses considered CO_2 emissions.

In contrast with the large amount of literature on alternative fuel and powertrain technologies that resorted to logit models, there is considerably less research when it comes to application of multicriteria decision-making methods to the same problematic. Safaei Mohamadabadi et al. (2009) compared six ICEV fuels using PROMETHEE. Uçtug et al. (2015) compared four powertrain technologies using TOPSIS, with ICEV emerging as preferred. These studies used some form of use restriction as criteria. However, they also considered either small samples or prototype vehicles.

More recently, the impact of incentives and charging infrastructure condition on BEV and PHEV attractivity has been estimated from sales data using regression models (Jenn et al., 2018; Wee et al., 2018; Clinton and Steinberg, 2019; Munzel et al., 2019) and structural equation models (Rietmann and Lieven, 2019). This research is however restricted to the electrified powertrain technologies.

The present research attempts to estimate consumer acceptance of alternative powertrains in a rather different way than survey-based or regression studies, a way that is more closely related to multicriteria decision-making research. Instead of asking consumers how they would react to certain prototype vehicles or abstract vehicle characteristics, subsequently deducing purchase choice log-odds from the replies, or checking sales data looking for significant explanatory variables, the proposed methodology operates the other way around, by considering a real market line-up of vehicles, whose consumer acceptance it tries to predict by applying an adequately calibrated multicriteria decision-making model. Note that it would be a rather daunting (if feasible) task to ask a large sample of consumers for their personal opinion on dozens of vehicles. Even more because subjective factors would inevitably come to play, even if subconsciously. It is only because market availability of models with alternative powertrains has grown substantially that it became possible to get statistically significant insight into consumer preferences in ways which go beyond stated preference methods. This research is one such step in that direction.

The proposed methodology presents a novel, cumulative contribution to the state-of-the-art on consumer acceptance of alternative powertrain vehicles because of the above-mentioned different methodological approach and also because it makes use of a non-compensatory multicriteria method, which mimics the human decision-making process more closely than compensatory methods, thus filling the literature gap on the subject. In fact, to best of our knowledge, it is the first time ELECTRE TRI is used to approach the problem. The large-scale case study to which the methodology is applied makes it possible to use statistical tools to identify whether the specific market under scrutiny exhibits significant tendencies towards a certain powertrain technology or set thereof. It can also, through the sensitivity analysis, anticipate such tendencies, should the automotive industry and governments take steps to increase the attractiveness of the more modern powertrains.

3 Multicriteria analysis – methodology and base scenario

This section presents the criteria, defines how they were evaluated, and presents a base scenario for the analysis; all according to a set of assumptions, which is also presented. The vehicles considered in the analysis are indicated as well.

3.1 Main assumptions

The analysis considers that a consumer wishes to buy a brand-new vehicle as her main car and is considering whether to choose an alternative powertrain model or an ICEV. Main car means this vehicle will be used more often, both in frequency and distance travelled, than any other vehicle in household, and may even be the only vehicle in the household. Research which explicitly considers multiple cars in the household can be found in Tamor et al. (2013), Jakobsson et al. (2016), Karlsson (2017) and Björnsson and Karlsson (2017). It was also assumed the driver has access to a slow charging point for PHEV and BEV at home or nearby in the street, as purchasing one such vehicle is not plausible without access to a reliable source of electric power. When choosing a vehicle for purchase, consumers also have a specific vehicle size and use profile in mind. The following main assumptions are thus considered:

- Four powertrain technologies: ICEV, HEV, PHEV, and BEV.
- Three vehicle sizes: small, medium and large.
- Two driver profiles: city and all-purpose.
- Holding period: 5 years.

The powertrain technologies, vehicle sizes, and driver profiles will act as disaggregation factors in the statistical analysis of the results.

Small vehicles correspond to market segments A and B; medium vehicles to segments C, D and medium SUV; and large vehicles to segments E, F and large SUV (EC, 1999).

Driver profiles define typical uses for the vehicle. This research considers two profiles, which are perhaps the most common ones: drivers with city and all-purpose profiles. City driver profile refers to a person who uses her car mostly within a city or for short-distance commutes, with occasional road trips. All-purpose profile drivers often use their car as part of their work, with road trips forming the bulk of its travelled distance. Drivers which do long-distance commutes are also considered to be in this profile. City and short-distance commutes are termed “urban use” below, whereas road and long-distance commutes are termed “road use”. For the two driver profiles defined above, the following assumptions were made:

- City driver profile: annual travelled distance of 15,000 km, of which 80% km are urban use and 20% km road use.
- All-purpose driver profile: annual travelled distance of 30,000 km, of which 20% km are urban use and 80% km road use.

The annual travelled distances and urban/road percentages are assumptions, as no data could be found on the clustering of driving profiles for Portugal (nor for other countries, for that matter). Although data does exist on total urban/road use percentages, these could not be used because they are averages over all drivers and do not reflect the actual urban/road use percentages of individual drivers. The same applies to travelled distances, although in this case the assumptions are in line with the upper range of a study for six EU member states, which found that daily driven distances by ICEV vehicles vary from 40 km to 80 km, depending on the country (Pasaoglu et al., 2014). To cater for the lower range of that study, an analysis considering 7,500 km for city driver profile and 15,000 km for all-purpose driver profile, was carried out in the sensitivity analysis section.

Finally, the 5-year holding period is typical of European standards (BEUC, 2012) and battery life exceeds this period, which is why costs associated to battery replacement were not considered. An analysis considering a longer holding period (10-year) was carried out in the sensitivity analysis section, but again battery replacement was not considered as a cost because evidence begins to appear that batteries can hold for this long without degrading below usability thresholds (Pelletier et al., 2017; Bini et al., 2015).

3.2 Analysis criteria

Focusing now on the criteria, four of these were considered in the analysis, one cost-related and three others having to do with possible use restrictions on the vehicles, which are sometimes colloquially referred to as "range anxiety" criteria. This is one of the major obstacles to the BEV-wide adoption (Bonges and Lusk, 2016), even though this sensation tends to decrease after purchase with use experience (Franke et al., 2017). Range anxiety is due to both limited driving range and charging uncertainty (Charilaos et al., 2017; Wager et al., 2016).

As already mentioned in the introduction, the criteria considered are total cost of ownership, range, availability of charging points, and charging time. Except for one particular vehicle, the BMW i3 Range Extender PHEV which has a very small petrol tank and consequently a low range, use restrictions only apply to BEV. Although it may seem excessive to devote three criteria to aspects which only affect one of the powertrain technologies, this is justified by the fact BEV are in practice, and in the foreseeable future, the only alternative powertrain that is truly different than the combustion engine. It is therefore important to understand how the various sources of use restrictions contribute to affect consumer's choices, despite them affecting mostly just one vehicle type. A fifth aspect, CO_2 emissions, was also added in the sensitivity analysis section.

Performance, comfort and practicality criteria (e.g. trunk space) were not considered since the statistical analysis was carried out per vehicle segment and those properties are similar throughout the segment. Likewise, other criteria, such as brand image or aesthetics, were not considered due to their subjectivity.

Prior to exposing the criteria values calculation procedure, additional considerations on the four criteria are now given. Concerning ownership costs, the purchase price of vehicles that are more fuel-efficient is usually higher than the one of comparable conventional vehicles. The difference is due to battery costs for the case of BEV, and battery plus more complex powertrains for the case of HEV and PHEV. Albeit a reduction of the purchase price of alternative powertrains is expected in the future due to economies of scale in manufacturing, that reduction has not yet reached the market (Berckmans et al., 2017). On the other hand, vehicles that are more energy-efficient lead to lower running costs. Purchase price is often the key figure consumers look at, but potential buyers of alternative powertrain technologies also consider running costs and put all these factors into equation (Rezvani et al., 2015). However, Dumortier et al. (2015) found that fuel economy information did not influence consumers choice as the total cost of ownership information did. In light of this conclusion, it is the total cost of ownership, rather than purchase price, that is used as the financial criterion in this research. Given interest rates are at presently near 0%, net present values were not considered in the analysis. Nevertheless, in the sensitivity analysis section, a scenario with 4% discount rate was considered.

Concerning use restrictions, it can be argued that range, charging points availability and charging time may be dependent criteria. One can however counterargue that it is always possible to envision situations where each one of these criteria may be, individually, responsible for restricting vehicle use. Because the three are relevant for the decision-making process, the option was made to consider them as separate criteria, rather than trying to find some way to combine the three. This approach was also followed by other multicriteria research in the field (Yavuz et al., 2015). Note also that treating these criteria as independent clarifies the multicriteria analysis, making all the dimensions of this analysis explicit.

The criteria value calculation procedure is now presented. The values themselves were defined for the Portuguese context. Note that the driver profile affects this calculation.

3.2.1 Total cost of ownership

TCO includes purchase price, energy cost, insurance premium, maintenance, circulation tax and resale value. These were obtained as follows.

Purchase price

These were obtained from Portuguese brand websites, as of 2017, including shipment and legal costs (turnkey cost). For BEV a purchase rebate of 2,250 EUR was considered in accordance with the Portuguese Government's Environmental Fund (Fundo Ambiental, 2017).

Energy costs

Powertrain energy cost is the monetary cost of the energy necessary to run the vehicle, which in turn depends on powertrain type and driven distance. For fuel and electricity, average 2017 prices to date were used: 1.47 EUR/liter for petrol, 1.21 EUR/liter for diesel and 0.12 EUR/kWh for electricity. The energy cost was then calculated by combining fuel/charge price, annual km travelled, and official New European Drive Cycle (NEDC) mixed consumption figures. Although urban and road uses usually lead to different consumptions, for many of the case study vehicles only the NEDC mixed values were available, and an option was made to use these figures for all vehicles. Note that all new combustion vehicles have start/stop technology, which diminishes the consumption gap between urban and road uses. Any imprecision in final results due to this issue is thus expected to be very small. For PHEV, calculations were carried out on a daily basis (41 km/day for city driver profile, 82 km/day for all-purpose driver profile), considering one full charge per day. It was assumed that the car would run on battery power until its depletion, at the end of the reported range, after which it would enter combustion mode.

Authors also acknowledge that there is a gap between NEDC fuel consumption and fuel consumption during real-world driving conditions, as reported by several authors (e.g. Zhang et al., 2014; Pavlovic et al., 2016; Triantafyllopoulos et al., 2017). The gap has been growing over the years, leading to real-world adjustment factors (ICCT, 2015). Consequently, Europe is adopting the World Harmonised Light Vehicle Test Procedure (WLTP) in the type-approval process (EC, 2017b; Tsokolis et al., 2016), whose consumption figures are expected be higher than NEDC ones (Pavlovic et al., 2016). However, as real-world adjustment factors for BEV and PHEV are not well established and WLTP figures are yet to come, NEDC consumption figures had to be considered instead. Since this research carries out a comparative analysis, this is not expected to have a significant impact in the final results. If something, using WLTP figures would slightly benefit BEV due to their lower cost/km, but that would not alter its use restrictions.

Insurance

The insurance premium prices were simulated from one of the major insurance companies in Portugal. As the values are owner-specific, an average owner was considered (35 years old and 15 accident-free years). Prices depended mostly on tech and vehicle size and the average values of Table A.1 (see Appendix A) were used. BEV have higher insurance premium values except when the battery is rented, which is the case of the Renault ZOE.

Maintenance

Maintenance cost includes warranty planned maintenance and other costs. Concerning warranty maintenance, data from the largest brand dealerships operating in Portugal was obtained and averages values were considered. For other maintenance costs, tire replacement and assorted costs were considered. Table A.1 (Appendix A) summarizes the costs obtained gathering all this information. BEV have fewer mechanical systems and components, and consequently have a lower maintenance cost than other vehicles. For these vehicles, maintenance costs of 65% of a non-BEV vehicle within the same segment was considered, as suggested by Lebeau et al. (2013).

Circulation tax

The Portuguese annual circulation tax is based on engine capacity, CO2 emissions and age (IUC, 2017). BEV are exempt from this tax. Tax values were obtained directly from the legal formula, for each vehicle.

Resale value

Vehicles depreciation over the holding period usually depends on several factors (Messagie et al., 2013; Lévay et al., 2017). Despite this fact, in practice the 5-year resale value tables of one of Portugal's leading car magazines, Autohoje (now Automag), shows an average of circa 42% retention of the original purchase price, with very little dispersion over segment and powertrain technology (Autohoje, 2018) (coefficients of variation in the 8-17% range, indicating an overall low variance). Also, there was no data on resale value after 5 years for PHEV and some BEV, so an estimate had to be made. For these two reasons, the 42% figure was used to evaluate resale value for all vehicles.

3.2.2 Range

For BEV, manufacturer-reported driving ranges were considered. For the remaining technologies a driving range of 700 km was used, as this was the minimum range for vehicles with combustion engine, except for the BMW i3 Range Extender PHEV, whose combined autonomy is circa 300 km, owing to its small fuel tank. No other range or charging restrictions were considered for the remaining PHEV.

3.2.3 Charging points

Availability of charging points affects the choice for PHEV and BEV (see e.g. Achtnicht et al., 2012). Two different charging availability values for BEV were considered. For urban use, because of the assumption of user access to a charge point at home or close by, an availability of 100% was considered. Drivers living in multi-unit residential buildings without charging provisions would have a lower availability, but this was not considered in the analysis because it is very unlikely such drivers would buy PHEV or BEV at all. Note however that new public (and private) charging points are being installed daily (EAFO, 2019), increasing the number of drivers for which these vehicles become an option, potentially reaching the same density as regular fuel stations (Gnann et al., 2018). For policy implications of charging in multi-unit dwellings see e.g. Lopez-Behar et al. (2019). For road use, some researchers expressed charging availability as a percentage of the existing fuel stations (Tanaka et al., 2014; Hackbarth and Madlener, 2013). As of 2017, there were 65 fuel stations in the Portuguese highways (APETRO, 2017), of which 16 had fast-charging points (MOBI-E, 2017). This results, by that measure, in a charging availability of 25% (16 chargers/65 fuel stations), which was the assumed value for road use. Considering only highway coverage is acceptable because Portugal has an exceptionally good network of these road infrastructures, reaching out to all its provinces and still growing (OECD, 2015). Combining the above assumption with driver profiles yields (recall city driver profile 80/20% urban/road use; all-purpose driver profile 20/80% urban/road use) BEV charging availabilities of 85% and 40%, for the city and the all-purpose driver profiles. As for ICEV, HEV and PHEV, an availability of 100% was considered instead, given the abundance of fuel stations.

3.2.4 Charging time

Charging time is only an issue for BEV and depends almost entirely on the power of the charge station. Charging can be carried out at home or in public points, the latter consisting of slow- and fast-charging points. For urban use, charging times were estimated dividing battery capacity by the power of a 3.7 kW charger (230 V, 16 A current), the maximum power output available in Portugal for domestic use without specialized charging equipment and in slow public points. For road use, fast-charging of 40 kW was considered, the standard at highway service stations. Two BEV cap fast-charging; Smart fortwo ED at 22 kW and Mercedes B ED at 11 kW, so for these BEV the respective maximum power values were used instead of 40 kW. For non-BEV vehicles, a refueling time of 5 minutes was considered for this criterion (Hackbarth and Madlener, 2013; Ito et al., 2013). Finally, as was done for charging availability, BEV final charging times were obtained for each vehicle and driver profile by averaging over the respective urban/road use percentages.

3.3 Case study vehicle set

A total of 94 vehicles was considered, including all the HEV, PHEV, and BEV available in the Portuguese market as of 2017, together with the ICEV base model they derived from, if available (otherwise a comparable model was selected). Table 1 presents the considered vehicles, per segment and powertrain technology. The full set of criteria values can be found in Tables B.1 and B.2 (Appendix B), for both driver profiles. These tables also present for each vehicle the energy cost per km. Average values for the purchase price, running costs (the sum of energy costs, maintenance costs, circulation tax and insurance value), resale value, and total cost of ownership are depicted in Figure 1.

Note that for medium vehicles the TCO is favorable for BEV in Portugal, in contrast with other markets like e.g. the German one, for which both small and medium BEV were found to be uneconomical (Letmathe and Suares, 2017).

