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King Abdullah Petroleum Studies and Research Center

KAPSARC vehicle fleet model: Cost of electrification

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About KAPSARC

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Summary

This paper discusses the model we have developed at KAPSARC for estimating the relative costs of passenger car fleets containing low-emission vehicles of different types, particularly with emphasis on electric vehicles. The main purpose of the model is to enable analysis of low-emission vehicle policy; in particular, we have so far applied it to the analysis of the cost implications of supporting different types of EVs and battery charging infrastructures. The model has been designed for simplicity, transparency and ease of use by non-expert stakeholders. As such the approach taken is inspired by meta-modelling, i.e.,: we draw on the results of different existing pieces of techno-economic analysis and we bring them together in a simple modelling framework, which allows for the testing of the high-level cost implications in a transparent way. The model has also been designed such that it can be easily updated when new evidence becomes available or adapted to analyze different vehicle and infrastructure technologies.

The model calculates the Relative Cost of Ownership (RCO) of individual vehicles, selected as representative of main market segments in the passenger car fleet that is the subject of our study. For each of these vehicles, we model both its internal combustion engine (ICE) version and all main electric powertrain types, i.e.,: battery electric (BEV), range-extended electric (RE-EV) and plug-in hybrid (PHEV). In the case of the electric powertrain vehicles, the user can select the desired battery size and charging infrastructure coverage. The user can then also select fleet penetration levels of each powertrain type by market segment, and the model adds up all the RCO of the individual vehicles over the whole fleet to return the incremental annual cost of passenger car electrification under the scenario selected.

In addition to the total cost of the fleet, the model can also estimate fleet average CO2 emissions, both tailpipe and Well-to-Wheel, and overall infrastructure utilization levels. Analysis of vehicle cost and emissions at segment level is also possible. A quick guide on how to use the simplified version of the model, which is available online is provided at the end of the paper.

Overview of the KAPSARC Vehicle Fleet Model: Cost of Electrification

What it is and who it is for

The KAPSARC vehicle fleet model is an Excel-based techno-economic scenario model. Its main purpose is to calculate the incremental user cost and related CO_2 emission reduction of given mixes of internal combustion engine vehicles (ICEVs), electric vehicles (EVs) and charging/fueling infrastructures, at a country or state level, relative to the case where the whole passenger car fleet is composed of ICEVs. EV types included in the model are: pure battery electric vehicles (BEVs); plug-in hybrid electric vehicles (PHEVs) of both the parallel and series type (the latter are also referred to as range-extended electric vehicles or RE-EVs). Hydrogen fuel cell vehicles (FCEVs) and related hydrogen fuel infrastructure is also included in the full version of the model but has not yet been used as part of the research conducted at KAPSARC, hence it is not discussed in detail in this paper.

The model first calculates the Relative Cost of Ownership (RCO) and CO_2 emissions of single vehicles by market segment and powertrain type, and then adds them up based on the fleet shares of the different EV types as chosen by the user, to return the total incremental cost of EVs and CO_2 emissions saved at fleet level. The calculation is performed over the lifetime of the vehicle and infrastructure elements. However, the total incremental cost is also presented as an annual figure for ease of comparison with other national or state budget items. The model, therefore, can be used as a tool to analyze the cost and CO_2 emission implications of policy promoting EV innovation and adoption. In particular, by comparing the relative cost and CO_2 emissions of different mixes of EV types across market segments in a given passenger car fleet, we can identify those mixes that are likely to achieve the desired CO_2 emission reduction at lower cost, and hence derive policy insights for electrification

The user cost as calculated by the model excludes all types of subsidies and hence assumes that all incremental EV costs are passed on to the user. The cost so calculated corresponds to the private cost of electrification of the passenger car fleet. The model as it stands does not take into account societal costs, i.e.,: external costs, however it could easily be adapted to include them. In the current version the absence of external costs can be circumvented by comparing only those scenarios that have similar levels of fleet average CO_2 emissions; the latter are also a good proxy for regulated air pollutants, which is the other major source of environmental external costs. The analysis we perform at the vehicle level is called RCO because the cost items that are common to both EVs and ICEVs, e.g.,: tire use, are not considered in the model. Vehicle and fuel taxation is also not accounted for in our study, although these could be included in the model if desired. This corresponds to modelling non-CO_2 related taxation of EVs as the same of ICEVs.

In the accompanying KAPSARC discussion paper "Will current electric vehicle policy lead to cost-effective electrification of passenger car transport?" we have applied the model to the study of EV policy in the UK and California. A web-based user interface based on a simplified version of the model is available on OpenKAPSARC, for interested parties to test its capabilities. The full version of the model has been designed so as to ensure transparency, flexibility and ease of use, and could also be shared with third parties interested in reproducing our results or testing alternative scenarios. Its use does not require particular technical knowledge and therefore it is suitable for government analysts, industry experts and researchers. Provided the necessary data is available, the model can easily be extended and adapted to any country case study, as well as used for conducting other types of analysis, such as assessing the cost of different EV transition pathways over time.

Given its purpose, the model design is inspired by the meta-modelling philosophy. In other words, the model only calculates endogenously those variables the value of which is directly dependent on the particular model scenario chosen, while treating as exogenous all those variables that don't present strong feedback relations with the key scenario input variables. In this way we can exclude from the model much of the detailed complexity of the problem, while adequately capturing the main factors that influence the incremental user cost of different passenger car powertrain portfolios. As for the other factors, the model is designed so that best available data resulting from detailed technical studies can be easily plugged into it and updated as appropriate when new evidence becomes available. Finally, for the sake of simplicity of use and flexibility, we have decided to deal with uncertainty by providing value ranges for all the main variables, allowing the user to select the desired value from a drop-down menu, as opposed to equipping the model with a Monte Carlo sensitivity analysis utility; the latter could however be added in order to conduct this particular type of analysis.

What is novel about it

The future cost and emissions of different types of EVs have been the subject of much research over the last decade. A large number of studies can be found in the literature that cover the whole spectrum of economic assessments of EVs, from detailed powertrain cost and performance modelling aimed at guiding the design of systems or components, to studies comparing the lifetime cost and emissions of different EV types in order to inform policymaking. Common to most of these studies is the use of the RCO metrics, which enables the estimating of the cost of individual EVs over their lifetime and comparing across different powertrain types; as the name suggests, RCO does not consider all costs but only those that are relevant to the comparison being made. Appendix A provides a brief review of the main studies in this area. They have generated a large amount of knowledge on the economics of EVs, both present and future with a focus on single vehicles as opposed to whole fleets. The studies tend not to consider the cost of different EV charging infrastructure configurations. We are seeking to factor in the complexity of the passenger car market by including different vehicle segments and taking into account the effects of non-powertrain fuel efficiency improvements that come from vehicle weight reduction through the use of lightweight materials, better vehicle aerodynamics and reduction of tire rolling resistance. Perhaps the greatest need that we identify is that results are based on the use of fairly complex models, which may lack transparency and flexibility. It can be difficult to communicate new results or update the models when new evidence becomes available.