Table 1 – Vehicles per segment and powertrain technology

	ICEV	HEV	PHEV	BEV
Small	Citroën C1 Fiat Panda Peugeot 108 Smart fortwo Toyota Yaris (D+P) Toyota Aygo VW Up	Toyota Yaris	BMW i3 REx	BMW i3 Citroën C-zero Mitsubishi i-MIEV Peugeot i-on Renault ZOE Smart fortwo ED VW e-Up
Medium	Audi A3 Sportback (D+P) BMW 2 Series (D+P) BMW 3 Series (D+P) Citroën DS5 (D+P) Kia Soul Mercedes B-Class (D+P) Mercedes C-Class (D+P) Nissan Qashqai (D+P) Toyota Auris (D+P) Toyota Auris TS (D+P) VW Golf (D+P) Volvo V60 (D+P)	Citroën DS5 Hyundai IONIC Lexus CT Lexus IS Lexus NX Mercedes C-Class Toyota Auris Toyota Auris TS Toyota Prius Toyota Prius Plus Toyota Rav4	Audi A3 Sportback BMW 2 Series BMW 3 Series Mercedes C-Class Toyota Prius VW Golf Volvo V60	Kia Soul Mercedes B-Class Nissan Leaf-24 Nissan Leaf-30 VW Golf
Large	BMW X5 (D+P) Ford Mondeo (D+P) Mercedes E-Class (D+P) Mercedes S-Class (D+P) Mitsubishi Outlander Peugeot 508 (D+P) VW Passat Volvo XC90 (D+P)	Ford Mondeo Lexus RX Lexus GS Mercedes S-Class Peugeot 508	BMW X5 Mercedes S-Class Mitsubishi Outlander VW Passat Volvo XC90	Tesla S-75D Tesla X-75D

Legend: **D**-Diesel ICEV; **P**-petrol ICEV

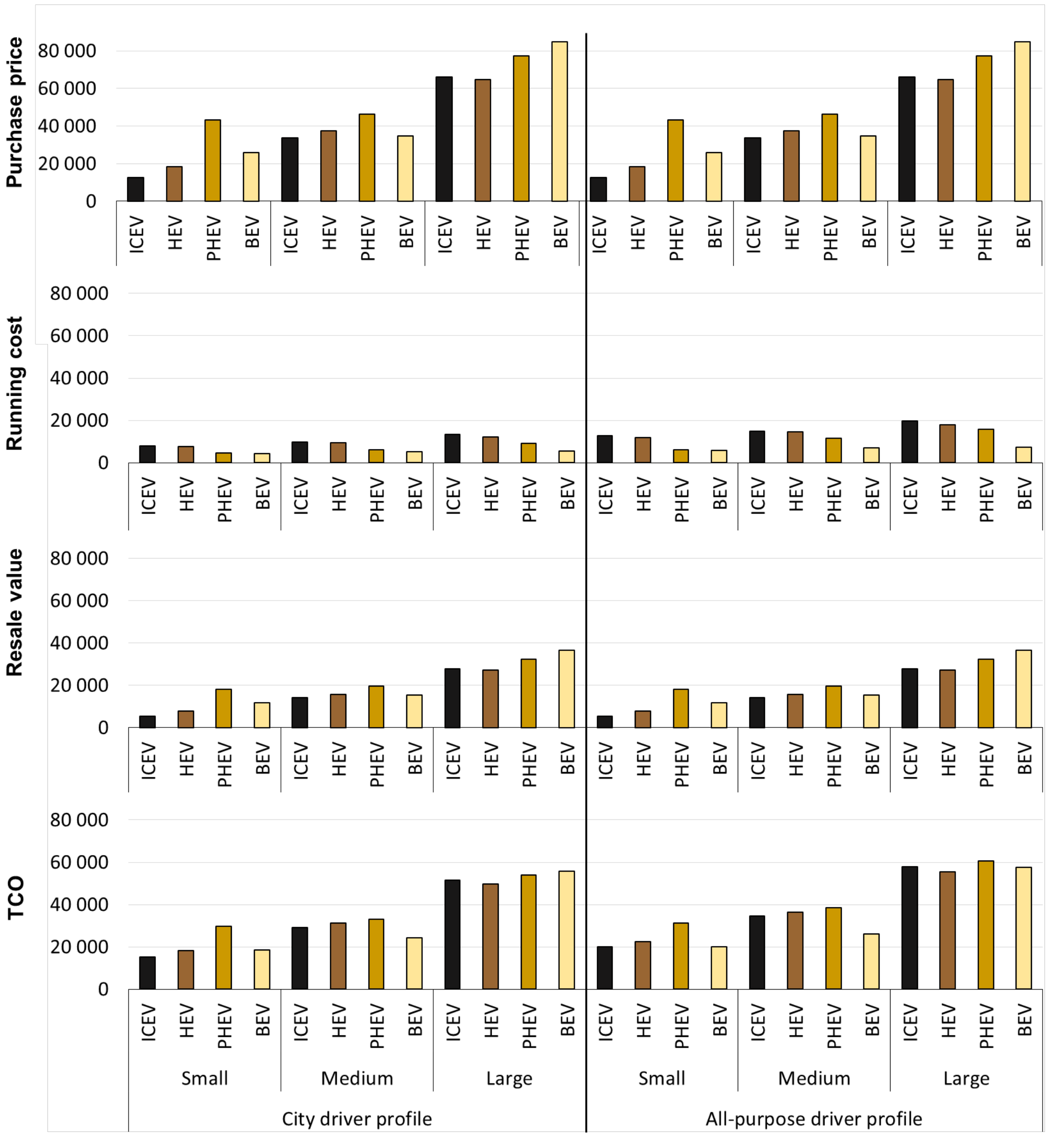


Figure 1 – Average values for purchase price, running cost, resale value, and total cost of ownership

3.4 ELECTRE TRI Method and Parameterization

With the datasets defined in the previous sections, the last piece of the methodology is the multicriteria method. As mentioned in the introduction, the ELECTRE TRI non-compensatory outranking method was selected for the purpose. A short, qualitative description of this method is provided below. More details on principles of this method can be found in Appendix C and in Mousseau et al. (2001).

In ELECTRE TRI the alternatives (vehicles) are compared against pre-defined and ordered performance (or reference) classes, ultimately being assigned to one of those classes. For the decision problem of this research, four classes were defined *a priori*, which can be seen qualitatively as consumer decisions of “1-Avoid”, “2-Consider”, “3-Shortlist”, “4-Buy” over the vehicle under consideration. The “buy” class can have multiple vehicles, from which the consumer would ultimately choose one according to her subjective preferences. In the end, each vehicle in the set under study gets assigned by the method to one specific class, which reflects its consumer appreciation.

The comparison is carried out making use of the criteria values that characterize the vehicle and criteria values that characterize the reference classes' borders, or breakpoints (see Figure 2, section 3.4.2). This is done in a non-compensatory way, meaning that significant low performances on some criteria cannot be compensated with very high performances in other criteria (whereas in compensatory methods it can). Therefore, each individual criterion can individually play a crucial role in the aggregated performance of an alternative (Mousseau et al., 2001). If a given alternative (vehicle) has all its criteria values sitting between the values of two consecutive reference class breakpoints, it is clear to assign that vehicle to the class delimited by those breakpoints. However, this is not always the case: often vehicles will have criteria values spanning across various class breakpoints. Situations like these are sorted out using the concept of *outranking*. Formally, an outranking relationship states that even though two alternatives A and B do not dominate each other, it is realistic to accept the risk of regarding A as almost surely better than B if a majority of criteria supports it (concordance) and no individual criterion strongly opposes to it (non-discordance). ELECTRE TRI constructs outranking relationships between an alternative (vehicle) and reference classes breakpoints and the outcome is then used to assign the vehicle to a class. In order to express the outranking relations more realistically, the imprecision and uncertainty inherent to human decision processes are accommodated in ELECTRE TRI through the use of indifference, preference and veto thresholds. These thresholds enter the calculation of concordance and discordance indexes and are at the core of the method's non-compensatory nature.

In practice, applying ELECTRE TRI requires defining a series of technical parameters, namely criteria weights; reference classes breakpoints; thresholds; cut level and class assignment rule. These were determined as follows.

3.4.1 Weights

In ELECTRE TRI, weights are internal parameters which indicate the relative importance of each criterion and are used to calculate concordance indexes. Weights were defined using the pairwise comparison Analytic Hierarchy Process (AHP) method (Saaty, 1987). In AHP, weights are derived by transforming a matrix of pairwise comparisons between criteria to a vector (matrix eigenvector), whose normalized values are the weights. The comparisons are in turn done by (subjectively) judging the importance of one criterion relatively to another, using a standardized integer scale of 9 levels (1 = equally important, 9 = absolutely more important). Following AHP standard practice these judgements are to be exercised by a small number of experts (see e.g. Bilsel et. al [2006] and references therein), thus three researchers, selected by their experience in the field of automotive science, were summoned. Their pairwise scores were obtained independently of one another, after which the experts met and discussed to agree on final scores by consensus (Bilsel et. al, 2006). These final scores passed the AHP self-consistency checks and led to the weight vectors presented in Table 2.

Table 2 - Criteria weights

	TCO	Range	Charging Points	Charging Time
City driver profile	68.1%	12.3%	8.4%	11.2%
All-purpose driver profile	52.4%	21.1%	13.2%	13.2%

The AHP pairwise comparison matrices are presented in Table A.3 (Appendix A), together with the judgements' consistency ratio, which is required to be below 10%.

3.4.2 Reference classes

Defining the aforementioned reference classes, avoid/consider/shortlist/buy, requires setting three breakpoints, on a per-criteria basis, for each driver profile. Breakpoints essentially define the class borders, i.e. where one class ends and the next one begins.

TCO: breakpoints were defined as quartiles of the TCO set for each of the six cases (three segments × two driver profiles).

Range: the average daily km travelled was evaluated for both driver profiles (41 km city profile, 82 km all-purpose profile). Then the lowest breakpoint for range was set as 50% over daily average kms. This 50% margin was considered to cater for eventual fluctuations (not all days are the same) and to alleviate range anxiety. Breakpoints defining classes 3 and 4 were then defined as 50% over ranges which would require 2 and 1 recharges/week. Afterwards range was linearly normalized to a 0-1 scale, with ranges of 700+ km corresponding to 1. This resulted in class breakpoints of 0.088/0.308/0.615 for city and 0.176/0.615/1 for all-purpose driver profiles.

Charging points: breaks were defined as 0.33/0.50/1 for all segments and both driver profiles. The rationale for the lowest break was the recommendation that drivers should rest every two hours of driving (PRP, 2018), which translates to about 150 to 200 km at average road speeds. Since the average distance between service stations in highways is roughly 50 km, a coverage of at least 33% would be required for a BEV to be able to complete a road journey. Hence 0.33 was chosen as lowest break point for charging points.

Charging time: given the slow/fast charging assumption for urban/road use, different breakpoints were considered for city and all-purpose driver profiles, of respectively 8/4/0.167 hours and 0.50/0.33/0.167 hours. The common 0.167 break means any vehicle that refills/recharges in less than 10 minutes is class 4 "buy" in this criterion, which is about the maximum time one is willing to spend at a station for a simple refill. For the city driver profile, the 8/4 hours represent a whole/half night for recharging. In other words, if a vehicle which takes more than a whole night to charge, it should score 1 "avoid" in this criterion. For all-purpose driver profiles these values come down to 1/0.5 hours (fast charge at service stations). Again, only BEV are affected by charging time issues.

Figure 2 shows the class breaks in a graphical format.

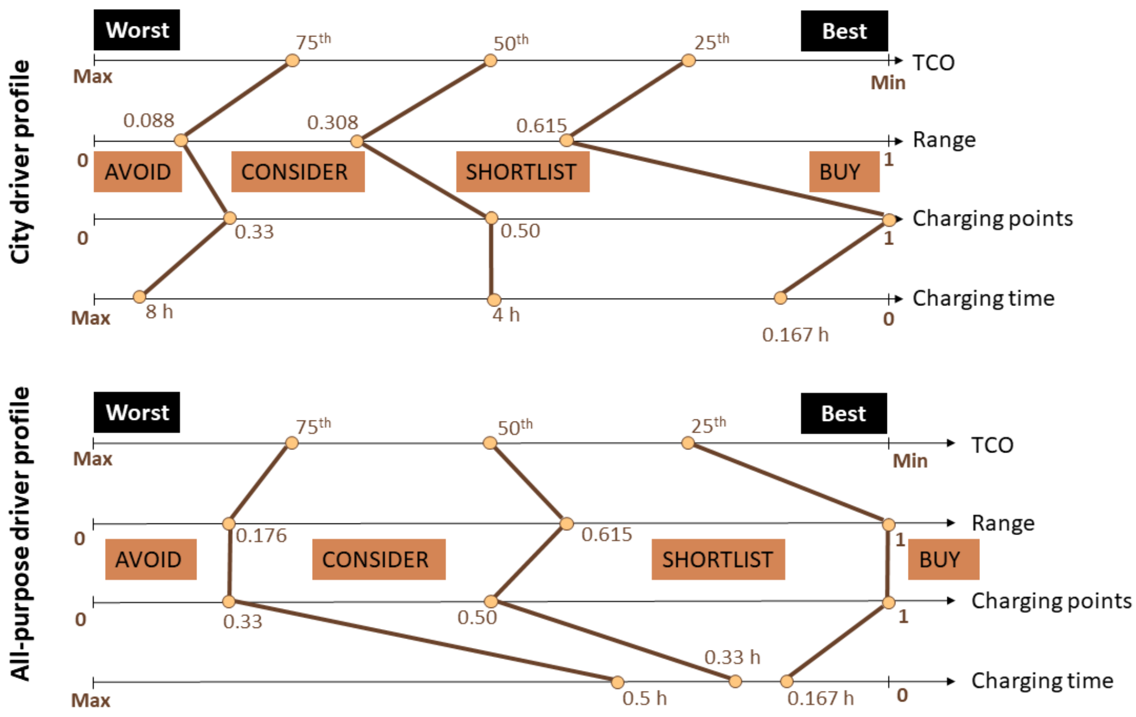


Figure 2 – Breakpoints and corresponding classes

3.4.3 Thresholds

Indifference, preference and veto thresholds are internal parameters common to most ELECTRE family methods, which are used to account for imprecision and uncertainty aspects of human decisions. In summarized way, *indifference* reflects the fact that humans are insensitive to small differences in criterion values, e.g. it doesn't matter if, when comparing two houses, house A has a price of 150 k€ and house B 151 k€. But if B costs 180 k€, then one would have a *preference* for the cheaper one, when it comes to price. If house B were to cost 400 k€, it could not be considered as better than A, regardless of the remaining criteria (e.g. areas, location, nr. of bedrooms, etc.), because it would be too expensive. I.e. the price criterion puts a *veto* on the assertion "house B is at least as good as house A" (semantic of the outranking relationship used as preference model in ELECTRE methods (Mousseau et al., 2001)). Thresholds simply define the limits where indifference, preference and veto lie.

For all criteria, all thresholds were chosen as percentages in indirect preference (i.e. percentage of best value vs worst value) (Tam et al., 2003; Almeida-Dias et al., 2010). For TCO, these thresholds were 4/7/10%, as TCO values are tightly packed and higher thresholds could cause indifference and preference to span multiple classes. For range, charging points and charging times, the slightly higher values 10/20/30% were considered instead, since criteria values have a higher spreading.

3.4.4 Cut level and class assignment rule

The cut level is an internal parameter of the ELECTRE TRI method governing the outranking relations, which should lie between 0.5 and 1 (Mousseau et al., 2001). This was set to 76%, which means TCO alone is not enough to dictate the outcome of the comparisons between a vehicle and the break it is being compared with (prior to vetoes), i.e. other criteria also matter. Finally, class assignment choices regulate how the outranking relations are handled to assign a vehicle to a particular class and the conjunctive rule was used for this purpose.

4 Case study results and discussion

With the vehicle dataset defined and ELECTRE TRI adequately parameterized, the method can now be run. Results for the baseline scenario are presented in section 4.1 below, after which a sensitivity analysis is carried out (section 4.2) and the overall picture and its policy implications are discussed. The baseline scenario represents present status-quo, whereas the sensitivity analysis is aimed at predicting future acceptance, as technology evolves.

4.1 Baseline scenario

Baseline calculations yield the results summarized in Figure 3 below, for the six combinations of segment size and driver profile. This figure presents the percentage distribution of the vehicles in each powertrain technology in the ELECTRE TRI performance classes. These combinations will henceforth be designated in the form [size]/[profile], for short.

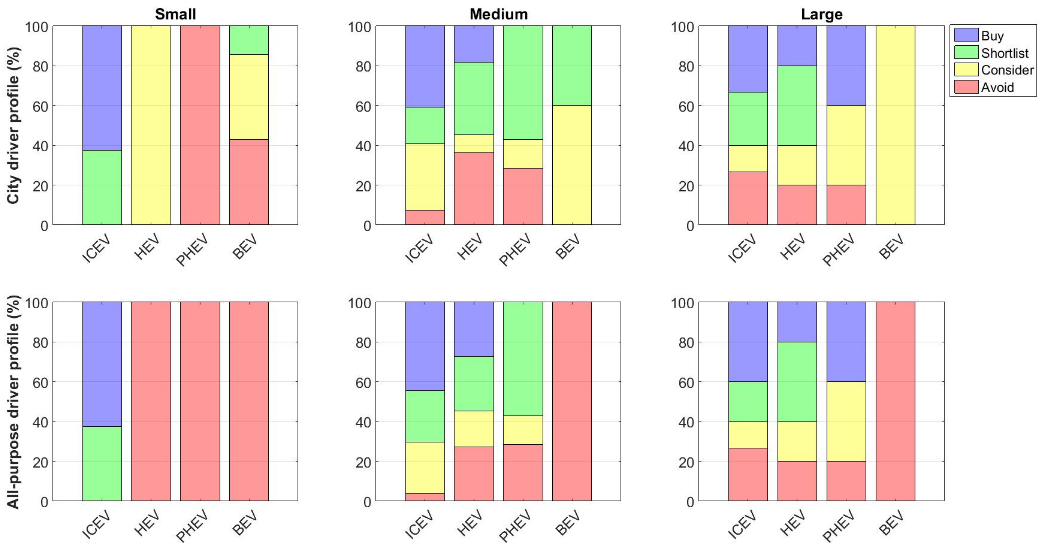


Figure 3 - Baseline ELECTRE TRI classes per powertrain technology, vehicle size and driver profile

A quick glance at the results indicates two main observations: (1) ICEV are clearly preferred in the small car segment, and (2) BEV score poorly in all-purpose driver profile. To assign statistical significance to these findings, Kruskal-Wallis analysis of variance tests were carried out separately for each of the six cases, with ELECTRE TRI class, expressed in a 1-to-4 Likert scale, as dependent variable, and powertrain technology as factor. Because Kruskal-Wallis testing is based on ranks of the dependent variable, it is ideal to analyze outputs that presented a discrete, ordered scale, as these are. For Kruskal-Wallis p-values below 10%, post-hoc Dunn tests were also carried out to identify deviant technologies, with Benjamini-Hochberg (BH) false discovery rate correction for p-values. Although the link between powertrain technology and ELECTRE TRI class is best represented by an ordinal logistic regression model, insufficient number of observations for each technology type and ELECTRE TRI class makes it impossible to consider such a model for most cases. Note that such a logistic model would have powertrain technology as predictor and thus be very different than existing logit models, which use as predictors the vehicle characteristics used here as criteria.

Table 3 below summarizes statistically significant findings for the baseline scenario.

Table 3 - Kruskal-Wallis and significant Dunn/BH p-values for baseline scenario

	Small	Medium	Large
City driver profile	Kruskal-Wallis 0.7% ICEV > BEV 0.5%	Kruskal-Wallis 30%	Kruskal-Wallis 89%
All-purpose driver profile	Kruskal-Wallis 0.2% ICEV > BEV 0.1%	Kruskal-Wallis 0.2% ICEV > BEV 0.1% HEV > BEV 2.5%	Kruskal-Wallis 33%

The statistical analysis confirms that indeed (1) ICEV are better choices than BEV for small vehicles in both driver profiles and that (2) medium sized BEV are inferior to ICEV and HEV for the all-purpose driver profile.

Looking at small vehicles, the first conclusion can be attributed to lower TCO and higher use flexibility for ICEV. As for other technologies, although the low number of small HEV and PHEV makes it difficult to identify a statistically significant tendency, Figure 3 hints at these technologies also not being competitive with ICEV. Note that the extra fabrication costs of alternative powertrain technologies make up for a more sizeable difference in the purchase price when the model has a low base price. Sharma et al. (2012) also concluded that electrification is less attractive economically for small vehicles than it is for large vehicles. Deprived of TCO advantages, HEV and PHEV lose appeal. The same goes for BEV which, hampered by use restrictions as well, cannot compete with ICEV.

The situation for medium sized vehicles is very interesting because it depends on the driver profile: medium/all-purpose drivers have higher use flexibility demands on the vehicles, which BEV simply cannot deliver due to their use restrictions. For medium/city drivers however, those use requirements loosen and BEV become competitive due to lower TCO. HEV and PHEV show no significant advantage and the end result is that for this case all powertrain technologies are similar in appeal. It should be noted that both Hoen and Koetse (2014) and Hackbarth and Madlener (2013) also found people with lower annual km travelled to be more likely to prefer a BEV. The later study also found a preference for small BEV, rather than medium sized ones, but that is likely to be an independent effect, since there was no testing for small BEV × price effects.

For large sized vehicles there are also no significant differences between powertrain technologies. However, looking at the descriptive statistics of Figure 3, there is a hint that the situation might in fact be similar to that of medium sized vehicles: BEV mildly competitive for large/city but not for large/all-purpose. Again, the fact that there exist only two BEV in this case makes it difficult to assign statistical significance to this observation. One can speculate that if other large BEV enter the market, they will have similar characteristics to the two models already present. If so, it is likely that the tendency for medium sized vehicles carries through to large sized ones, i.e. that large BEV are an option for city profile, but not for all-purpose profile.

4.2 Sensitivity analysis

The sensitivity analysis aims at predicting changes to consumer acceptance stemming from the foreseeable evolution of technology and reality. In this section sensitivity to ELECTRE TRI parameter changes and comparison with a compensatory multicriteria method (TOPSIS) is also assessed. As technology and charging infrastructure evolve, the shortcomings to BEV will mitigate. It is therefore natural to ask what would happen if some, or all, use restrictions are lifted in the future. Changes in fiscal policy (incentives), fuel price or holding period could also result in TCO structures more favorable to BEV and PHEV, as well as adding an environmental component. Table 4 below describes the scenarios considered in the sensitivity analysis. Some of these scenarios are similar to those considered by Sharma et al. (2012).

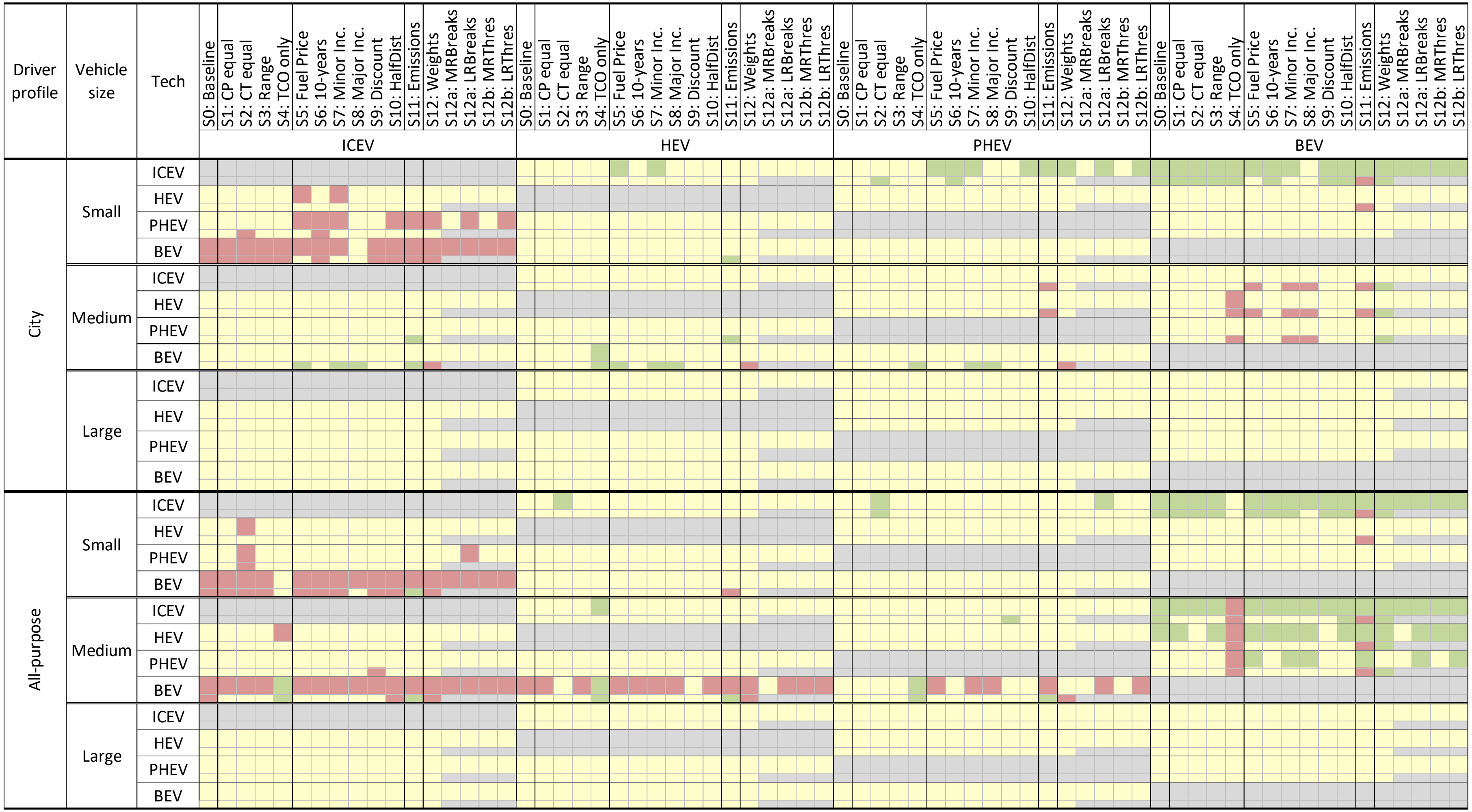
Table 4 – Sensitivity analysis scenarios

Scenario – S0	Baseline
Scenario – S1	Abundance of EV fast-charging points – all powertrains have max charging/fueling points.
Scenario – S2	Reduced EV charging time – all powertrain have the same charging/fueling time.
Scenario – S3	Higher battery capacity – all BEV range increased to 700 km.
Scenario – S4	No use restrictions to BEV – S1, S2 and S3 combined.
Scenario – S5	Higher fuel prices – double the baseline values for diesel and petrol fuel.
Scenario – S6	Higher holding period – considering a 10 years-holding period.
Scenario – S7	Minor purchase incentive – incentives of 5,000 EUR for BEV and 2,500 for PHEV.
Scenario – S8	Major purchase incentive – incentives of 10,000 EUR for BEV and 5,000 for PHEV.
Scenario – S9	Discount rate of 4% – on all financials except purchase price.
Scenario – S10	Half annual travelled distances – 7,500 km city, 15,000 km all-purpose.
Scenario – S11	Environmental awareness – addition of a CO2 emissions criterion with a 33% weight.
Scenario – S12	ELECTRE TRI parameter sensitivity – weights, class breaks, thresholds.

Figure 4 below shows a graphical summary of the statistical tests for the various sensitivity analysis scenarios.

Figure 4 – Powertrain technology pairwise comparisons

Green: tech in row more desirable than tech in column | **Red**: tech in row less desirable than tech in column| **Yellow:** no statistically significant differences



Note: the top thicker row in each tech shows ELECTRE TRI results, while the bottom thinner one shows TOPSIS results. Grey is N/A (not applicable).

The figure presents the outcome of powertrain technology pairwise comparisons, depicting in color-code and for each driver profile and vehicle size, if a powertrain technology is (or is not) more desirable than another. Note that the figure has two types of row, a thicker one at the top with ELECTRE TRI results, and a thinner bottom one with TOPSIS results (see section 4.2.2). Taking the first row of the table as an example, i.e. city/small vehicles in the ELECTRE TRI analysis, it is seen that ICEV are more desirable than HEV in scenarios S5 and S7; more desirable than PHEV in S5-7, S10-12, S12aLRB and S12bLRT; and more desirable than BEV in all scenarios except S8. For the second (thinner) row, i.e. city/small vehicles in the TOPSIS analysis, ICEV are similar to HEV in all scenarios; more desirable than PHEV in S2 and S6; more desirable than BEV in all scenarios except S5 and S7-8, and less desirable than BEV in S11.

In Appendix D, Table D.1, a complete description of these results is presented, including output variable means and test p-values, together with an alternative way to visualize of the results: Figures D.1 and D.2 show, for all scenarios, the percentage distribution of the vehicles in ELECTRE TRI performance classes, clustered by size/tech/profile. Likewise, Figures D.3 and D.4 show, for all scenarios, boxplot of TOPSIS scores, for the same clustering type.

A summary of the data curation and findings for the various scenarios is now given, after which comparison with the compensatory multicriteria method TOPSIS is carried out and a global view is presented and discussed.

4.2.1 ELECTRE TRI results

Scenarios 1-4: alleviation/lifting of BEV use restrictions

For scenarios S1-3, results were obtained by changing the values of the criterion under consideration on the decision matrix. For S1 charging point criterion values were set to 1 for all vehicles; for S2 all charging times were set to 5 minutes; and in S3 all ranges were set to 1 (700+ km). For S4, the above was done simultaneously for the three use restriction criteria, meaning only TCO would matter for calculations. Note that S2 would require massive electric currents, but it may be possible in the future. A run with Tesla-type superchargers (120 kW) was also carried (not shown in the results), with outcome slightly worse than S2 for BEV, but otherwise very similar.

Results for S1-3 show that, despite some fluctuations on the individual classifications, only slight changes appear in the statistical tendencies. Thus, conclusions from the baseline scenario still hold: ICEV are preferable to BEV for small vehicles; all technologies are competitive for the medium/city case; and BEV perform poorly for all-purpose driver profile. The conclusion is that solving one limitation from BEV alone is not enough to make them more competitive.

Scenario S4 (no use restrictions) however does exhibit different statistical tendencies. ICEV are still preferable to BEV for the small/city case, but for the other three small and medium cases, BEV become competitive, even surpassing all other powertrains in the medium/all-purpose case. This hints that if all use restrictions concerns are lifted, i.e. range anxiety is gone, the better TCO of BEV makes them very competitive options. Scenario S4 shows that a strong investment in battery development and charging infrastructure is necessary to reach a point where BEV become, *per se*, more attractive to consumers than other options.

Scenarios 5-10: financial issues

For scenario S5 (fuel price doubled), changes to TCO were calculated and new quartile class breaks for TCO were used, to adjust to the new reality. As can be seen from Figure 4 and Appendix D, and despite some positive class changes for PHEV (see figures D.1 and D.2, medium PHEV), S5 results do not differ substantially from the baseline scenario. A test with original TCO breaks was also carried out (not shown in table), the outcome being a tendency for all technologies to have similar scores, but all bad ones: all non-BEV become expensive to run and drop classes (in some cases the 4 “buy” class even disappears), whereas BEV could not reach better classes due to use restrictions. Regardless of whether the original or new breaks are considered, the conclusion is fuel price hikes do not directly make PHEV and BEV more attractive. If something, they make combustion engine cars more expensive to run. This conclusion is different than Rudolph (2016): while, as by that author, consumers would be willing to change to BEV with financial incentives, here it is found that use restrictions put a serious dent into realizing that intention.

For scenarios S6-8 new TCO were calculated and new breaks were also defined. For S6, tech-averaged depreciation percentage over 10 years was considered. The baseline conclusions again do not change significantly, although for S8 (major incentive) all powertrain technologies become competitive for the small/city case. Results with original class breaks were also derived (not shown), the outcome being that in this case ICEV remain better than PHEV and BEV. The conclusion for scenarios S6-8 is that, again due to use restrictions, neither the cumulative savings from 10 years of km travelled nor incentives, even major ones, are enough, in general, to make BEV more attractive.

Scenarios S9 (4%-discount rate) and S10 (half distance travelled) are also similar to baseline (new TCO breaks were defined for these two scenarios). In S9 a (fairly high) discount rate of 4% was considered, led to only one TCO-related statistical change in comparison to the baseline scenario, namely the medium/all-purpose case, where the HEV advantage over BEV disappears. Discounting affects all the financials except purchase price. Since purchase price is a large fraction of the TCO, it is unclear in what direction high discounts would, in general, point out. Tests with a more realistic discount rate of 0,64%, the average inflation in Portugal 2014-2018 (PORDATA, 2019), did not show any statistically significant difference when compared to S0. These results proved there is robustness against including interest rates in the calculations, so this factor is not expected to have much of an impact, at least up to 4% rates. As for scenario S10, the annual km travelled were set to 7,500 km for city driver profile and 15,000 km for all-purpose. The lower mileage decreases running costs, thus reducing the advantage of PHEV and BEV. This is indeed reflected in the p-values of Table D.1, but in terms of statistical significance most of the baseline results still hold. It is only for the small/city case that a difference is found, namely that ICEV become so cheap to run that they surpass PHEV.

Rounding up on S5-10, the absence of a clear-cut result such as "a saving of X euros makes BEV the better choice" is an important conclusion of this research, indicating that financial issues alone may not be sufficient to make BEV attractive, because BEV have fundamental barriers to their use, which are captured by the methodology. Another important conclusion is that delivering on the PHEV promise of giving drivers the best of both worlds has extra tech costs which, in practice, are difficult get back, even with incentives.