Our approach is to develop a dedicated model that allows to estimate the incremental user cost of EVs relative to ICEV in passenger car fleets, taking into account all the necessary factors highlighted in the literature. Due to regional differences in policy as well as passenger car transport use and vehicle preferences, we have also identified the need for a model that is flexible enough so as to be easily adapted to different regional case studies. A useful feature of our model is that it allows the user to define the desired electric vehicle range of the vehicle and charging infrastructure coverage;

these are fixed in most other studies at the expense of flexibility. We also make use of vehicle usage statistics, particularly distributions of daily distances driven and their variation across vehicle segments, which allow us to determine the percentage of total miles driven on electricity by PHEVs (the so-called utility factor) as well as the level of utilization of public charging infrastructure by BEVs. Finally, we have sought to make the model transparent and user-friendly, so that it could be made available for stakeholders to use as a tool for facilitating discussion around EV policy. The next Section of this paper provides a detailed description of the model structure and equations. The following Section discusses the techno-economic vehicle and fleet data used in the model. Finally, a quick guide to the use of the web-based user interface available on OpenKAPSARC is provided.

Model Description

In the following sections we first provide a brief description of the model's overall structure, followed by a more detailed discussion of each of the main model calculations in turn.

Model structure

The structure of the model is summarized in Figure 1. The model first calculates the RCO of single vehicles taking a bottom-up approach, i.e.,: it adds up the capital cost (CAPEX) and operating cost (OPEX) of the vehicle over its ownership period or lifetime.

$$RCO_n = CAPEX + \sum_{i=1}^{n} OPEX_i - resale\ value_n$$

Equation 1: Definition of RCO for an ownership period of n years. If n corresponds to the entire lifetime of the vehicle the resale value is zero.

In addition to the above calculation, the model also calculates the present value of the RCO, by discounting operating costs as appropriate. This is not discussed here because it is not relevant to the analysis conducted in the accompanying KAPSARC discussion paper; however the discounted RCO can be useful in other types of analysis supported by the model.

The calculation of CAPEX and OPEX are discussed below. They depend on a number of techno-economic variables as well as on driving patterns. Techno-economic variables include the vehicle's size and performance, the scale and type of fuel infrastructure and a range of techno-economic data pertaining to the powertrain and the fuel infrastructure. Driving data considered include average annual distance driven for each car segment and its breakdown into daily distances driven.

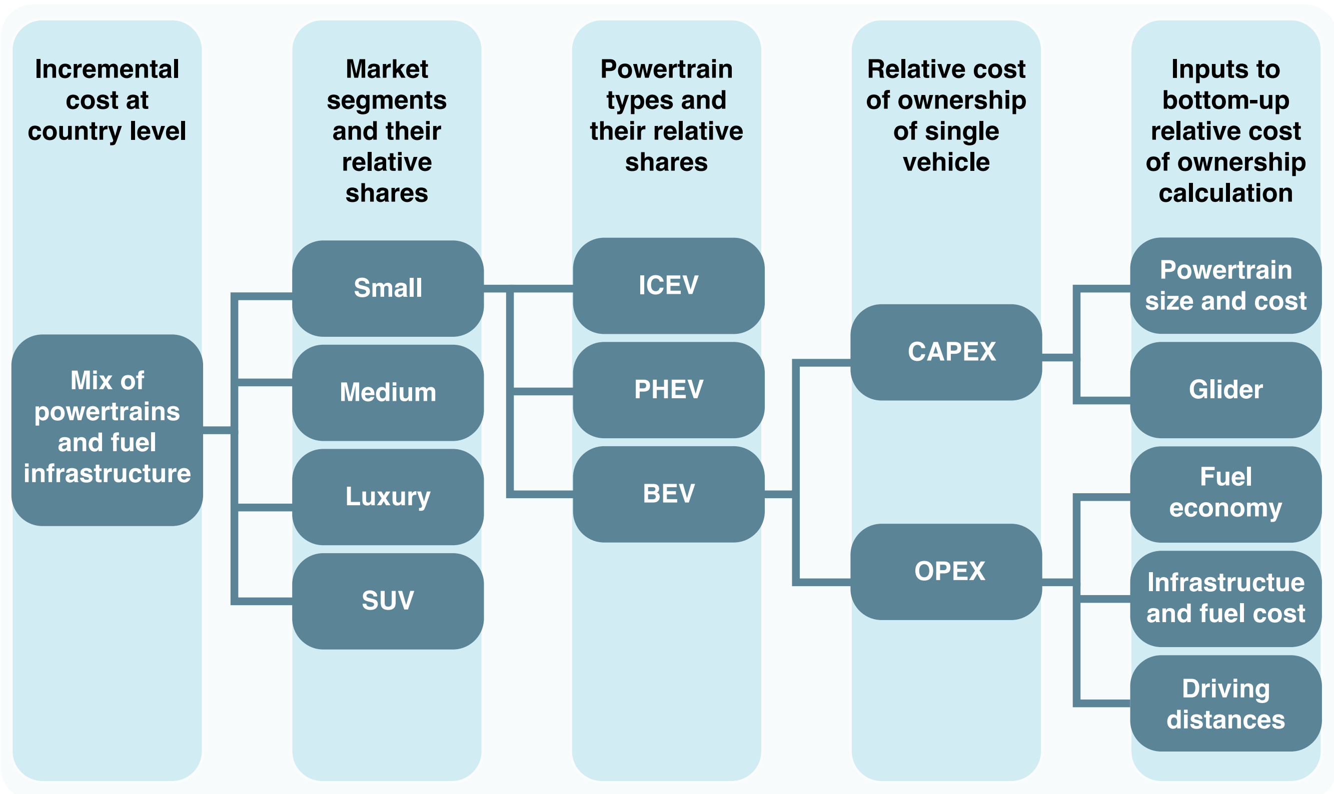

Figure 1. Schematic representation of the model structure.

Source: KAPSARC.

The latter is particularly important in the case of powertrain types using more than one fuel (i.e.,: PHEVs running on electricity and gasoline) or using electricity only but charging from different types of infrastructure (i.e.,: rapid vs slow charging).

The single vehicles for which RCO is calculated are modelled based on the key characteristics of the most popular car models in the main market segments. For each representative vehicle, RCO is calculated across all powertrain options, namely ICEV, PHEV parallel and series (RE-EV) and BEV. Market segments over which the passenger car fleet is divided are categorized based on the common definitions used by the car industry. Although the model is capable of representing the entire passenger car fleet, it is also possible to only model those segments that are most significant for the analysis due to their size or relevance.

Once the RCOs of all vehicles and powertrains modelled have been calculated, they are added based on their relative market shares in each of the market segments as chosen by the model user, and divided by the number of years over which the RCO is performed. This returns the annual incremental user cost of the particular vehicle and infrastructure mix chosen at a country level:

$$Annual\ incremental\ user\ cost\ of\ fleet = \frac{1}{n}\sum_{i=1}^{m}\sum_{j=1}^{p} RCO_{i,j}\ X_i\ Y_{i,j}$$

Equation 2: Calculation of annual incremental user cost of the passenger car fleet. n = vehicle ownership period or lifetime; $RCOi,j$ = Relative Cost of Ownership for vehicle representative of market segment i equipped with powertrain type j; Xi = Number of vehicles belonging to market segment i; m = number of market segments modelled; Yi,j = Percentage of powertrain type j in market segment I; p = number of powertrain types modelled.

Finally, it is worth noting that the model also calculates CO_2 emissions for each vehicle modelled and for the fleet as a whole, which allows the user to identify different EV mixes characterized by similar average CO_2 emission levels and compare them based on their relative costs.

Vehicle capital cost

In order to calculate the capital cost of vehicles equipped with different powertrains, we start with the selling price of the representative ICEV chosen for each one of the segments we want to model. We estimate the capital cost of the ICEV by subtracting the manufacturer's and retailer's markup to the selling price. We then estimate the capital cost of the ICE powertrain based on the rated maximum power of the vehicle and the capital cost of the ICE powertrain components, per unit or unit power whichever applies. By subtracting the cost of the ICE powertrain to that of the ICEV we estimate the cost of the glider. The glider can be defined as all the non-powertrain components of the vehicle, and we assume that this is common across all powertrain types for a given vehicle model representative of a market segment. The calculation of the glider cost is summarized below:

glider cost =ICEV selling price-markups-ICE powertrain cost

Equation 3: Estimation of glider cost from ICEV selling price.

Where the ICE powertrain cost is calculated as follows:

ICE powertrain cost =ICEV rated power ×(ICE cost per unit power+transmission cost per unit power)+fuel tank+exhaust aftertreatment

Equation 4: Estimation of ICE powertrain cost from the cost of its components as reported in the literature.

In order to estimate the capital cost of electric powertrain vehicles (BEV, RE-EV and PHEV), we calculate the cost of the respective electric powertrain and we add it to the cost of the glider. Different types of electric powertrains, however, are characterized by different sizing factors for their key components. This is because electric powertrains perform differently from ICE powertrains and if we want the former to guarantee the same performance level as the latter we cannot simply model the electric powertrain vehicle as having the same weight-to-power ratio of the ICEV. The particular powertrain sizing factors used in the model are discussed in the following Section. However, the generic calculation of the capital cost of an electric powertrain can be expressed as follows:

$$\begin{aligned}&\textit{Electric powertrain cost}_i\\&\quad=\{\textit{ICEV rated power}\\&\quad\times[(\textit{electric motor cost per unit power} \times \textit{electric motor sizing factor}_i)\\&\quad+(\textit{ICE cost per unit power} \times \textit{ICE sizing factor}_i)\\&\quad+(\textit{transmission cost per unit power} \times \textit{transmission sizing factor}_i)]\}\\&\quad+(\textit{battery cost per unit energy}_i \times \textit{energy needed for desired range})\\&\quad+\textit{fuel tank}_i+\textit{exhaust aftertreatment}_i\end{aligned}$$

Equation 5: Estimation of the capital cost of the generic electric powertrain type i. Different powertrain types (BEVs, RE-EVs and PHEVs) have different component sizing factors and use different battery types. Only the electric powertrain types including an internal combustion engine also have a fuel tank and exhaust after-treatment.

The size of the battery pack needed to ensure the vehicle the desired range is calculated based on the vehicle's fuel consumption when operating in electric mode and the depth of discharge that the battery can achieve without compromising its safety and durability. In our model we do not consider the effects of battery degradation or cold weather on the electric range of the vehicle, both of which can be substantial. The calculation of the vehicle's fuel consumption when in electric mode is discussed below and it is here only worth noting that it is a function of the size of the battery, as additional vehicle weight comes with a fuel economy penalty.

Vehicle operating cost

The annual operating costs for all vehicle segments and powertrains modelled are calculated as the sum of the annual cost of fuel, servicing and maintenance. We model the annual mileage of the vehicle as constant over the years, therefore annual operating costs do not change over the lifetime of the vehicle. In reality though this is an overestimation of the lifetime utilization of the vehicles, as the annual mileage of a passenger car is typically observed to decrease as the vehicle ages. Hence the way in which we calculate operating costs over the lifetime of the vehicle favors BEVs over less electrified EVs and ICEVs.

We model the annual cost of servicing as a flat rate based on literature numbers, which suggest that maintenance of BEVs is cheaper than that of ICEVs due to the greater simplicity of the electric powertrain compared to the ICE powertrain. Due to the relative nature of our analysis, all the operating cost components that are the same for a passenger car of the same model and performance irrespective of the powertrain type, e.g.,: tire cost, are here not included. As also mentioned in the accompanying KAPSARC discussion paper, non-carbon related vehicle and fuel taxation is assumed to be the same across all powertrain types and hence excluded. Insurance cost is also assumed to be the same across all powertrain types, despite other studies suggest that this may not be the case at least initially (Element Energy 2011). The most complex calculation is that pertaining to annual fuel cost.

For this we need to calculate the fuel economy of the vehicle, which depends on the type of powertrain, the weight and other endogenous variables, and the cost of the fuel, which is a function of the amount of charging infrastructure deployed and its level of utilization. The calculation is explained in detail below.

Fuel economy calculation

The fuel economy of a vehicle in our model is calculated based on its road load, or energy required at the wheel in order to propel the vehicle over the relevant drive cycle, divided by the energy efficiency of the powertrain.

$$fuel\ economy\ \left(\frac{kWh}{km}\right) = vehicle\ load\ \left(\frac{kWh}{km}\right) / \ \eta$$

Equation 6: vehicle fuel economy calculation. η is the energy conversion efficiency of the powertrain

The vehicle road load is a function of the particular drive cycle considered and of the vehicle's weight, aerodynamics and rolling resistance. We can estimate the road load of a current ICEV model by dividing the measured value of fuel economy (over a particular test cycle on in real driving conditions) by the estimated energy efficiency of the powertrain. However estimating the fuel economy of future vehicles, be they advanced ICEVs or electric, which use lightweight materials, improved aerodynamics, low rolling resistance tires and advanced powertrain components generally requires computer simulations. As discussed in more detail in Appendix A, some RCO studies in the literature make use of sophisticated vehicle simulation software, while others use simplified approaches that also draw on results of vehicle simulations from other studies. Given the purpose of our model and the need for simplicity and transparency, we have developed a simplified method for estimating the fuel economy of future vehicles that does not rely on vehicle simulation but is based on fundamental equations taken from the literature. The results so obtained are then calibrated and validated against relevant vehicle simulation studies, in order to ensure that the error introduced by our simplified approach does not significantly affect the overall results of our analysis. The simplified method is described below.