Scenario 11: inclusion of CO2 emissions

CO2 emissions can be considered both at the TCO level and as an environmental impact. At the TCO level, CO2 prices already feature in the circulation and import taxes (the latter get reflected in purchase price). Considering CO2 environmental impact requires treating it as a separate criterion. Since the degree of environmental concern varies significantly according to consumer conscience, the option was made to consider this as a criterion and add it to the calculation only in this sensitivity analysis section. The CO2 emissions of NEDC type-approval test for mixed circuit were considered and PHEV (electric mode)/BEV emissions were estimated from the 2017 electricity mix of Portugal (EDP, 2018), which is largely renewable and outputs 101.30 g of CO2 per kWh. Based on those figures and official BEV consumption, emissions per km were calculated. A weight of 33% was assigned for the emissions criterion, with remaining weights maintaining their previous proportions. This resulted in BEV emissions within the 10-20 g/km range. Class breakpoints considered were 30/120/180 g/km. The 120/180 breaks coincide with circulation tax echelons, whereas the 30 break was chosen to generate some distinction between electrical and combustion-driven powertrains. Thresholds used were 10/20/30%, indirect preference.

The results for this scenario showed no major changes with respect to the baseline case. Albeit several ICEV and HEV vehicles dropped classes, they still kept a statistical lead over other powertrain technologies similar to the baseline one, regardless of user profile. This suggests that even if the consumer has environmental concerns when choosing a vehicle, these will not penalize combustion engine vehicles enough to make a difference statistically. These findings go in line with those of Mohamed et al. (2016), which found that while environmental concerns do form an important part of a person's interest in buying a BEV, they are not a significant determinant towards actually making that purchase, because they are pondered along with other factors such as TCO, range and charging issues.

Scenario 12 – changing ELECTRE TRI parameters

This is essentially a robustness test, made against the baseline scenario for three types of parameter changes, namely weights, class breaks, and thresholds.

Weights. A natural test for criteria weights is to set them all equal (25%). This scenario tends to penalize BEV, given it puts more emphasis on the use restriction criteria. Indeed, some class drops for BEV are observed (Figure D.1, city/medium), but no major statistical changes appear with respect to baseline. The analysis shows that there is considerable robustness against weight changes, which means baseline conclusions should hold even if AHP expert judgement varies.

Class breaks. Class breaks were changed in two ways, so that it would be easier/harder to reach the top classes (less/more restrictive breaks – LRB/MRB). The middle break took the place of the break separating the best/worst classes respectively and new breaks were introduced. The new values can be found in the Table C.1 (Appendix C). The results yielded, as expected, a considerable amount of class changes (see Table D.1 of Appendix D for averages and p-values, and Figure D.1 and D.2, for city and all-purpose driver profile respectively), but from the statistical view point only minor differences were found between the baseline scenario and new breaks scenario. These slightly favor ICEV, but otherwise reinforce the baseline conclusions.

Thresholds. Thresholds were changed to more/less stringent values (less/more restrictive thresholds – LRT/MRT) (see Table C.2 of Appendix C for actual values), yielding again results in line with the baseline scenario.

Results for S12 essentially confirm that ELECTRE TRI results are robust to parameter changes, validating the baseline assumptions and parameter settings.

4.2.2 Comparison with TOPSIS scores

Instead of ELECTRE TRI, other multicriteria methods could be envisioned to obtain a ranking or a classification of the vehicles. It is therefore important to know how ELECTRE TRI results compare with those methods. An exhaustive method comparison is outside the scope of this article, so a particular method was selected for the purpose, namely TOPSIS. TOPSIS is a compensatory multicriteria method which works by comparing the various alternative solutions with ideal and anti-ideal solutions, ranking them by their relative closeness to the ideal solution, defined by a proportion between the Euclidean distances to the ideal and anti-ideal solutions (Massam, 1988). TOPSIS has been satisfactorily applied in many areas (Behzadian et al., 2012) and was tested against other multicriteria methods by Adil et al. (2014) for a public sector procurement problem, having come out as the method of choice. Its compensatory nature, i.e. poor scores in one criterion can be compensated by good scores on other criteria, makes it inherently different from ELECTRE TRI, and is thus a good benchmark the comparative analysis. TOPSIS requires criteria value normalization (ratio normalization was used) and defining criteria weights. For the latter, the same weights as in the ELECTRE TRI analysis were used.

Because ELECTRE TRI and TOPSIS are both important methods in the literature whose philosophy is different, the comparative analysis was extended from the baseline scenario to all the sensitivity analysis scenarios. The statistical significance was carried out using the same tools as in the ELECTRE TRI case, namely Kruskal-Wallis and Dunn tests with corrected p-values run over the dependent variable, which for this case is the totally ordered set of TOPSIS scores. Results are presented as the bottom thinner lines in the comparisons of Figure 4, with complementary means and p-values indicated in the Table D.1 of Appendix D, brown lines. Light brown highlights indicate cases where both methods give different statistical conclusions that are relevant. Boxplots with TOPSIS scores for the sensitivity analysis are presented in Appendix D, Figures D.3 and D.4.

For the baseline scenario, which is arguably the most important one, both methods yield similar conclusions. This agreement carries through for most of the other scenarios, confirming the methods, in general, point in the same direction, but breaks down in some particular cases, namely those where TCO changes or emissions criteria are accounted for. These differences can all be attributed to one common factor: the difference between compensatory and non-compensatory methods. In the cases where the two methods exhibit discrepancies, BEV always have some advantage, be it TCO or emissions-related, which compensates their use restrictions in TOPSIS. However, in ELECTRE TRI, vetoes due to those use restrictions do not let BEV advantages materialize into better class scores. Focusing e.g. on S5-8, one sees that if, and only if, compensation is possible (in this case financial, via incentives or use savings), then BEV become more acceptable purchase options. Scenario S4 is paradigmatic as well: by focusing on TCO only, ELECTRE TRI vetoes due to use restrictions disappear and both methods line up their conclusions.

It is not unusual to have compensatory and non-compensatory methods to yield different conclusions (Bouyssou, 1986). Neither it is unacceptable. It is just a matter of understanding the decision problem at hand and selecting the most appropriate multicriteria method, which ultimately depends on the degree of intercriteria compensation the decision-maker is willing to accept (Guitouni and Martel, 1998; Doumpos and Zopounidis, 2014). So, the question may be asked: what is the most appropriate multicriteria method to predict consumer acceptance of alternative powertrains? There is no definite answer to this question but, given the premises of this study, i.e. the vehicle is the household main car, authors believe non-compensatory methods should be used because one can hardly buy a vehicle if use restrictions prevent it from performing the transportation tasks it is meant to. Hence the choice for ELECTRE TRI. Compensatory methods, such as TOPSIS, could be used for e.g. selecting a second vehicle for the household or for main cars whose owner has a reasonable expectation for road trips being of limited distance.

4.3 Discussion

The base scenario and sensitivity analysis provide important clues which hint at general conclusions concerning acceptance of alternative powertrains. The scenario reflects 2017 Portuguese market and fiscal realities, but most conclusions are arguably representative of global trends when vehicles are seen in their multiple dimensions, especially if this is done in a non-compensatory way. The methodology can, in any case, be applied to any region, provided the relevant data is collected and curated.

Rounding up the results, and starting by financial issues, the extra price of PHEV and BEV powertrains has a considerable negative impact on small, cheaper vehicles, which cannot be recouped by energy savings during the holding period, even an extended one. For BEV, use restrictions worsen the situation, making this technology less desirable than ICEV regardless of driver profile. The extra price dilutes for costlier, medium sized vehicles and in this case TCO becomes favorable for BEV, but not for PHEV. Use restrictions then dictate whether BEV are a viable option: they are so for the medium/city case, but not for the medium/all-purpose one. These conclusions, derived from real market conditions, go, in general, in the same direction of consumer-centered stated preference research. For the particular case of the USA market, recent regression analysis by Jenn et al. (2018), Wee et al. (2018), and Clinton and Steinberg (2019) also conclude that financial incentives increase the odds of BEV purchase. However, the result that use restrictions impede better scores of BEV regardless of TCO is an important complementary finding.

If a compensatory method like TOPSIS is used instead, TCO advantages counterbalance these use restrictions and BEV become competitive in more scenarios, even favorites in some. The monetary breakpoint at which this happens depends on that scenario, but for e.g. incentives, it appears to lie somewhere between the minor and major incentive levels, i.e. 5,000-10,000 €, in line with findings from other research (see e.g. Prud'homme and Koning, 2012). The Norwegian case validates these figures: VAT exemption for BEV leads to savings in the order of 7,000 € (Holtsmark and Skonhoft, 2014) which, coupled with an adequate charging infrastructure, is believed to be one of the chief reasons BEV and PHEV already represent over 45% of the sales in that country (EAFO, 2018).

However, as argued, it is hard to justify using compensatory methods for a household main vehicle. In this case use restrictions are definitely an issue. The current Portuguese BEV market line up provides vehicles whose use is starting to be flexible enough for drivers with city profile, but not for all-purpose profile. TCO then makes BEV less attractive than ICEV for small cars but keeps the former competitive for medium sized vehicles. The sensitivity analysis makes it clear that resolving one use restriction issue alone is insufficient to improve BEV acceptance and that a thorough solution is necessary to achieve that acceptance. This conclusion was already hinted at by the researches of Santos and Davies (2019) and Rietmann and Lieven (2019), as well as by the overview of econometric studies of Munzel et al. (2019); these studies found that both the charging infrastructure and financial incentives are important factors driving preferences for BEV. It is interesting to note that some TCO studies indicate higher incentive values for BEV to become attractive, up to 20,000 € (Hoen and Koetse, 2014) or even 32,000€ (Bubeck et al., 2016). Incentives of this level of magnitude are essentially equivalent to compensating use restrictions by buying a second, ICEV vehicle for the household. Solving BEV use restrictions requires input from both car manufacturers and governments, which highlights the importance of these entities having to work together to find ways to promote a change towards an (arguably cleaner) BEV mobility. If such a solution could be implemented, scenario S4 (no restrictions) shows BEV could become very competitive. Until that really comes to fruition, it is unlikely consumers will embrace BEV in a large scale and that only consumers who can cope with its shortcomings consider these for purchase.

For large cars, which so far haven't been discussed much, all technologies are on similar grounds, regardless of scenario. Still, this is in part due to the small BEV sample, which makes it difficult to statistically validate previous conclusions concerning use restrictions. Looking at Figure 3 baseline descriptive results, one finds all BEV in class 2 for city profile and in class 1 for all-purpose profile, which is indeed a strong hint that large BEV might be ok for city profile but not for all-purpose. Should new large BEV enter the market in the short term, that tendency is likely to start to hold at a statistically significant level.

A cultural change towards low-carbon technologies is not expected to drive BEV and PHEV sales significantly. For BEV this is due to use restrictions; for PHEV it is due to costs. Again, it is only if the buyer is in a position to disregard use restrictions that BEV become attractive (indeed the better choice).

A global, cross-scenario look at Figure 4 reveals interesting conclusions, which complement the per-scenario analysis. First one notes that, despite all the technological advances in powertrain technology, ICEV are still good choices in the present and practically all future scenarios. This can also be seen from Appendix D Figures D.1 and D.2, where ICEV always have plenty representatives in the "buy" class in all scenarios except S11 (emissions). The global look also confirms that if BEV use restrictions were lifted (S4), these vehicles would become very competitive overall, pulling out to the preferred choice for the important medium/all-purpose case, and losing only to ICEV in the small/city case, the only case where they would underperform. Figures D.1 and D.2 confirm this is practically the only scenario making BEV appealing. In other scenarios, where use restrictions persist, BEV appeal may increase but would still remain limited. No matter what the financial or environmental advantages of BEV are, their lower TCO and emissions values can only mitigate use restrictions up to a point. Extending to other powertrains, HEV relation to ICEV can be done from a purely financial perspective (both have no use restrictions) and comparing the emissions scenario S11. In both cases HEV have no statistically significant advantages in terms of consumer acceptance. The PHEV technology, despite performance improvement in some financial-related scenarios, also fails to provide significant statistical advantages, a fact which is somewhat surprising but can be attributed to the difficulties in recouping, through savings in vehicle use, the high purchase costs stemming from the more complex PHEV powertrain. What does stand out, from a global perspective, is that the BEV powertrain is the only truly revolutionary technology, with a lot of potential to shape the market once its limitations are lifted.

Finally, a note on regional issues. While the proposed methodology is, as argued, completely general, the criteria values may vary depending on the study region, as different countries have different vehicles on sale, financials/taxation and charging infrastructure condition. However, upon exploration, it was found that the Portuguese reality is close to the average EU conditions (see ACEA [2019] (tax benefits/incentives); Statista [2019] (purchase price); EAFO [2019] (charging points); and FuelsEurope [2018], Eurostat [2019] (energy costs, slightly higher in Portugal)), so the results found in this research are expected to extend to most of the European market. Confronting Portuguese results with other country-specific findings, obtained by different methodologies, some similar conclusions can indeed be found. The conclusion that BEV require high subsidies to be financially competitive also holds in Germany, as found by Bubeck et al. (2016) and Letmathe and Suares (2017). The cross-country analyses of Lévay et al. (2017) and Munzel et al. (2019) found that higher incentives correlate to higher BEV sales, a conclusion the present article also supports, albeit indirectly. The study of Valeri and Danielis (2015) on the Italian market found that a combination of factors would be necessary to increase BEV market share (more range, incentives, higher petrol/diesel prices), confirming that solving one isolated issue of BEV may not enough to make them attractive. The conclusion that combined action is needed to increase BEV attractiveness is, in a way, justification for the non-compensatory approach to the problem. However, caution is advised: because of this non-compensatory nature, which is necessary to more adequately reproduce human judgement, the results the methodology yields may not be directly comparable to those of other studies. Regions outside the EU have different financials, which may lead to different conclusions. Although some conclusions are common, like e.g. Sharma et al. (2012), Jenn et al. (2018), Wee et al. (2018) and Clinton and Steinberg (2019), who corroborate that BEV require incentives to be on par with other choices, others occasionally deviate. An example is Tamor et al. (2013), who estimated PHEV to be more attractive than BEV in their payback model case-study in the USA. However, that study uses a very different methodology and its authors acknowledge a strong regional bias in the analysis.

5 Summary and policy implications

This research presented a multicriteria methodology for estimating consumer acceptance of four alternative powertrain technologies, considering as criteria total costs of ownership and electric vehicle use restrictions, and using the non-compensatory ELECTRE TRI method. It was designed to predict consumer acceptance of new vehicles that would be the household main car. The analysis was segmented by car size and driver profile and demonstrated in a mid-scale case study, the Portuguese market as of 2017 and its context. The approach is considerably different than the more commonly used stated preference methodologies: rather than surveying consumers what would be their preference on an abstract or limited vehicle set, the present analysis considers the market as it currently is and estimates whether the supply is good enough for a prototype consumer.

Results obtained have considerable policy implications. In the first place, they show that use restrictions form a major barrier to widespread battery electric vehicles adoption and that it takes non-trivial actions from governments and car makers to overcome these limitations, if widespread greener private transportation is to be pursued. Those actions will need to go beyond financial incentives, since lower costs or lower emissions alone will not make the vehicle more usable; improving the charging infrastructure is key, as automakers are already doing their share by increasing electric vehicle range (Nykvist et al., 2019). Indeed, if use restrictions can be effectively lifted, this powertrain technology can become the better option due to its lower running costs. Governments should, however, resist the temptation to finance investment on the charging infrastructure by hiking electricity prices on public charging points or raising taxes on electric vehicles. Doing so may remove the financial advantages these vehicles have, delaying the transition towards cleaner powertrains. This recommendation is reinforced by the fact that a lot of similarity between combustion vehicles and plug-in hybrids is also seen in this article's results, making plausible the claim that only battery electric vehicles can actually make a difference in the transportation status-quo in the long run. Policy implications on incentives are also clear and partly go in line with other findings in the literature (Jenn et al., 2018; Wee et al., 2018; Clinton and Steinberg, 2019): they are necessary to make plug-in hybrid and battery electric vehicles competitive, at least until the charging infrastructure matures. This is especially true for small vehicles, since conventional vehicles are considerably cheaper to buy than other options. The novelty brought by the present research is that incentives are, however, *per se* insufficient to make battery electric vehicles a viable choice for the all-purpose driver profile, as use restrictions may impede considering them. This also confirms the consumer and expert's intuitive perception that charging infrastructure maturity is an important factor for widespread battery electric vehicle acceptance (Santos and Davies, 2019; Rietmann and Lieven, 2019) and helps explaining the fact. Care is also needed with incentives to plug-in hybrid vehicles. On the one hand this powertrain technology makes the vehicle more complex and expensive, a cost difference hard to recoup during the holding period, as shown by the results. On the other hand, excessively large incentives may make these vehicles financially attractive, but that does not guarantee drivers will actually charge them at a power outlet. In fact, research shows that a small, but considerable, fraction of drivers disregards this possibility (Ligterink et al., 2013).