Starting from the published fuel economy values for today's vehicles, the model estimates the vehicle road load by multiplying the fuel economy by the estimated powertrain efficiency. The latter is calculated as follows:

$$\eta_{powertrain} = (1 - idling\ losses) * \eta_{engine} * \eta_{driveline}$$

Equation 7: Estimation of ICE powertrain efficiency. Idling losses is the fraction of total fuel used when idling

So for a reference ICEV model the road load will decrease in future as lightweight materials, better aerodynamics and low rolling resistance tires are used, which will lead to improved fuel economy. Moreover, the efficiency of the ICE powertrain will increase, which will further improve fuel economy. Hence, we estimate the future fuel economy of the reference ICEV model based on the combined effects of these improvements as reported in the literature. Having estimated the new fuel economy value for the improved ICEV, we derive the new road load figure that corresponds to the lighter vehicle where non-powertrain weight savings have been realized. We then use the two road load values so estimated for the current and future reference ICEV model as a basis for estimating the road load of the electric powertrain vehicles we model as a function of their weight. In particular we use the linear relationship below because it is found in the literature that vehicle fuel consumption varies roughly linearly with weight (Brooker, Ward, and Wang 2013, Lotus Engineering Inc. 2010).

$$EV\ load = \left(\frac{ICEV\ load_{current} - ICEV\ load_{future}}{ICEV\ weight_{current} - ICEV\ weight_{future}}\right) * EV\ weight + ICEV\ load_{future} - \left(\frac{ICEV\ load_{current} - ICEV\ load_{future}}{ICEV\ weight_{current} - ICEV\ weight_{future}}\right) * ICEV\ weight_{future}$$

Equation 8: Estimation of electric vehicle road load as a function of its weight. For each segment, the EV is modelled based on the reference ICEV model and is assumed to benefit from the same non-powertrain weight reduction, aerodynamics and rolling resistance improvements as future ICEVs.

The weight of the glider is assumed to be the same across all EV types for a given car model, whereas the weight of the powertrain components is calculated based on its sizing and relative power/energy densities of each component:

$$\begin{aligned} &Electric\ powertrain\ weight_i \\ &= \{ICEV\ rated\ power \\ &\times[(electric\ motor\ power\ density \times electric\ motor\ sizing\ factor_i) \\ &+ (ICE\ power\ density \times ICE\ sizing\ factor_i) \\ &+ (transmission\ power\ density \times transmission\ sizing\ factor_i)]\} \\ &+ (battery\ energy\ density_i \times energy\ needed\ for\ desired\ range) \\ &+ fuel\ tank\ weight + exhaust\ aftertreatment\ weight \end{aligned}$$

Equation 9: Estimation of weight of the generic electric powertrain type i. Different powertrain types (BEVs, RE-EVs and PHEVs) have different powertrain sizing factors and use different battery types. Only the electric powertrain types including an internal combustion engine have a fuel tank and exhaust after-treatment.

The architecture and sizing factors for the components of different electric powertrain types are discussed the following Section. The electric vehicle load so estimated can then be translated into fuel economy figures through the estimated efficiency value of the electric powertrain:

$$\eta_{electic\ powertrain} = \eta_{battery} * \eta_{electric\ driveline}$$

Equation 10: Estimation of electric powertrain efficiency. For hybrid powertrains (RE-EVs, PHEVs) this only applies to the powertrain when operating in EV mode (charge-depleting mode).

Finally, for electric vehicles that have a hybrid battery electric-internal combustion engine powertrain, two fuel economy values are calculated based on Equation 6: one for the vehicle when operating on batteries (i.e.,: charge depleting mode) and one when operating on the internal combustion engine (i.e.,: charge sustaining mode).

Annual fuel use calculation

The annual amount of fuel used by a particular vehicle model equipped with a particular type of powertrain is calculated by multiplying the fuel economy of the vehicle times the annual distance driven.

This calculation is straightforward for ICEV powertrains that only use one fuel. However, it is more complex in the case of powertrains that use more than one fuel, such as PHEVs and RE-EVs, and it requires using information on driving patterns in order to estimate the relative use of electricity, also known as utility factor, of the powertrain.

In particular, we assume that all plug-in electric vehicles have a primary charging point, such as a private home charger or a public dedicated charger (e.g.,: at the office or at a railway station) where they are fully charged every day. We also assume that every day the vehicles are driven on electricity only until they reach the limit of their all-electric range (AER), after which the internal combustion engine kicks in. This is certainly the case for RE-EVs but represents an approximation in the case of parallel PHEVs that operate in blended mode; however, this is considered as acceptable given the purpose of our model. In the case of both PHEVs and RE-EVs we do not account for opportunity charging in locations other than the primary charging place. In the case of BEVs, however, we assume that once the AER is reached, the BEVs will use secondary public chargers, be they rapid or slow, in order to complete their journeys; this calculation is not needed for the purpose of determining the total amount of fuel used, since BEVs only run on one fuel; however, it is important in order to determine the level of utilization of the public charging infrastructure modelled. The AER of any electric powertrain vehicle is estimated as follows:

$$AER\ (km) = \frac{battery\ size\ (kWh)}{fuel\ economy_{electric\ mode}(kWh/km)}$$

Equation 11: calculation of all-electric range (AER) of electric vehicles

In order to calculate the amount of electricity and gasoline used by PHEVs and RE-EVs annually, we make use of a distribution of daily distances driven, built on travel survey data. The data is manipulated so as to obtain frequency distributions of daily distances driven for each market segment considered. In the case of PHEVs and RE-EVs, therefore, the amount of electricity used in a year is calculated by adding all the daily distances driven up to the limit of the AER of the vehicle considered, and multiplying these for the fuel economy of the vehicle in electric vehicle mode:

$$\begin{aligned} &Annual\ electricity\ used\ (kWh) \\ &\quad = fuel\ economy_{electric\ mode}(kWh/km) * \sum_{i=1}^{n} electric\ daily\ distance\ driven_i\ (km) \\ &\quad * frequency_i \end{aligned}$$

$$\begin{aligned} where{:}\ &electric\ daily\ distance\ driven_i = daily\ distance\ driven_i\ if\ daily\ distance\ driven_i \le AER \\ &electric\ daily\ distance\ driven_i = AER\ if\ daily\ distance\ driven_i > AER \end{aligned}$$

Equation 12: Calculation of annual electricity used by PHEVs and RE-EVs. n is the number of bins into which the distribution of daily distances driven as derived from national travel surveys is divided

The amount of gasoline used in a year is calculated by adding the distances driven beyond the AER of the vehicle, and multiplying this for the fuel economy of the vehicle when operating on the internal combustion engine:

$$Annual\ gasoline\ used\ (kWh) = fuel\ economy_{ICE\ mode}(kWh/km) * \sum_{i=1}^{n} gasoline\ daily\ distance\ driven_i\ (km) * frequency_i$$

$$where: gasoline\ daily\ distance\ driven_i = daily\ distance\ driven_i - AER\ if\ daily\ distance\ driven_i > AER$$

$$gasoline\ daily\ distance\ driven_i = 0\ if\ daily\ distance\ driven_i \leq AER$$

Equation 13: Calculation of annual gasoline used by PHEVs and RE-EVs. n is the number of bins into which the distribution of daily distances driven as derived from national travel surveys is divided.