Although case study conclusions hold for the Portuguese market and context, the methodology is general, and can be applied to any country or even groups of countries. It would be for instance interesting to do a large-scale study over EU and other major car market countries (USA, Japan, China, etc.), using powertrain technology, and possibly country, as disaggregation factors. Repeating the analysis as new models hit the market, which is happening at a rapid pace, may also help identifying possible emerging shifts in consumer tendencies. Another interesting line of research would be to use the market data of this research on calibrated logit models to estimate the odds-ratio for purchase of each vehicle in the set. It would then be possible to ascertain the degree of agreement between the methodologies. This is however beyond the scope of this article. The present methodology can also be used by the buyer himself to select which vehicles should be considered more closely, calibrating ELECTRE TRI according to her own preferences and requirements.

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Appendix A – Supplementary data

Table A.1 - Insurance premium values per year

	Petrol ICEV/HEV/PHEV	Diesel ICEV/HEV/PHEV	BEV
Small	300.00 €	325.00 €	500.00 €
Medium	400.00 €	450.00 €	550.00 €
Large	600.00 €	650.00 €	750.00 €

Table A.2 - Maintenance costs per year

	Warranty planed	Tires replacement	Others	Total (City driver profile)	Total (All-purpose driver profile)
Small	150.00 €	50.00 €/tire	50.00 €	275.00 €	350.00 €
Medium	200.00 €	75.00 €/tire	75.00 €	387.50 €	500.00 €
Large	300.00 €	100.00 €/tire	100.00 €	550.00 €	700.00 €

Note: Tire replacement was considered every 40,000 km.

Table A.3 - AHP pairwise comparisons expert consensus and criteria weights

	City driver profile				**All-purpose driver profile**			
	TCO	Range	Charging Points	Charging Time	TCO	Rang e	Charging Points	Charging Time
TCO	1	7	8	5	1	4	3	3
Range	1/7	1	2	1	1/4	1	2	2
Charging Points	1/8	1/2	1	1	1/3	1/2	1	1
Charging Time	1/5	1	1	1	1/3	1/2	1	1
Weights (%)	68.1	12.3	8.4	11.2	52.4	21.1	13.2	13.2
Consistency ratio (%)	2.6				4.5			

Appendix B – Baseline decision matrix

Table B.1 – Baseline decision matrix for the city driver profile

ID	Vehicle model	Segment	Tech	TCO	Range	Charging points	Charging time	CO_2	Energy cost/km
1	Audi A3 Sportback e-tron	Medium	PHEV	30659.96	1.00	1.00	0.083	12	0.07
2	Audi A3 Sportback 1.0 TFSI	Medium	ICEV	25057.32	1.00	1.00	0.083	104	0.33
3	Audi A3 Sportback 1.6 TDI	Medium	ICEV	25385.88	1.00	1.00	0.083	99	0.23
4	BMW i3	Small	BEV	24565.15	0.27	0.85	4.18	13	0.08
5	BMW i3 (Range Extender)	Small	PHEV	29683.27	0.47	1.00	0.083	14	0.08
6	BMW 225xe (Active Tourer)	Medium	PHEV	28549.50	1.00	1.00	0.083	12	0.07
7	BMW 218i (Active Tourer)	Medium	ICEV	29211.01	1.00	1.00	0.083	119	0.38
8	BMW 218d (Active Tourer)	Medium	ICEV	31008.05	1.00	1.00	0.083	109	0.25
9	BMW 330e	Medium	PHEV	33022.59	1.00	1.00	0.083	14	0.07
10	BMW X5 xDrive 40e	Large	PHEV	56569.27	1.00	1.00	0.083	54	0.20
11	BMW 318 i	Medium	ICEV	32650.41	1.00	1.00	0.083	119	0.38
12	BMW 318 d	Medium	ICEV	32692.10	1.00	1.00	0.083	106	0.24
13	BMW X5 sDrive 25d	Large	ICEV	55455.73	1.00	1.00	0.083	146	0.34
14	BMW X5 xDrive 35i	Large	ICEV	70367.31	1.00	1.00	0.083	197	0.63
15	BMW X5 xDrive 30d	Large	ICEV	66544.01	1.00	1.00	0.083	156	0.36
16	Citroën C-ZERO	Small	BEV	20371.71	0.21	0.85	3.22	13	0.08
17	Citroën DS5 Hybrid4	Medium	HEV	36639.83	1.00	1.00	0.083	103	0.24
18	Citroën DS5 1.6THP165	Medium	ICEV	32707.13	1.00	1.00	0.083	136	0.43
19	Citroën DS5 1.6 BlueHDi	Medium	ICEV	31312.15	1.00	1.00	0.083	104	0.24
20	Citroën DS5 2.0 BlueHDi	Medium	ICEV	33442.15	1.00	1.00	0.083	113	0.26
21	Citroën C1 Feel 1.0 Vti 68-CMV	Small	ICEV	14379.34	1.00	1.00	0.083	97	0.31
22	Fiat Panda 0.9 Twinair 85cv	Small	ICEV	15769.37	1.00	1.00	0.083	99	0.31
23	Ford Mondeo Titanium HEV	Large	HEV	33507.28	1.00	1.00	0.083	92	0.29
24	Ford Mondeo 1.0 EcoBoost	Large	ICEV	27919.40	1.00	1.00	0.083	119	0.38
25	Ford Mondeo 1.5 TDCI ECO	Large	ICEV	29818.28	1.00	1.00	0.083	94	0.22
26	Hyundai IONIC Hybrid (1.6 GDI) 15''	Medium	HEV	27584.65	1.00	1.00	0.083	79	0.25
27	Kia Soul EV	Medium	BEV	22796.58	0.30	0.85	6.00	15	0.09
28	Kia Soul 1.6 CRDi TX	Medium	ICEV	22682.36	1.00	1.00	0.083	132	0.30
29	Lexus CT200h	Medium	HEV	27011.05	1.00	1.00	0.083	94	0.30
30	Lexux IS300h	Medium	HEV	35573.95	1.00	1.00	0.083	107	0.35
31	Lexus NX300h	Medium	HEV	39687.78	1.00	1.00	0.083	123	0.39
32	Lexus GS 300h	Large	HEV	44277.90	1.00	1.00	0.083	115	0.37
33	Lexus RX450h	Large	HEV	62489.10	1.00	1.00	0.083	127	0.41
34	Mercedes B Electric Drive	Medium	BEV	28131.90	0.29	0.85	6.60	17	0.10
35	Mercedes B 180	Medium	ICEV	30082.98	1.00	1.00	0.083	134	0.43
36	Mercedes B 180 d	Medium	ICEV	27017.62	1.00	1.00	0.083	112	0.26
37	Mercedes B 200 d	Medium	ICEV	31173.86	1.00	1.00	0.083	117	0.27
38	Mercedes C 350 e	Medium	PHEV	39172.80	1.00	1.00	0.083	42	0.15
39	Mercedes S500 Plug-iN Hybrid	Large	PHEV	82641.78	1.00	1.00	0.083	49	0.18
40	Mercedes S-Class 300h	Large	HEV	70140.33	1.00	1.00	0.083	126	0.29
41	Mercedes C 300 h	Medium	HEV	39155.36	1.00	1.00	0.083	103	0.24
42	Mercedes C 180	Medium	ICEV	34368.61	1.00	1.00	0.083	115	0.41
43	Mercedes C 200	Medium	ICEV	37764.29	1.00	1.00	0.083	136	0.43
44	Mercedes C 220 d	Medium	ICEV	36295.60	1.00	1.00	0.083	110	0.25
45	Mercedes C 200 d	Medium	ICEV	33103.86	1.00	1.00	0.083	100	0.25
46	Mercedes E 200	Large	ICEV	46833.98	1.00	1.00	0.083	142	0.46
47	Mercedes E 220 d	Large	ICEV	44955.85	1.00	1.00	0.083	112	0.26
48	Mercedes S 500	Large	ICEV	105756.49	1.00	1.00	0.083	213	0.66
49	Mercedes S 350 d	Large	ICEV	80812.60	1.00	1.00	0.083	159	0.37
50	Mitsubishi i-MIEV	Small	BEV	16278.75	0.21	0.85	3.56	14	0.08
51	Mitsubishi Outlander PHEV	Large	PHEV	35020.60	1.00	1.00	0.083	14	0.08
52	Mitsubishi Outlander DI-D 2WD	Large	ICEV	33350.58	1.00	1.00	0.083	134	0.31
53	Nissan Leaf 24 kWh Visia	Medium	BEV	20741.38	0.28	0.85	5.34	15	0.09
54	Nissan Leaf 30 kWh Acenta	Medium	BEV	24105.38	0.36	0.85	6.67	15	0.09
55	Nissan QASHQAI 1.2 DIG-T	Medium	ICEV	24846.10	1.00	1.00	0.083	129	0.41
56	Nissan QASHQAI 1.5dci	Medium	ICEV	24093.06	1.00	1.00	0.083	99	0.23
57	Peugeot iOn	Small	BEV	19903.95	0.21	0.85	3.56	13	0.08
58	Peugeot 508 RXH Hybrid4	Large	HEV	38587.10	1.00	1.00	0.083	109	0.28
59	Peugeot 508 RXH 2.0 BlueHDi 180	Large	ICEV	37537.30	1.00	1.00	0.083	119	0.28
60	Peugeot 508 1.6BlueHDI	Large	ICEV	28904.16	1.00	1.00	0.083	99	0.23
61	Peugeot 108 Active 1.0	Small	ICEV	14852.62	1.00	1.00	0.083	95	0.30
62	Renault ZOE Life (battery hire)	Small	BEV	16896.95	0.34	0.85	4.89	13	0.08
63	Smart fortwo	Small	ICEV	15339.82	1.00	1.00	0.083	93	0.30
64	Smart fortwo ED	Small	BEV	13875.75	0.23	0.85	3.99	13	0.08
65	Toyota Yaris Hybrid Active	Small	HEV	18187.56	1.00	1.00	0.083	82	0.27
66	Toyota Auris Hybrid	Medium	HEV	23916.05	1.00	1.00	0.083	91	0.29
67	Toyota Auris Touring Sports Hybrid	Medium	HEV	24606.60	1.00	1.00	0.083	92	0.29
68	Toyota Yaris 1.0 VVT-i	Small	ICEV	15708.82	1.00	1.00	0.083	99	0.32
69	Toyota Yaris 1.4D-4D	Small	ICEV	16998.61	1.00	1.00	0.083	91	0.21
70	Toyota Auris 1.2T	Medium	ICEV	23958.12	1.00	1.00	0.083	109	0.39
71	Toyota Auris 1.6 D-4D	Medium	ICEV	25619.81	1.00	1.00	0.083	110	0.26
72	Toyota Auris Touring Sport 1.2T	Medium	ICEV	24875.22	1.00	1.00	0.083	112	0.41
73	Toyota Auris Touring Sport 1.6 D-4D	Medium	ICEV	26315.81	1.00	1.00	0.083	107	0.26
74	Toyota Prius Hybrid	Medium	HEV	27446.15	1.00	1.00	0.083	76	0.24
75	Toyota Prius Plug-in	Medium	PHEV	27687.65	1.00	1.00	0.083	44	0.14
76	Toyota Prius Plus Hybrid	Medium	HEV	30083.20	1.00	1.00	0.083	101	0.32
77	Toyota Rav4 Hybrid	Medium	HEV	32802.60	1.00	1.00	0.083	115	0.37
78	Toyota Aygo x 1.0 VVT-i 3portas	Small	ICEV	14229.12	1.00	1.00	0.083	95	0.30
79	Toyota e-Up	Small	BEV	18228.68	0.23	0.85	4.16	12	0.07
80	Toyota Up 1.0 60 take up!	Small	ICEV	14457.06	1.00	1.00	0.083	96	0.30
81	VW Golf VII e-Golf	Medium	BEV	26483.37	0.27	0.85	5.38	13	0.08
82	VW Golf VII GTE Plug-in	Medium	PHEV	31204.54	1.00	1.00	0.083	12	0.07
83	VW Passat GTE Limousine	Large	PHEV	35842.34	1.00	1.00	0.083	12	0.07
84	VW Golf 1.0 TSI BlueMotion	Medium	ICEV	22323.66	1.00	1.00	0.083	99	0.32
85	VW Golf 1.6 TDI BlueMotion	Medium	ICEV	23800.74	1.00	1.00	0.083	98	0.23
86	VW Passat Limousine 1.6 TDI BlueMotion	Large	ICEV	29530.52	1.00	1.00	0.083	105	0.24
87	Volvo V60 PHEV	Medium	PHEV	42057.50	1.00	1.00	0.083	14	0.08
88	Volvo XC90 T8	Large	PHEV	59238.52	1.00	1.00	0.083	22	0.12
89	Volvo V60 T3 kinetic Geartronic	Medium	ICEV	33660.77	1.00	1.00	0.083	138	0.43
90	Volvo V60 D3 Kinetic	Medium	ICEV	31865.02	1.00	1.00	0.083	105	0.24
91	Volvo XC90 T6 AWD	Large	ICEV	69301.27	1.00	1.00	0.083	186	0.59
92	Volvo XC90 D4	Large	ICEV	47260.41	1.00	1.00	0.083	136	0.31
93	Tesla Model S-75D	Large	BEV	52215.94	0.70	0.85	8.53	15	0.09
94	Tesla Model X-75D	Large	BEV	59252.84	0.60	0.85	8.64	18	0.11