The same logic is applied in the case of BEVs to the calculation of electricity used from home charging and public charging, respectively.

Finally, it is worth mentioning that in the model there is a utility that allows changing the distribution of daily distances driven by different passenger car segments, in order to simulate the effect of moving from the current car ownership model to one dominated by shared ownership and mobility services. This however has been disabled in the simplified version of the model that is available on OpenKAPSARC and was not used for the analysis presented in the accompanying KAPSARC Discussion Paper either.

Fuel cost calculation

Once we know the amount of electricity and gasoline consumed by all powertrain types over all the passenger car models considered, we can calculate the total annual fuel cost for each one of them by multiplying the amount of fuel used by its cost:

$$annual\ fuel\ cost\ (\$) = annual\ fuel\ used\ (kWh) * fuel\ cost\ (\frac{\$}{kWh})$$

Equation 14: Calculation of annual fuel cost (electricity or gasoline) for any particular powertrain and vehicle segment modelled.

We model gasoline cost as its untaxed price at the pump. As for electricity though, we model charging infrastructure explicitly in order to allow analyzing the impact of different infrastructure policies on the RCO of different BEV segments. Therefore, we calculate the contribution of infrastructure to the cost of the electricity it delivers by adding a capital cost component to the price of the electricity that the infrastructure provider acquires from the grid. The capital cost component is calculated by dividing the total annual cost of the infrastructure by the total annual amount of electricity it delivers to EVs:

$$cost\ electricity\ from\ public\ infrastructure\ \left(\frac{\$}{kWh}\right)$$
$$= price\ electricity\ for\ infrastructure\ provider\ \left(\frac{\$}{kWh}\right)$$
$$+ \frac{capital\ cost\ public\ charging\ infrastructure\ (\$)}{lifetime\ infrastructure\ (years) * total\ annual\ electricity\ used\ from\ infrastructure\ (\frac{kWh}{years})}$$

Equation 15: Calculation of unit cost of electricity delivered by public charging infrastructure

Thanks to the fact that the infrastructure is modelled explicitly, the model allows analyzing various aspects of the charging infrastructure including its level of utilization, which we measure as the average daily number of charging events per charging point and gives us an indication on whether or not the infrastructure can be operated economically.

Techno-Economic Input Data

The passenger car fleet

Since the analysis that the model performs is at the level of the entire fleet, for a country or state, in this section we discuss how the fleet under analysis is characterized and what sources of techno-economic and market data are generally used.

Market segments

The size of the passenger car market and its breakdown into segments is an input to the model. Typically this is based on market data for the country that is the subject of the study, extrapolated for future scenarios as appropriate. In particular, in the accompanying KAPSARC discussion paper we have assumed that the overall size of the market does not change between now and the year 2030, and that the breakdown of the whole fleet into segments will be based on today's respective market shares. As for the characterization of market segments, there is no universally valid definition for them. Passenger cars are generally classified into vehicle size classes, however these are defined differently in different countries and regions. In particular, the U.S. Environmental Protection Agency has defined a number of vehicle size classes based on vehicle type (sedan, station wagon, pickup truck, SUV, etc.) and interior passenger and cargo volume or gross vehicle weight rating (small, mid-size, large, etc.) (EPA 2016). In Europe there is no formal characterization or regulation of vehicle segments, however individual car models are categorized based on comparison with well-known models that are commonly taken as example of particular segments. Car segments in Europe are defined with names describing the vehicle type and use (city car, supermini, compact, executive, luxury, etc.) and letters that can be largely used interchangeably. Since we apply the model to a UK case study, in this case we refer to the passenger car classification by segment provided by the UK Society of Motor Manufacturers and Traders (SMMT 2013).

Vehicle annual mileage and lifetime

The vehicle annual mileage figures for each of the market segments modelled are taken from the relevant national travel surveys; in the case of the UK and California, they are the UK National Travel Survey and the U.S. National Household Travel Survey respectively. The vehicle lifetime is based on other literature sources, both for the UK (SMMT 2013) and California (IHS 2015), and are average figures for the whole passenger car market.

Distribution of daily driving distances

The distribution of daily driving distances presented in the accompanying KAPSARC discussion paper and used as a key input to the model here discussed have been obtained by manipulating data from the above-mentioned national travel surveys. In particular, after filtering out any data point that did not contain complete information on trips, driver or vehicle, we aggregate the daily trips for each individual driver and the associated car to find the total distances driven on each day reported. We then linked car models to market segments and for each segment we grouped daily distances driven into a set of bins so as to obtain a discrete frequency distribution of daily driving distances by vehicle segment.

The vehicle

In this section we will briefly discuss the input data used for all main vehicle components in turn, followed by a discussion of powertrain architectures and component sizing. The powertrain components explicitly included in the model are: internal combustion engine, electric motor, battery system, power electronics and other components of the electric powertrain, transmission, gasoline tank and exhaust after-treatment. The remainder of the vehicle minus the powertrain is considered as common across all powertrain types within a given market segment and is called the glider.

Glider cost

A discussion of how the glider cost is estimated was provided earlier. The purchase price of today's most popular passenger car model are taken from car magazines (Cars.com 2016, Whatcar.com). Since these vary significantly for the same car model depending on the trim level and engine choice, we have identified the most popular versions according to the same car magazines and used our judgment in choosing a medium trim level that is reasonably priced. As for the producers and sellers markup on the vehicle, this is assumed to be the same across all vehicle segments and technologies. We use a 24 percent markup figure based on (Element Energy 2011, AEA 2012).

Internal combustion engine powertrain

Cost figures for current and future internal combustion engines and transmissions are available from the literature. However, these vary significantly based on the type of internal combustion engine (petrol, diesel, turbocharged, etc.) and transmission (manual, automatic, etc.) considered. So modelling the cost of these components is not straightforward. Things are further complicated by the fact that future costs will depend on the fuel efficiency and emission control technology that will be introduced: increasing efficiency and reducing emissions comes at a cost. Technical modelling of internal combustion engine powertrains is beyond the scope of our model. We have reviewed a number of technical studies (AEA 2012, Thiel et al. 2014, Smokers et al. 2011) and eventually decided to rely on the recently published study by Argonne National Laboratory (Moawad et al. 2016) because it contains up to date figures and provides one internally coherent source for all the input data we require. The main internal combustion engine powertrain input data, i.e., cost and weight/ power density, we use for our 2030 vehicles are summarized in the table below:

Table 1. Main cost data used for the 2030 ICE powertrain. Three scenarios are provided (low, medium and high) that capture the uncertainty on future development of ICE powertrain components

ICE powertrain component	Unit	low	medium	high
Petrol ICE	$/kW	18	19	20
ICE after treatment petrol	$/vehicle	315	350	430
Gearbox	$/kW	13	14	12
Gasoline tank	$/vehicle	270	230	205

Source: Moawad et al. 2016.