Table B.2 - Baseline decision matrix for the all-purpose driver profile

ID	Vehicle model	Segment	Tech	TCO	Range	Charging points	Charging time	CO_2	Energy cost/km
1	Audi A3 Sportback e-tron	Medium	PHEV	35341.64	1.00	1.00	0.083	48	0.17
2	Audi A3 Sportback 1.0 TFSI	Medium	ICEV	30594.57	1.00	1.00	0.083	104	0.33
3	Audi A3 Sportback 1.6 TDI	Medium	ICEV	29396.88	1.00	1.00	0.083	99	0.23
4	BMW i3	Small	BEV	25969.90	0.27	0.40	1.40	13	0.08
5	BMW i3 (Range Extender)	Small	PHEV	31273.27	0.47	1.00	0.083	14	0.08
6	BMW 225xe (Active Tourer)	Medium	PHEV	34949.04	1.00	1.00	0.083	68	0.23
7	BMW 218i (Active Tourer)	Medium	ICEV	35411.56	1.00	1.00	0.083	119	0.38
8	BMW 218d (Active Tourer)	Medium	ICEV	35291.30	1.00	1.00	0.083	109	0.25
9	BMW 330e	Medium	PHEV	39046.26	1.00	1.00	0.083	65	0.22
10	BMW X5 xDrive 40e	Large	PHEV	65491.13	1.00	1.00	0.083	114	0.37
11	BMW 318 i	Medium	ICEV	38850.96	1.00	1.00	0.083	119	0.38
12	BMW 318 d	Medium	ICEV	36884.60	1.00	1.00	0.083	106	0.24
13	BMW X5 sDrive 25d	Large	ICEV	61287.73	1.00	1.00	0.083	146	0.34
14	BMW X5 xDrive 35i	Large	ICEV	80514.06	1.00	1.00	0.083	197	0.63
15	BMW X5 xDrive 30d	Large	ICEV	72648.26	1.00	1.00	0.083	156	0.36
16	Citroën C-ZERO	Small	BEV	21749.46	0.21	0.40	1.08	13	0.08
17	Citroën DS5 Hybrid4	Medium	HEV	40741.58	1.00	1.00	0.083	103	0.24
18	Citroën DS5 1.6THP165	Medium	ICEV	39792.08	1.00	1.00	0.083	136	0.43
19	Citroën DS5 1.6 BlueHDi	Medium	ICEV	35504.65	1.00	1.00	0.083	104	0.24
20	Citroën DS5 2.0 BlueHDi	Medium	ICEV	37906.90	1.00	1.00	0.083	113	0.26
21	Citroën C1 Feel 1.0 Vti 68-CMV	Small	ICEV	19397.44	1.00	1.00	0.083	97	0.31
22	Fiat Panda 0.9 Twinair 85cv	Small	ICEV	20787.47	1.00	1.00	0.083	99	0.31
23	Ford Mondeo Titanium HEV	Large	HEV	38679.28	1.00	1.00	0.083	92	0.29
24	Ford Mondeo 1.0 EcoBoost	Large	ICEV	34307.45	1.00	1.00	0.083	119	0.38
25	Ford Mondeo 1.5 TDCI ECO	Large	ICEV	33835.28	1.00	1.00	0.083	94	0.22
26	Hyundai IONIC Hybrid (1.6 GDI) 15''	Medium	HEV	31905.85	1.00	1.00	0.083	79	0.25
27	Kia Soul EV	Medium	BEV	24485.20	0.30	0.40	2.01	15	0.09
28	Kia Soul 1.6 CRDi TX	Medium	ICEV	27782.36	1.00	1.00	0.083	132	0.30
29	Lexus CT200h	Medium	HEV	32106.10	1.00	1.00	0.083	94	0.30
30	Lexux IS300h	Medium	HEV	41332.30	1.00	1.00	0.083	107	0.35
31	Lexus NX300h	Medium	HEV	46109.43	1.00	1.00	0.083	123	0.39
32	Lexus GS 300h	Large	HEV	50555.40	1.00	1.00	0.083	115	0.37
33	Lexus RX450h	Large	HEV	69319.35	1.00	1.00	0.083	127	0.41
34	Mercedes B Electric Drive	Medium	BEV	29991.52	0.29	0.40	3.56	17	0.10
35	Mercedes B 180	Medium	ICEV	37057.38	1.00	1.00	0.083	134	0.43
36	Mercedes B 180 d	Medium	ICEV	31482.37	1.00	1.00	0.083	112	0.26
37	Mercedes B 200 d	Medium	ICEV	35820.11	1.00	1.00	0.083	117	0.27
38	Mercedes C 350 e	Medium	PHEV	45572.34	1.00	1.00	0.083	83	0.27
39	Mercedes S500 Plug-iN Hybrid	Large	PHEV	90201.66	1.00	1.00	0.083	97	0.32
40	Mercedes S-Class 300h	Large	HEV	75246.33	1.00	1.00	0.083	126	0.29
41	Mercedes C 300 h	Medium	HEV	43257.11	1.00	1.00	0.083	103	0.24
42	Mercedes C 180	Medium	ICEV	41011.36	1.00	1.00	0.083	115	0.41
43	Mercedes C 200	Medium	ICEV	44849.24	1.00	1.00	0.083	136	0.43
44	Mercedes C 220 d	Medium	ICEV	40669.60	1.00	1.00	0.083	110	0.25
45	Mercedes C 200 d	Medium	ICEV	37477.86	1.00	1.00	0.083	100	0.25
46	Mercedes E 200	Large	ICEV	54548.63	1.00	1.00	0.083	142	0.46
47	Mercedes E 220 d	Large	ICEV	49608.10	1.00	1.00	0.083	112	0.26
48	Mercedes S 500	Large	ICEV	116345.44	1.00	1.00	0.083	213	0.66
49	Mercedes S 350 d	Large	ICEV	87098.35	1.00	1.00	0.083	159	0.37
50	Mitsubishi i-MIEV	Small	BEV	17737.50	0.21	0.40	1.19	14	0.08
51	Mitsubishi Outlander PHEV	Large	PHEV	40593.29	1.00	1.00	0.083	56	0.20
52	Mitsubishi Outlander DI-D 2WD	Large	ICEV	38728.83	1.00	1.00	0.083	134	0.31
53	Nissan Leaf 24 kWh Visia	Medium	BEV	22457.00	0.28	0.40	1.78	15	0.09
54	Nissan Leaf 30 kWh Acenta	Medium	BEV	25821.00	0.36	0.40	2.23	15	0.09
55	Nissan QASHQAI 1.2 DIG-T	Medium	ICEV	31599.40	1.00	1.00	0.083	129	0.41
56	Nissan QASHQAI 1.5dci	Medium	ICEV	28104.06	1.00	1.00	0.083	99	0.23
57	Peugeot iOn	Small	BEV	21281.70	0.21	0.40	1.19	13	0.08
58	Peugeot 508 RXH Hybrid4	Large	HEV	43511.60	1.00	1.00	0.083	109	0.28
59	Peugeot 508 RXH 2.0 BlueHDi 180	Large	ICEV	42461.80	1.00	1.00	0.083	119	0.28
60	Peugeot 508 1.6BlueHDI	Large	ICEV	33102.66	1.00	1.00	0.083	99	0.23
61	Peugeot 108 Active 1.0	Small	ICEV	19760.17	1.00	1.00	0.083	95	0.30
62	Renault ZOE Life (battery hire)	Small	BEV	18337.70	0.34	0.40	1.64	13	0.08
63	Smart fortwo	Small	ICEV	20247.37	1.00	1.00	0.083	93	0.30
64	Smart fortwo ED	Small	BEV	15280.50	0.23	0.40	1.60	13	0.08
65	Toyota Yaris Hybrid Active	Small	HEV	22542.36	1.00	1.00	0.083	82	0.27
66	Toyota Auris Hybrid	Medium	HEV	28790.00	1.00	1.00	0.083	91	0.29
67	Toyota Auris Touring Sports Hybrid	Medium	HEV	29591.10	1.00	1.00	0.083	92	0.29
68	Toyota Yaris 1.0 VVT-i	Small	ICEV	20837.47	1.00	1.00	0.083	99	0.32
69	Toyota Yaris 1.4D-4D	Small	ICEV	20549.86	1.00	1.00	0.083	91	0.21
70	Toyota Auris 1.2T	Medium	ICEV	30379.77	1.00	1.00	0.083	109	0.39
71	Toyota Auris 1.6 D-4D	Medium	ICEV	30084.56	1.00	1.00	0.083	110	0.26
72	Toyota Auris Touring Sport 1.2T	Medium	ICEV	31517.97	1.00	1.00	0.083	112	0.41
73	Toyota Auris Touring Sport 1.6 D-4D	Medium	ICEV	30780.56	1.00	1.00	0.083	107	0.26
74	Toyota Prius Hybrid	Medium	HEV	31656.80	1.00	1.00	0.083	76	0.24
75	Toyota Prius Plug-in	Medium	PHEV	32893.25	1.00	1.00	0.083	73	0.22
76	Toyota Prius Plus Hybrid	Medium	HEV	35509.90	1.00	1.00	0.083	101	0.32
77	Toyota Rav4 Hybrid	Medium	HEV	38892.60	1.00	1.00	0.083	115	0.37
78	Toyota Aygo x 1.0 VVT-i 3portas	Small	ICEV	19136.67	1.00	1.00	0.083	95	0.30
79	Toyota e-Up	Small	BEV	19525.43	0.23	0.40	1.39	12	0.07
80	Toyota Up 1.0 60 take up!	Small	ICEV	19364.61	1.00	1.00	0.083	96	0.30
81	VW Golf VII e-Golf	Medium	BEV	27992.00	0.27	0.40	1.80	13	0.08
82	VW Golf VII GTE Plug-in	Medium	PHEV	35886.23	1.00	1.00	0.083	51	0.17
83	VW Passat GTE Limousine	Large	PHEV	40986.92	1.00	1.00	0.083	47	0.18
84	VW Golf 1.0 TSI BlueMotion	Medium	ICEV	27639.81	1.00	1.00	0.083	99	0.32
85	VW Golf 1.6 TDI BlueMotion	Medium	ICEV	27811.74	1.00	1.00	0.083	98	0.23
86	VW Passat Limousine 1.6 TDI BlueMotion	Large	ICEV	33910.52	1.00	1.00	0.083	105	0.24
87	Volvo V60 PHEV	Medium	PHEV	46723.93	1.00	1.00	0.083	66	0.18
88	Volvo XC90 T8	Large	PHEV	66024.55	1.00	1.00	0.083	80	0.26
89	Volvo V60 T3 kinetic Geartronic	Medium	ICEV	40745.72	1.00	1.00	0.083	138	0.43
90	Volvo V60 D3 Kinetic	Medium	ICEV	36057.52	1.00	1.00	0.083	105	0.24
91	Volvo XC90 T6 AWD	Large	ICEV	78895.27	1.00	1.00	0.083	186	0.59
92	Volvo XC90 D4	Large	ICEV	52729.41	1.00	1.00	0.083	136	0.31
93	Tesla Model S-75D	Large	BEV	54056.77	0.70	0.40	3.54	15	0.09
94	Tesla Model X-75D	Large	BEV	61328.57	0.60	0.40	3.59	18	0.11

Appendix C – ELECTRE TRI method

ELECTRE TRI is a non-compensatory outranking multicriteria method for the sorting problematic, i.e. the assignment of alternatives (vehicles) to predefined categories (“avoid”, “consider”, “shortlist”, “buy”). The assignment of an alternative a results from the comparison of a with the profiles defining the limits of the categories. Let F denote the set of indices of the criteria $g_1, g_2, \dots, g_m$ ($F = \{1, 2, \dots, m\}$) and B the set of indices of the profiles defining $p + 1$ categories ($B = \{1, 2, \dots, p\}$), b_h being simultaneously the upper limit of category C_h and the lower limit of category C_{h+1}, $h = 1,2, \dots, p$ (see Figure C.1). The profiles b_{p+1} and b_0 correspond to the ideal and the anti-ideal alternatives, respectively.

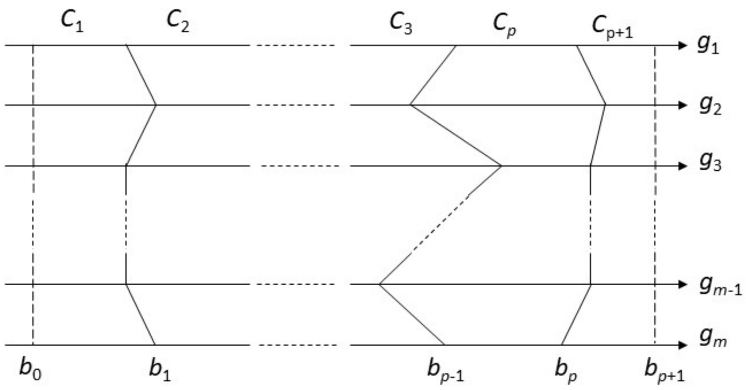

Figure C.1 - Definition of categories using limit profiles

In what follows it is assumed, without any loss of generality, that the preference is maximization for all criteria. Schematically, ELECTRE TRI assigns alternatives to categories following two consecutive steps: (1) construction of an outranking relation S that characterises how alternatives compare to the limits of categories; and (2) exploitation of the relation S in order to assign each alternative to a specific category.

Construction of the outranking relation

ELECTRE TRI defines an outranking relation S, which validates or invalidates the assertion aSb_h (and b_hSa), whose meaning is “a is at least as good as b_h”. The indifference and preference thresholds constitute the intra-criterion preferential information. They account for the imprecise nature of the evaluations $g_j(a)$.

- The indifference threshold $q_j(b_h)$ specifies the largest difference $g_j(a) - g_j(b_h)$ for which a is indifferent to b_h on criterion g_j.
- The preference threshold $p_j(b_h)$ represents the smallest difference $g_j(a) - g_j(b_h)$ compatible with a preference in favour of a on criterion g_j.

At the comprehensive level of preferences, in order to validate the assertion aSb_h (or b_hSa), two conditions should be verified.

- *concordance*: for an outranking aSb_h (or b_hSa) to be accepted, a sufficient majority of criteria should be in favour of this assertion;
- *non-discordance*: when the concordance condition holds, none of the criteria in the minority should oppose to the assertion aSb_h (or b_hSa) in a too strong way.

Two types of inter-criteria preference parameters intervene in the construction of S:

- the set of weight coefficients $(w_1, w_2, \dots, w_m)$ is used in the concordance test when computing the relative importance of the coalitions of criteria being in favor of the assertion aSb_h;
- the set of veto thresholds $\{v_1(b_h), v_2(b_h), \dots, v_m(b_h)\}$ is used in the discordance test; $v_j(b_h)$ represents the smallest difference $g_j(b_h) - g_j(a)$ incompatible with the assertion aSb_h.

ELECTRE TRI builds an outranking relation S using an index $\sigma(a, b_h) \in [0, 1]$ ($\sigma(b_h, a)$, respectively) that represents the degree of credibility of the assertion aSb_h (b_hSa), $\forall a \in A$, $\forall h \in B$. The assertion aSb_h (b_hSa) is considered to be valid if $\sigma(a, b_h) \geq \lambda$ ($\sigma(b_h, a) \geq \lambda$), λ being a "cutting level" such that $\lambda \in [0.5, 1]$.

Determining $\sigma(a, b_h)$ consists of the following steps (the value of $\sigma(b_h, a)$ is computed analogously):

1. compute the partial concordance indices $c_j(a, b_h)$ $\forall j \in F$

$$c_j(a, b_h) = \begin{cases} 0 & \text{if } \; g_j(b_h) - g_j(a) \geq p_j(b_h) \\ 1 & \text{if } \; g_j(b_h) - g_j(a) \leq q_j(b_h) \\ \dfrac{p_j(b_h) + g_j(a) - g_j(b_h)}{p_j(b_h) - q_j(b_h)} & \text{otherwise} \end{cases}$$

2. compute the comprehensive concordance index $c(a, b_h)$

$$c(a, b_k) = \frac{\sum_{j \in F} w_j c_j(a, b_h)}{\sum_{j \in F} w_j}$$

3. compute the discordance indices $d_j(a, b_h)$ $\forall j \in F$

$$d_j(a, b_h) = \begin{cases} 0 & \text{if } \; g_j(b_h) - g_j(a) \leq p_j(b_h) \\ 1 & \text{if } \; g_j(b_h) - g_j(a) \leq v_j(b_h) \\ \dfrac{g_j(b_h) - g_j(a) - p_j(b_h)}{v_j(b_h) - p_j(b_h)} & \text{otherwise} \end{cases}$$

4. compute the credibility index $\sigma(a, b_h)$ of the outranking relation

$$\sigma(a, b_h) = c(a, b_h) \prod_{j \in \bar{F}} \frac{1 - d_j(a, b_h)}{1 - c(a, b_h)}$$

where

$$\bar{F} = \{j \in F : d_j(a, b_h) > c(a, b_h)\}$$

The values of $\sigma(a, b_h)$, $\sigma(b_h, a)$ and λ determine the preference situation between a and b_h:

- $\sigma(a, b_h) \geq \lambda$ and $\sigma(b_h, a) \geq \lambda \Rightarrow aSb_h$ and $b_hSa \Rightarrow aIb_h$, i.e. a is indifferent to b_h;
- $\sigma(a, b_h) \geq \lambda$ and $\sigma(b_h, a) < \lambda \Rightarrow aSb_h$ and not $b_hSa \Rightarrow a \succ b_h$, i.e. a is preferred to b_h (weakly or strongly);
- $\sigma(a, b_h) < \lambda$ and $\sigma(b_h, a) \geq \lambda \Rightarrow$ not aSb_h and $b_hSa \Rightarrow b_h \succ a$, i.e. b_h is preferred to a (weakly or strongly);
- $\sigma(a, b_h) < \lambda$ and $\sigma(b_h, a) < \lambda \Rightarrow$ not aSb_h and not $b_hSa \Rightarrow aRb_h$, i.e. a is incomparable to b_h.

Two assignment procedures are then available. The role of these exploitation procedures is to analyze the way in which an alternative a compares to the profiles so as to determine the category to which a should be assigned.

Pessimistic (or conjunctive) procedure:

- compare a successively to b_i, for $i = p, p-1, \ldots, 1$,
- b_h being the first profile such that aSb_h, assign a to category C_{h+1} $(a \longrightarrow C_{h+1})$

Optimistic (or disjunctive) procedure:

- compare a successively to b_i, for $i = 1, 2, p$,
- b_h being the first profile such that $b_h \succ a$, assign a to category C_h $(a \longrightarrow C_h)$

If b_{h-1} and b_h denote the lower and upper profile of the category C_h, the pessimistic (or conjunctive) procedure assigns alternative a to the highest category C_h such that a outranks b_{h-1}, i.e., aSb_{h-1}. When using this procedure with $\lambda = 1$, an alternative a can be assigned to category C_h only if $g_j(a)$ equals or exceeds $g_j(b_h)$ (up to threshold) for each criterion (conjunctive rule).

The optimistic (or disjunctive) procedure assigns a to the lowest category C_h for each the lowest profile b_h is preferred to a, i.e., $b_h \succ a$. When using these procedure with $\lambda = 1$, an alternative a can be assigned to category C_h when $g_j(b_h)$ exceeds $g_j(a)$ (up to a threshold) at least for one criterion (disjunctive rule). When λ decreases, the conjunctive and disjunctive characters of these rules are weakened.