Battery cost and power density

BEV and PHEV batteries have different performance requirement and use different chemistries (with the exception of long-AER PHEVs that can also use BEV batteries), hence their current and future cost and energy densities are bound to be different. Because the purpose of our study is to compare different mixes of BEV and PHEVs, the relative cost and performance of their batteries are particularly important. The latest figures from industry sources suggest that battery costs for BEVs and PHEVs are decreasing rapidly (IEA 2016, Nykvist and Nilsson 2015); however, the top-down projections following from them are not directly comparable. Moreover, such projections do not deal with the energy density of the battery per unit weight, which we also need for modelling purposes. Hence, we combine figures from the latest studies with those from others that also include energy density figures (Element Energy 2012, Moawad et al. 2016). The Element Energy study in particular estimates future BEV and PHEV battery cost and energy density from the bottom-up in an internally consistent way. In this way we derive the battery cost and performance projections for 2025-2030 that we use for BEVs and PHEVs in our model; these are summarized in Table 2 and Table 3. Finally, we assume that the batteries will last the entire lifetime of the vehicle, which is probably optimistic and makes our cost calculations conservative, thus particularly favoring BEVs over other types of electric vehicles.

Table 2. Range of BEV battery cost and energy density values used in our model. The high case is in line with today's cost and energy density of BEV batteries and assumes no further improvement. The low case cost represents the long-term target for automotive OEMs and battery manufacturers; no specific target is set for energy density and the value used in our analysis may be conservative.

BEV battery pack	Cost ($/kWh)	Energy density (Wh/kg)
high	300	100
medium	200	150
low	100	200

Source: Element Energy 2012, Nykvist and Nilsson 2015, Moawad et al. 2016

Table 3. Range of PHEV battery cost and energy density values used in our model. High, medium and low cases have been chosen to be as consistent as possible with those of BEV batteries.

PHEV battery pack	Cost ($/kWh)	Energy density (Wh/kg)
high	350	70
medium	275	130
low	135	150

Source: Element Energy 2012, IEA 2016, Moawad et al. 2016.

Other electric powertrain components

Aside from batteries, electric powertrains are also characterized by the presence of electric motors, generators and power electronics. Just like the case of internal combustion engine powertrains, there are different literature sources for current and future expected cost and performance of the electric powertrain components. For the sake of consistency, we decided to use the same source for both powertrain types, i.e., a recent study from Argonne National Laboratory (Moawad et al. 2016). The input we use in our study are reported in the table below:

Table 4. Main cost data used for the 2030 BEV powertrain

Electric powertrain component	Unit	low	medium	high
Electric Motor	$/kW	10	12	14
Electric Powertrain	$/vehicle	1,290	1,290	1,290
Controller	$/kW	6	12.5	19

Source: KAPSARC

Powertrain architectures and component sizing

At the level of resolution that characterizes our study, the powertrain architectures of ICEVs and BEVs are straightforward. As for RE-EVs and PHEVs, it is important to note that we model the former as series hybrid and the latter as parallel hybrid. This means that RE-EVs will have a large generator enabling the battery pack to be recharged using the internal combustion engine. However, it will have no mechanical transmission connecting the internal combustion engine to the wheels, while the opposite is true for the PHEV. Due to the different operating strategies, the sizing of all common components between RE-EVs and PHEVs will also be different.

In order to correctly size the components of a future powertrain based on the desired level of vehicle performance and its characteristics (mass, aerodynamics, etc.), vehicle simulation tools are required (Moawad and Rousseau 2014). In our analysis we do not make use of vehicle simulation tools, hence we use powertrain component sizing factors for electric powertrains that we derive from the literature, and particularly from (Moawad et al. 2016, AEA 2012). These are reported in the table below:

Table 5. Component sizing factors for different electric and hybrid powertrains. All percentages are relative to the rated power of the corresponding internal combustion engine vehicle

% of ICEV rated power	BEV	RE-EV	PHEV
Internal combustion engine	-	50%	45%
Electric motor(s)	105%	90%	80%
Generator	-	50%	-

Source: KAPSARC

Fuel economy

Fuel economy calculations in our model rely on a number of different inputs. Firstly, the fuel economy values of current vehicles are based on real driving figures, where available, from specialized car magazines and other online sources (Whatcar.com, Fuelly.com, Fueleconomy.gov). Where these are lacking, we use government fuel economy figures based on test cycles and convert them into real driving figures using uplift factors from (Mock et al. 2014). Future fuel economy of different powertrain types across vehicle segments is calculated as discussed earlier. These calculations rely on specific relationships taken from the literature (Aaron Brooker 2013, AEA 2012, Pagerit, Sharer, and Rousseau 2006, Lotus Engineering Inc. 2010) and describing the effect of weight, aerodynamics and rolling resistance on fuel economy. In the case of aerodynamics and rolling resistance, we simply use exogenous scenarios that the users can select from the model user interface, and their effect on the results generated by the model is relatively minor. Weight however has both a stronger influence on the fuel economy values calculated by the model and is treated endogenously. The relationship that we have built from literature data and that we use in our model in order to link weight reduction with fuel economy gains for internal combustion engine vehicles is illustrated in Table 6 and Figure 2.

Applying the above relationship to the calculation of fuel economy of electric vehicles, we obtain values of energy consumption as a function of vehicle weight that are in good agreement with those obtained at the Argonne National Laboratory through detailed modelling of electric vehicles (Moawad et al. 2016).

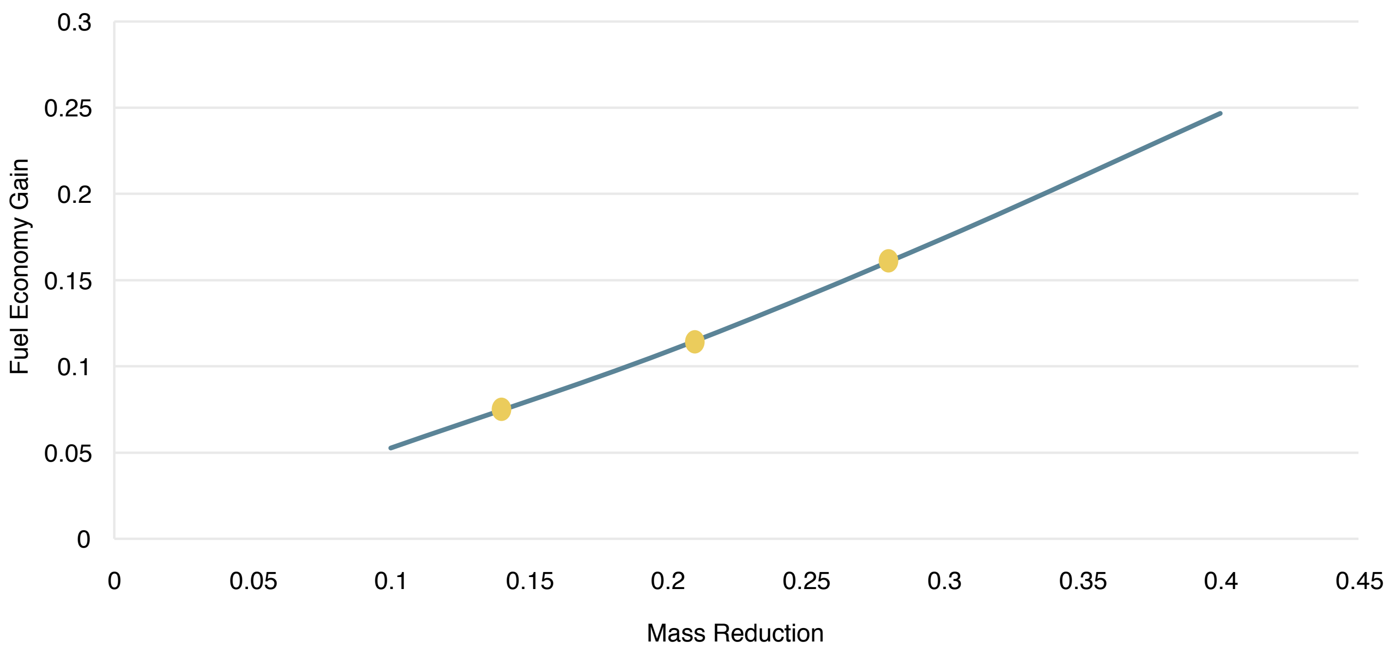

Figure 2. Diagrammatic representation of the relationship presented in Table 6. The figure illustrates that the relationship between non-powertrain weight reduction and fuel economy gains is approximately linear.

Source: KAPSARC

Table 6. Relationship between non-powertrain weight reduction through the use of lightweight materials and fuel economy gains for internal combustion engine vehicles.

Non-powertrain weight reduction scenarios		vehicle weight reduction	fuel economy gain
Low	**14%**	11%	7.50%
Medium	**21%**	17%	11.41%
High	**28%**	22%	16.12%

Source: KAPSARC analysis based on (Lotus Engineering Inc. 2010, Pagerit, Sharer, and Rousseau 2006, Aaron Brooker 2013)

Fuel and infrastructure

As discussed earlier, the untaxed cost of electricity is calculated by adding the infrastructure cost component to the price of the electricity as acquired by the infrastructure provider from the grid; the wholesale price of grid electricity in turn depends on the power generation mix, the grid structure and the power market regulation. The untaxed cost of gasoline at the pump is based on scenarios, largely driven by crude oil price.

Scenarios for future untaxed cost of gasoline and grid electricity are an input to our model. These however are affected by a substantial degree of uncertainty and it is also to mitigate this that we have chosen to compare electric powertrain mixes with similar overall consumption of electricity and gasoline. The electricity to gasoline price ratio though has a substantial influence on the absolute value of the annual incremental cost of electrification and this is why in the accompanying KAPSARC discussion paper we emphasize the relative nature of the analysis performed.

More important to the analysis we performed is the infrastructure cost component of the total untaxed electricity cost. The infrastructure cost inputs used in our model are discussed below, whereas in section 3.3.2 we briefly touch on Well-to-Wheel CO2 emissions from ICEVs and EVs.

Infrastructure cost

In our analysis we model three different types of charging points: open-access home chargers, restricted-access slow public chargers and restricted-access rapid chargers. Their characteristics and costs are drawn from literature. In particular, an overview of the figures reported in selected literature sources is provided in Table 7. The figure we decided to use for our analysis are reported in Table 8. It should be noted that the installation of rapid charging points in particular may require upgrades to the local distribution network, which if factored in the cost of individual rapid chargers would make this exceed the $100,000 mark (Element Energy 2015).

Well to Wheel carbon emissions

In order to get a complete picture of the carbon emissions of different technologies, it is essential to include the carbon content of the production process of the different fuels. In the case of gasoline, the emissions associated with the production and delivery of the fuel (Well-to-Tank) are a small fraction of the total and the majority of emissions are associated with the use of the fuel in the vehicle (Tank-to-Wheel) (JRC, EUCAR and CONCAWE 2014). For electricity used in electric vehicles the opposite is true: electric vehicles are zero emission vehicles and all the carbon emissions associated with it are Well-to-Tank. In the model we use scenarios from literature where available. Particularly for the UK we use a detailed study of the future electricity mix (Grant and Skillings 2009) and generic European data for gasoline (JRC, EUCAR, and CONCAWE 2014). The corresponding scenarios are reported in Table 9 below.

Table 7. Cost figures for different types of chargers are reported in the literature.

	Capital cost of charging point (USD)			
Charger type	**Schoeder 2012**	**Neubauer, 2013**	**IEA, 2013**	**Element Energy, 2015**
Home 3kW	**550**	1,200	650	1,500
Public slow 7 kW	**6,000**	-	6,600	7,250
Public Rapid 50 kW	**50,000**	-	33,000	65,000

Source: Element Energy 2015, IEA 2013, Neubauer and Pesaran 2013, Schoeder and Traber 2012.

Table 8. Cost figures used in our model for different types of chargers.

type	unit cost (USD)
home (3kW)	750
public (7kW)	6,000
rapid (50kW)	72,500

Source: KAPSARC analysis based on (Element Energy 2015, IEA 2013, Neubauer and Pesaran 2013, Schoeder and Traber 2012)

Table 9. 2030 scenarios for the carbon content of gasoline and electricity in the UK.

Fuel	2030 Low (gCO2/kWh)	2030 Mid (gCO2/kWh)	2030 High (gCO2/kWh)
Gasoline	**309**	**309**	309
Electricity	**110**	**120**	180

Source: 2030 scenarios for the carbon content of gasoline and electricity in the UK.

How to Use the Model

This section provides a guide for the simplified model user interface that is available on OpenKAPSARC. The user interface allows the user to test some of the functionalities of the full model by building custom scenarios of future penetration of different electric vehicle and charging infrastructure types. The model user interface is based on the UK version of the full model, hence the passenger car fleet data and all other relevant inputs are the same as those used for the UK case study presented in the accompanying KAPSARC discussion paper.

The user can start building the desired EV mix scenario by entering the relative shares of each EV type by market segment. The next step is to choose the desired all-electric ranges (AER) for the vehicles modelled by choosing the appropriate battery size value (see Figure 3). The model calculates the corresponding AER for each vehicle and the user can reach the desired AER value through a trial and error process. Please note that battery sizes chosen should be such that the AER of PHEVs does not exceed 50km, that of RE-EVs is comprised between 50km and 100km and the range of BEVs does not exceed 299km.

Next, is the choice of techno-economic scenarios for vehicle technology, the user can select technology development scenarios for batteries in terms of energy density and pack cost using the slider as shown in the figure 4.

Similarly the user can select scenarios for the cost and carbon content of gasoline and electricity; the cost of the latter excludes the infrastructure component. See Figure 5.