Table C.1 – S12 class breaks changes

	City driver profile				All-purpose driver profile			
	TCO (€)	Charging Points (0-1)	Charging Time (h)	Range (0-1)	TCO (€)	Charging Points (0-1)	Charging Time (h)	Range (0-1)
Baseline	75th Quartile	0.330	8.000	0.088	75th Quartile	0.330	0.500	0.176
	50th Quartile	0.500	4.000	0.308	50th Quartile	0.500	0.333	0.615
	25th Quartile	1.000	0.167	0.615	25th Quartile	1.000	0.167	1.000
More restrictive	50th Quartile	0.500	4.000	0.308	50th Quartile	0.500	0.333	0.615
	25th Quartile	0.750	2.000	0.615	25th Quartile	0.750	0.250	0.808
	10th Quartile	1.000	0.167	1.000	10th Quartile	1.000	0.167	1.000
Less restrictive	90th Quartile	0.167	16.000	0.044	90th Quartile	0.167	1.000	0.088
	75th Quartile	0.333	8.000	0.088	75th Quartile	0.333	0.500	0.176
	50th Quartile	0.500	0.167	0.308	50th Quartile	0.500	0.167	0.615

Table C.2 – S12 thresholds changes

	TCO			Charging Points/Charging Time/Range		
	Indifference	Preference	Veto	Indifference	Preference	Veto
Baseline	4%	7%	10%	10%	20%	30%
More restrictive	2%	5%	8%	5%	10%	15%
Less restrictive	8%	14%	20%	15%	30%	45%

Appendix D – Sensitivity analysis results

Table D.1 – Sensitivity analysis compilation

Blue: group means in the order ICEV HEV PHEV BEV / **Black:** ELECTRE TRI Kruskal-Wallis & Dunn/BH p-values / **Brown**: TOPSIS Kruskal-Wallis & Dunn/BH p-values / Shaded: ELECTRE TRI/TOPSIS relevant discrepancies

		S0 Baseline	S1 CP equal	S2 CT equal	S3 Range	S4 TCO only	S5 Fuel Price (2x)	S6 10-years	S7 Minor incentive	S8 Major incentive	S9 4% discount rate	S10 Half km travelled	S11 Emissions	S12 Equal Weights	S12a More/less restrictive breaks	S12b More/less restrictive thresholds
City driver profile	Small	3.6 / 2.0 / 1.0 / 1.7 ICEV > BEV (0.5%) 85 / 61 / 24 / 47 ICEV > BEV (0.5%)	3.6 / 2.0 / 1.0 / 1.7 ICEV > BEV (0.5%) 85 / 61 / 24 / 47 ICEV > BEV (0.5%)	3.6 / 2.0 / 1.0 / 1.7 ICEV > BEV (0.5%) 85 / 58 / 09 / 51 ICEV > BEV ICEV > PHEV (1.6, 3.5)%	3.6 / 2.0 / 1.0 / 2.0 ICEV > BEV (1.6%) 85 / 59 / 23 / 49 ICEV > BEV (0.7%)	3.6 / 2.0 / 1.0 / 2.1 ICEV > BEV (5.3%) **[1]** 84 / 55 / 00 / 56 ICEV > BEV **[1]** (5.9%)	3.5 / 1.0 / 1.0 / 2.0 ICEV > all **[2]** (1.5, 3.0, 4.5)% 53 / 42 / 24 / 47 All tech equal (KW 33%)	3.6 / 2.0 / 1.0 / 1.9 ICEV > BEV ICEV > PHEV (0.3, 2.7)% 85 / 62 / 26 / 44 ICEV > BEV ICEV > PHEV (0.3, 4.8)%	3.4 / 1.0 / 1.0 / 2.0 ICEV > all **[2]** (3.4, 3.5, 5.3)% 59 / 43 / 22 / 46 All tech equal (KW 15%)	2.4 / 1.0 / 1.0 / 2.0 All tech equal (KW 15%) 31 / 26 / 18 / 44 All tech equal (KW 17%)	3.6 / 2.0 / 1.0 / 1.6 ICEV > BEV (0.3%) 89 / 61 / 23 / 43 ICEV > BEV (0.5%)	3.9 / 3.0 / 1.0 / 1.6 ICEV > BEV ICEV > PHEV (0.0,4.8)% 88 / 60 / 22 / 41 ICEV > BEV (0.5%)	3.0 / 2.0 / 1.0 / 1.7 ICEV > BEV ICEV > PHEV (0.7, 4.7)% 43 / 35 / 51 / 67 BEV > ICEV BEV > HEV (0.3, 2.4)%	3.9 / 2.0 / 1.0 / 1.7 ICEV > BEV ICEV > PHEV (0.3, 4.8)% 94 / 85 / 58 / 19 ICEV > BEV (0.1%)	3.1 / 1.0 / 1.0 / 1.1 ICEV > BEV (0.3%) 4.0 / 3.0 / 1.0 / 2.6 ICEV > BEV ICEV > PHEV (0.2, 1.8)%	3.4 / 2.0 / 1.0 / 1.6 ICEV > BEV (0.6%) 3.9 / 2.0 / 1.0 / 2.0 ICEV > BEV ICEV > PHEV (0.5, 3.9)%
City driver profile	Medium	2.9 / 2.4 / 2.3 / 2.4 All tech equal (KW 30%) 55 / 49 / 43 57 All tech equal (KW 23%)	2.9 / 2.4 / 2.3 / 2.4 All tech equal (KW 30%) 55 / 49 / 43 / 57 All tech equal (KW 23%)	2.9 / 2.4 / 2.3 / 3.0 All tech equal (KW 32%) 51 / 44 / 37 / 64 All tech equal (KW 10%)	2.9 / 2.4 / 2.3 / 2.4 All tech equal (KW 30%) 53 / 46 / 40 / 61 All tech equal (KW 13%)	2.9 / 2.4 / 2.1 / 3.6 BEV > HEV **[1]** (5.6%) 46 / 37 / 29 / 72 BEV > HEV BEV > PHEV (2.7,1.7)%	2.6 / 2.3 / 2.7 / 2.4 All tech equal (KW 80%) 43 / 40 / 44 / 60 BEV > ICEV BEV > HEV (2.7,1.4)%	3.0 / 2.4 / 2.3 / 2.4 All tech equal (KW 24%) 55 / 49 / 46 / 57 All tech equal (KW 36%)	2.8 / 2.3 / 2.6 / 2.4 All tech equal (KW 61%) 44 / 40 / 41 / 58 BEV > all **[3]** (4.5, 4.1, 4.8)%	2.7 / 2.3 / 2.9 / 2.4 All tech equal (KW 60%) 32 / 30 / 34 / 60 BEV > all **[3]** (0.2, 0.1, 1.3)%	2.8 / 2.4 / 2.0 / 2.4 All tech equal (KW 28%) 59 / 52 / 43 / 57 All tech equal (KW 20%)	2.9 / 2.4 / 2.0 / 2.4 All tech equal (KW 24%) 61 / 54 / 43 / 57 All tech equal (KW 12%)	2.6 / 2.2 / 2.3 / 2.4 All tech equal (KW 71%) 31 / 29 / 55 / 67 BEV = PHEV > HEV = ICEV **[4]** (0.1, 0.1, 0.3, 0.2)%	3.0 / 2.4 / 2.3 / 2.0 All tech equal (KW 11%) 83 / 80 / 78 / 23 all > BEV **[5]** (0.0, 0.5, 3.1)%	2.3 / 1.9 / 1.6 / 1.4 All tech equal (KW 45%) 2.9 / 2.4 / 2.3 / 3.0 All tech equal (KW 32%)	2.8 / 2.4 / 2.0 / 2.0 All tech equal (KW 22%) 3.2 / 2.9 / 2.4 / 3.0 All tech equal (KW 37%)
City driver profile	Large	2.7 / 2.6 / 2.6 / 2.0 All tech equal (KW 89%) 56 / 51 / 48 / 31 All tech equal (KW 69%)	2.7 / 2.6 / 2.6 / 2.0 All tech equal (KW 89%) 56 / 51 / 48 / 31 All tech equal (KW 73%)	2.7 / 2.6 / 2.6 / 2.0 All tech equal (KW 89%) 52 / 47 / 44 / 32 All tech equal (KW 91%)	2.7 / 2.6 / 2.6 / 2.0 All tech equal (KW 89%) 55 / 50 / 47 / 31 All tech equal (KW 78%)	2.7 / 2.6 / 2.6 / 2.0 All tech equal (KW 89%) 51 / 47 / 42 / 32 All tech equal (KW 91%)	2.7 / 2.6 / 2.6 / 2.0 All tech equal (KW 89%) 58 / 53 / 57 / 40 All tech equal (KW 95%)	2.7 / 2.6 / 2.6 / 2.0 All tech equal (KW 89%) 57 / 53 / 51 / 32 All tech equal (KW 64%)	2.7 / 2.6 / 2.6 / 2.0 All tech equal (KW 89%) 56 / 51 / 52 / 35 All tech equal (KW 93%)	2.7 / 2.6 / 2.6 / 2.0 All tech equal (KW 89%) 56 / 51 / 57 / 42 All tech equal (KW 95%)	2.8 / 2.6 / 2.6 / 2.0 All tech equal (KW 89%) 54 / 49 / 45 / 27 All tech equal (KW 54%)	2.9 / 2.6 / 2.6 / 2.0 All tech equal (KW 68%) 53 / 48 / 43 / 27 All tech equal (KW 59%)	2.3 / 2.4 / 2.6 / 2.0 All tech equal (KW 86%) 35 / 33 / 51 / 50 All tech equal (KW 32%)	2.7 / 2.6 / 2.6 / 2.0 All tech equal (KW 88%) 78 / 75 / 74 / 17 All tech equal (KW 13%)	2.2 / 1.8 / 1.8 / 1.0 All tech equal (KW 48%) 3.3 / 3.4 / 3.2 / 3.0 All tech equal (KW 76%)	2.7 / 2.6 / 2.6 / 2.0 All tech equal (KW 89%) 2.9 / 3.0 / 2.6 / 2.0 All tech equal (KW 68%)
All-purpose driver profile	Small	3.6 / 1.0 / 1.0 / 1.0 ICEV > BEV (0.1%) 68 / 59 / 35 / 37 ICEV > BEV (0.2%)	3.6 / 1.0 / 1.0 / 1.0 ICEV > BEV (0.1%) 67 / 58 / 32 / 38 ICEV > BEV (0.2%)	3.6 / 1.0 / 1.0 / 1.9 ICEV > all **[2]** (0.7, 2.5, 3.8)% 66 / 55 / 25 / 40 ICEV > BEV ICEV > PHEV (0.3, 4.8)%	3.6 / 1.0 / 1.0 / 1.0 ICEV > BEV (0.1%) 63 / 51 / 36 / 43 ICEV > BEV (1.8%)	3.6 / 1.0 / 1.0 / 3.0 All tech equal (KW 13%) 54 / 37 / 00 / 58 All tech equal (KW 22%)	2.8 / 2.0 / 1.0 / 1.0 ICEV > BEV (0.1%) 48 / 46 / 35 / 37 ICEV > BEV (3.3%)	3.8 / 1.0 / 1.0 / 1.0 ICEV > BEV (0.1%) 66 / 59 / 37 / 34 ICEV > BEV (0.1%)	3.0 / 1.0 / 1.0 / 1.0 ICEV > BEV (0.1%) 56 / 50 / 33 / 38 ICEV > BEV (1.8%)	2.6 / 1.0 / 1.0 / 1.0 ICEV > BEV (0.1%) 41 / 39 / 29 / 39 All tech equal (KW 47%)	3.6 / 2.0 / 1.0 / 1.0 ICEV > BEV (0.0%) 75 / 62 / 32 / 38 ICEV > BEV (0.2%)	3.6 / 2.0 / 1.0 / 1.0 ICEV > BEV (0.0%) 87 / 68 / 35 / 37 ICEV > BEV (0.2%)	3.0 / 2.0 / 1.0 / 1.0 ICEV > BEV (0.0%) 37 / 35 / 58 / 63 BEV > ICEV BEV > HEV (0.4, 2.6)%	3.9 / 2.0 / 1.0 / 1.0 ICEV > BEV (0.1%) 86 / 81 / 61 / 18 ICEV > BEV (0.1%)	2.6 / 1.0 / 1.0 / 1.0 ICEV > BEV (0.1%) 4.0 / 3.0 / 1.0 / 1.7 ICEV > BEV ICEV > PHEV (0.1, 3.2)%	3.5 / 1.0 / 1.0 / 1.0 ICEV > BEV (0.1%) 4.0 / 3.0 / 1.0 / 1.0 ICEV > BEV (0.0%)
All-purpose driver profile	Medium	3.1 / 2.5 / 2.3 / 1.0 ICEV > BEV HEV > BEV (0.1, 2.5)% 58 / 56 / 52 / 47 ICEV > BEV **[1]** (6.6%)	3.1 / 2.5 / 2.3 / 1.0 ICEV > BEV HEV > BEV (0.1, 2.5)% 57 / 54 / 50 / 48 All tech equal (KW 21%)	3.1 / 2.5 / 2.3 / 2.0 ICEV > BEV **[1]** (5.1%) 54 / 51 / 47 / 52 All tech equal (KW 34%)	3.1 / 2.5 / 2.3 / 1.0 ICEV > BEV HEV > BEV (0.1, 2.5)% 52 / 49 / 44 / 54 All tech equal (KW 24%)	3.1 / 2.5 / 2.3 / 4.0 BEV > all **[6]** ICEV > HEV (4.5, 0.6, 0.8, 5.0)% 35 / 29 / 21 / 75 BEV > all **[3]** (0.5, 0.2, 0.2)%	2.9 / 2.6 / 3.0 / 1.0 all > BEV **[5]** (0.5, 1.2, 0.7)% 48 / 47 / 48 / 52 All tech equal (KW 41%)	2.9 / 2.6 / 2.3 / 1.0 ICEV > BEV HEV > BEV (0.3, 1.6)% 58 / 56 / 53 / 47 All tech equal (KW 12%)	2.8 / 2.5 / 2.4 / 1.0 all > BEV **[5]** (0.2, 2.1, 2.6)% 52 / 50 / 50 / 49 All tech equal (KW 62%)	2.7 / 2.4 / 3.0 / 1.0 all > BEV **[5]** (0.3, 1.7, 0.3)% 43 / 42 / 44 / 52 All tech equal (KW 16%)	3.1 / 2.4 / 2.3 / 1.0 ICEV > BEV (0.0%) 60 / 57 / 51 / 48 ICEV > PHEV **[1]** (9.6%)	3.0 / 2.4 / 2.3 / 1.0 ICEV > BEV HEV > BEV (0.0, 0.0)% 65 / 60 / 56 / 45 ICEV > BEV (0.8%)	2.7 / 2.4 / 2.3 / 1.0 all > BEV **[5]** (0.0, 0.8, 1.3)% 33 / 33 / 34 / 66 BEV > all **[3]** (0.1, 0.1, 1.0)%	3.2 / 2.8 / 2.3 / 1.0 ICEV > BEV HEV > BEV (0.1, 0.8)% 81 / 79 / 77 / 22 all > BEV **[5]** (0.0, 0.6, 3.0)%	2.3 / 1.9 / 1.6 / 1.0 ICEV > BEV (1.6%) 3.7 / 3.2 / 3.0 / 1.0 all > BEV **[5]** (0.0, 0.5, 1.0)%	2.8 / 2.4 / 2.3 / 1.0 ICEV > BEV HEV > BEV (0.4, 4.7)% 3.2 / 3.0 / 2.6 / 1.0 all > BEV **[5]** (0.1, 0.4, 4.5)%
All-purpose driver profile	Large	2.7 / 2.6 / 2.6 / 1.0 All tech equal (KW 33%) 63 / 59 / 56 / 35 All tech equal (KW 35%)	2.7 / 2.6 / 2.6 / 1.0 All tech equal (KW 33%) 62 / 57 / 54 / 36 All tech equal (KW 50%)	2.7 / 2.6 / 2.6 / 2.5 All tech equal (KW 98%) 57 / 53 / 48 / 40 All tech equal (KW 91%)	2.7 / 2.6 / 2.6 / 1.0 All tech equal (KW 33%) 60 / 56 / 52 / 37 All tech equal (KW 77%)	2.7 / 2.6 / 2.6 / 2.5 All tech equal (KW 98%) 53 / 49 / 44 / 41 All tech equal (KW 94%)	2.6 / 2.8 / 2.6 / 1.0 All tech equal (KW 28%) 63 / 59 / 61 / 48 All tech equal (KW 96%)	2.7 / 2.8 / 2.6 / 1.0 All tech equal (KW 29%) 63 / 60 / 57 / 37 All tech equal (KW 40%)	2.7 / 2.6 / 2.6 / 1.0 All tech equal (KW 34%) 63 / 59 / 59 / 39 All tech equal (KW 52%)	2.7 / 2.6 / 2.6 / 1.0 All tech equal (KW 34%) 63 / 59 / 63 / 45 All tech equal (KW 90%)	2.7 / 2.8 / 2.6 / 1.0 All tech equal (KW 29%) 62 / 57 / 52 / 32 All tech equal (KW 35%)	2.7 / 2.8 / 2.6 / 1.0 All tech equal (KW 25%) 61 / 57 / 54 / 29 All tech equal (KW 16%)	2.3 / 2.6 / 2.2 / 1.0 All tech equal (KW 20%) 36 / 35 / 37 / 61 All tech equal (KW 14%)	2.7 / 3.0 / 2.6 / 1.0 All tech equal (KW 26%) 81 / 78 / 77 / 19 All tech equal (KW 13%)	2.3 / 1.8 / 1.8 / 1.0 All tech equal (KW 44%) 3.3 / 3.6 / 3.2 / 1.0 All tech equal (KW 10%)	2.7 / 2.6 / 2.6 / 1.0 All tech equal (KW 34%) 2.8 / 3.0 / 2.6 / 1.0 All tech equal (KW 22%)

Notes: [1] Possible false positive: Kruskal-Wallis p-value below 10%, but Dunn post-hoc tests with BH correction could not identify deviant groups. The reported post-hoc comparison is the one closest to H0 rejection.

P-value orders: **[2]** ICEV vs BEV, HEV, PHEV. **[3]** BEV vs ICEV, HEV, PHEV. **[4]** BEV vs ICEV, HEV; PHEV vs ICEV, HEV. **[5]** ICEV, HEV, PHEV vs BEV. **[6]** BEV vs ICEV, HEV, PHEV; ICEV vs HEV.

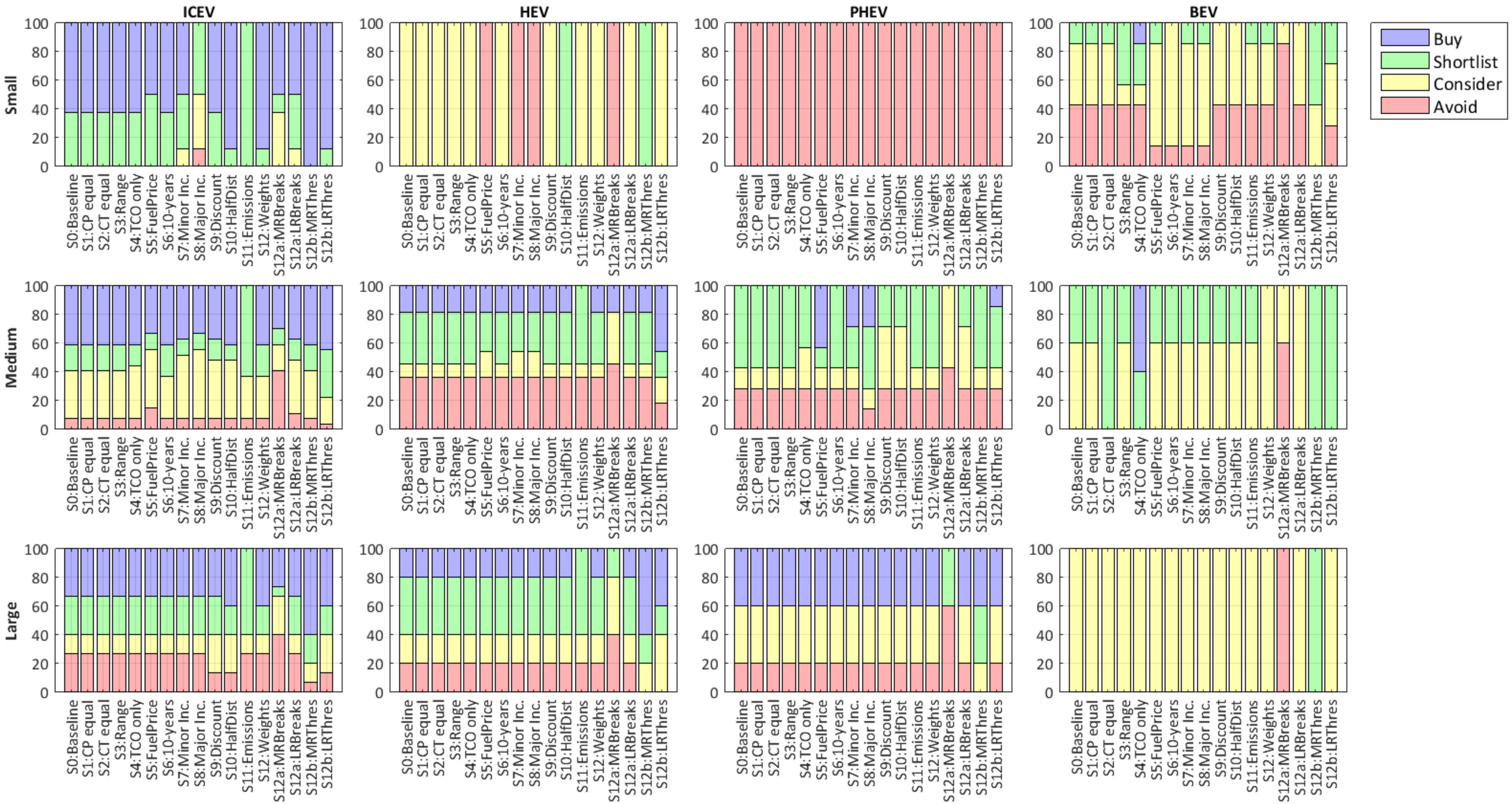

Figure D.1 – ELECTRE TRI results for city driver profile

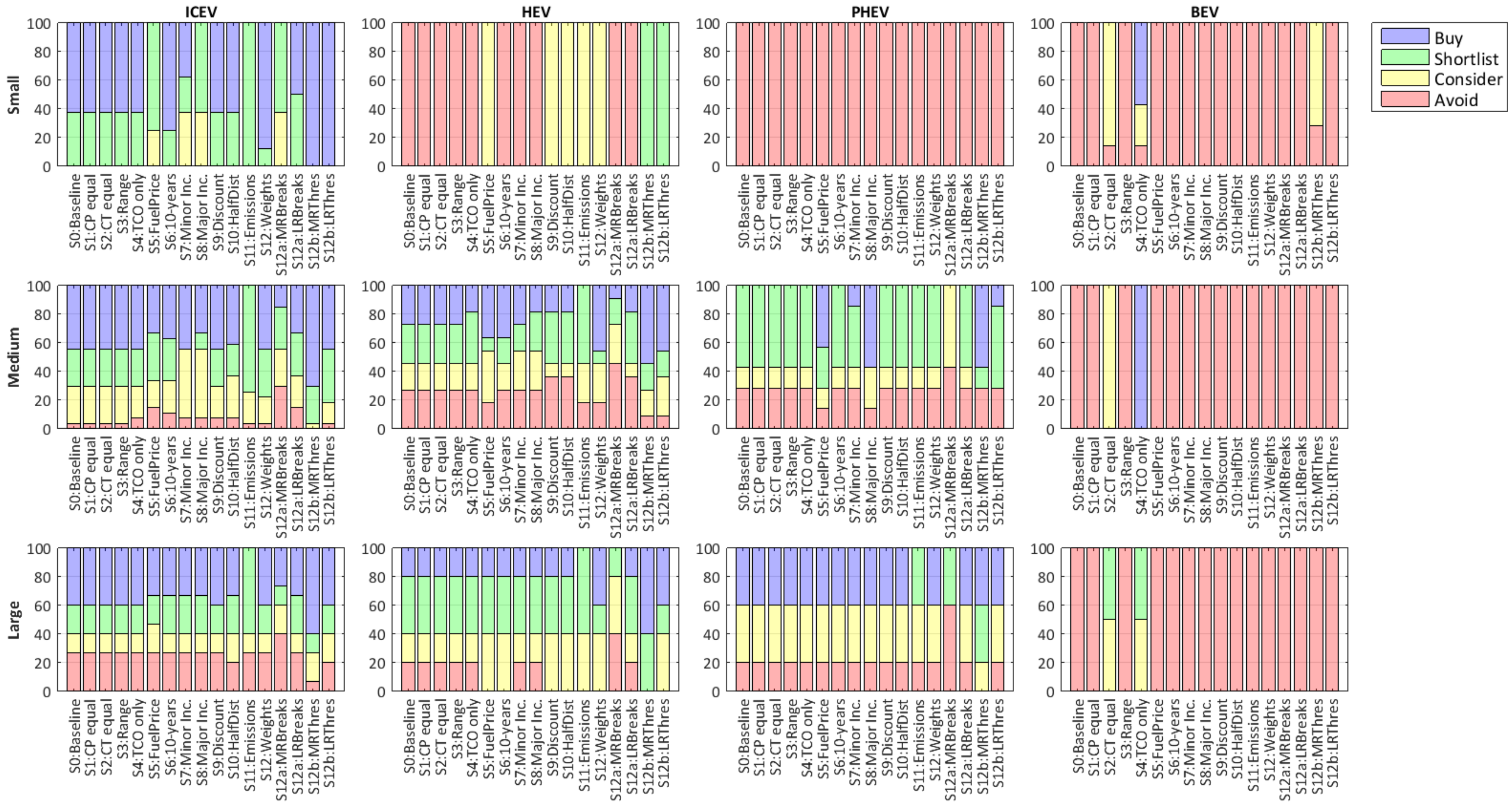

Figure D.2- ELECTRE TRI results for all-purpose driver profile

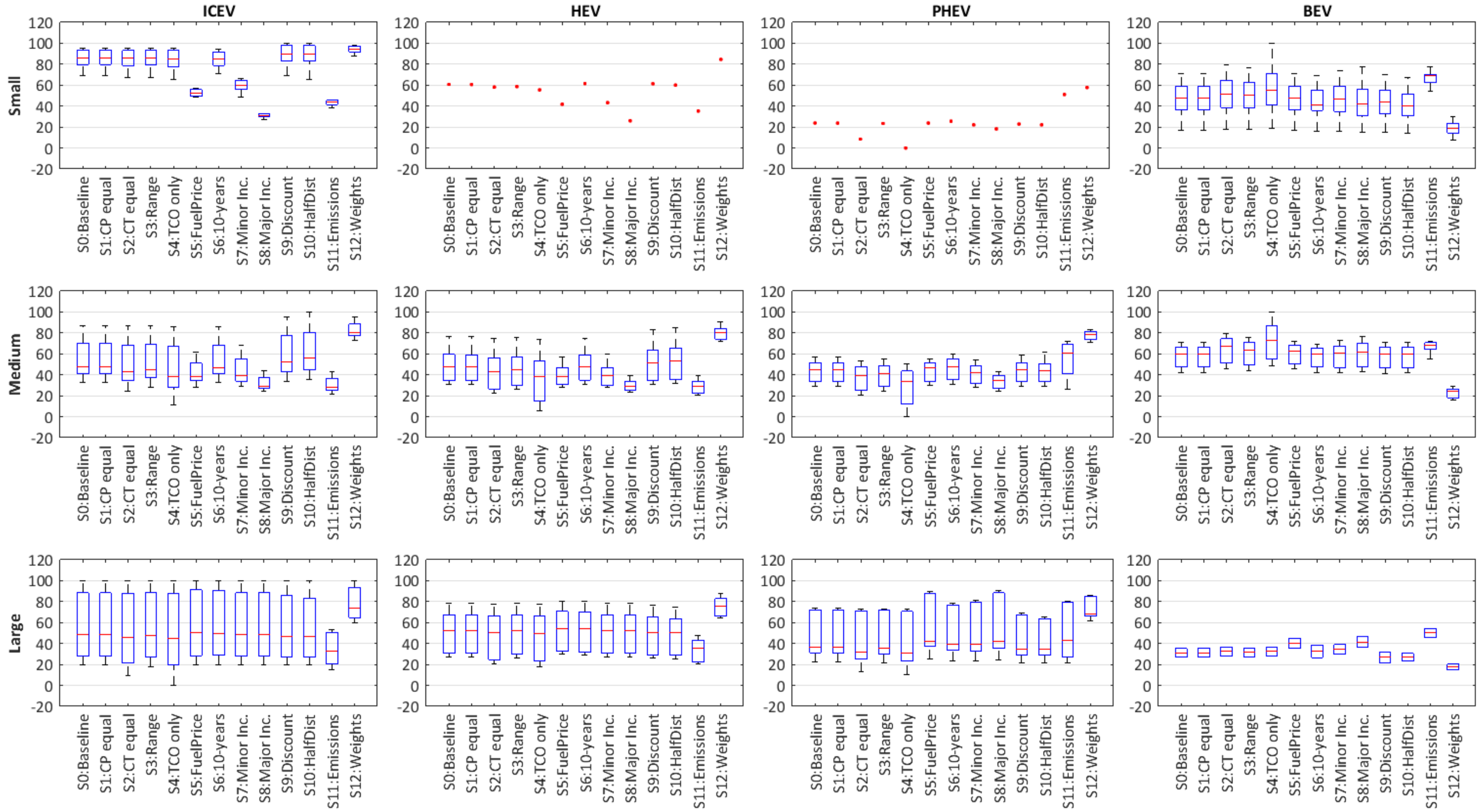

Figure D.3 - TOPSIS results for the city driver profile

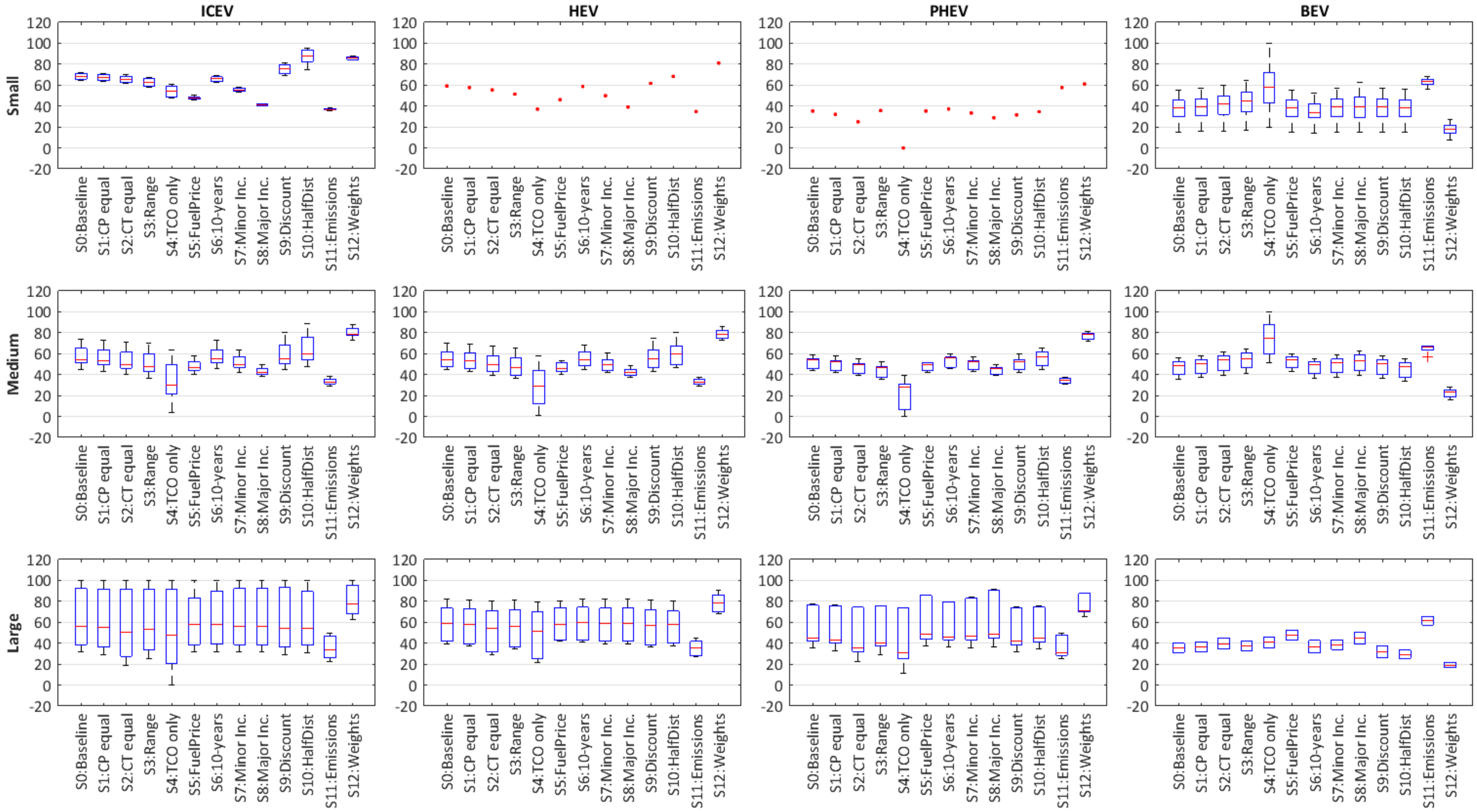

Figure D.4 - TOPSIS results for all-purpose driver profile