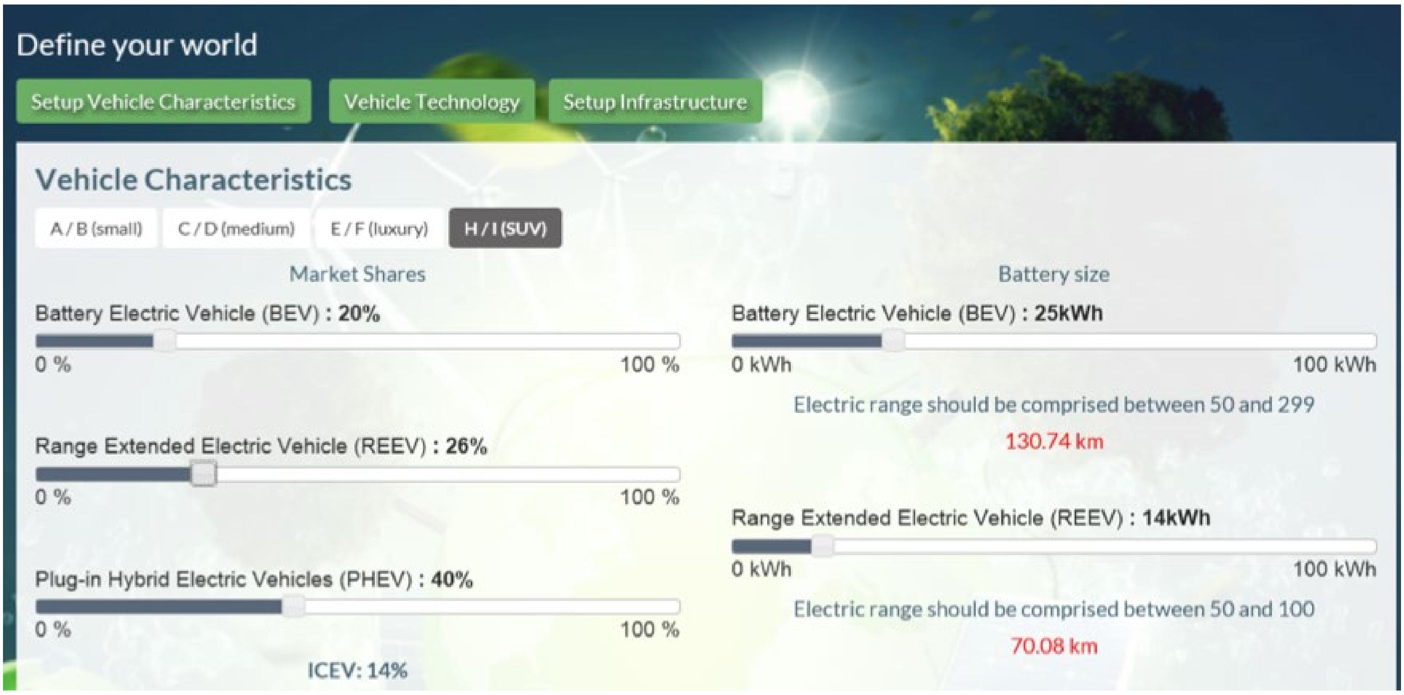

Figure 3. The desired EV fleet mix and the desired electric range for different types of EVs can be obtained by appropriate battery size, by moving the sliders for both.

Source: KAPSARC.

Figure 4. Techno-economic scenarios for the development of battery

Source: KAPSARC.

Figure 5. Techno-economic scenarios for the development of battery

Source: KAPSARC.

Future cost scenarios of battery charging infrastructure and the number of charging points for each type can also be set. See Figure 6.

Based on the scenario so created, the model generates the following output:

The total annual incremental user cost of the scenario

The fleet average tailpipe and Well-to-Wheel emissions associated with it

- The fleet cost shares by segment and EV type
- The relative cost of ownership of different EV types over their lifetime by segment

The user can compare up to three scenarios, where each scenario can be saved and added for comparison. The user can then download or email a pdf report summarizing all the input chosen for each scenario and relevant outputs, including graphs and breakdown of the costs.

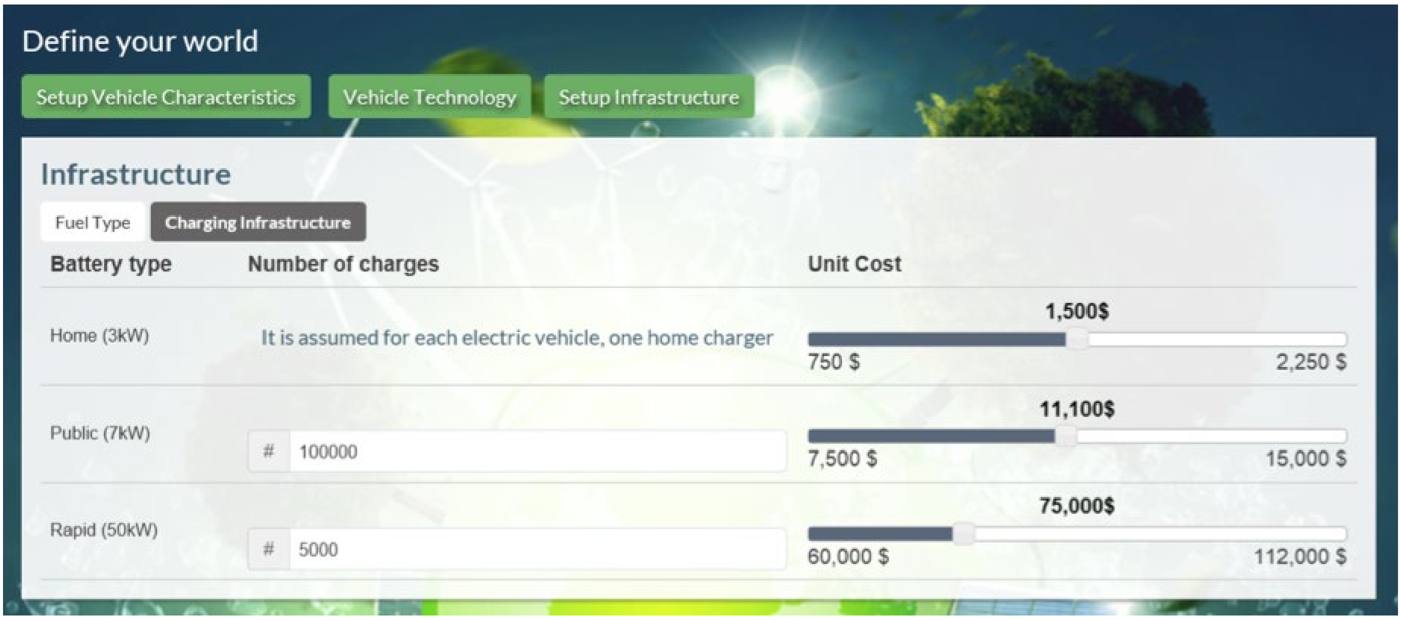

Figure 6. Scenarios for future cost of different types of battery charging points can be set using the slider and entering a value for the number of charging points.

Source: KAPSARC.

Figure 7. Aggregate outputs of the model are the incremental annual user cost of the particular electrification scenario modelled, relative to the base case of 100 percent advanced ICEVs, and the associated fleet average Well-to-Wheel and tailpipe emissions.

Source: KAPSARC.

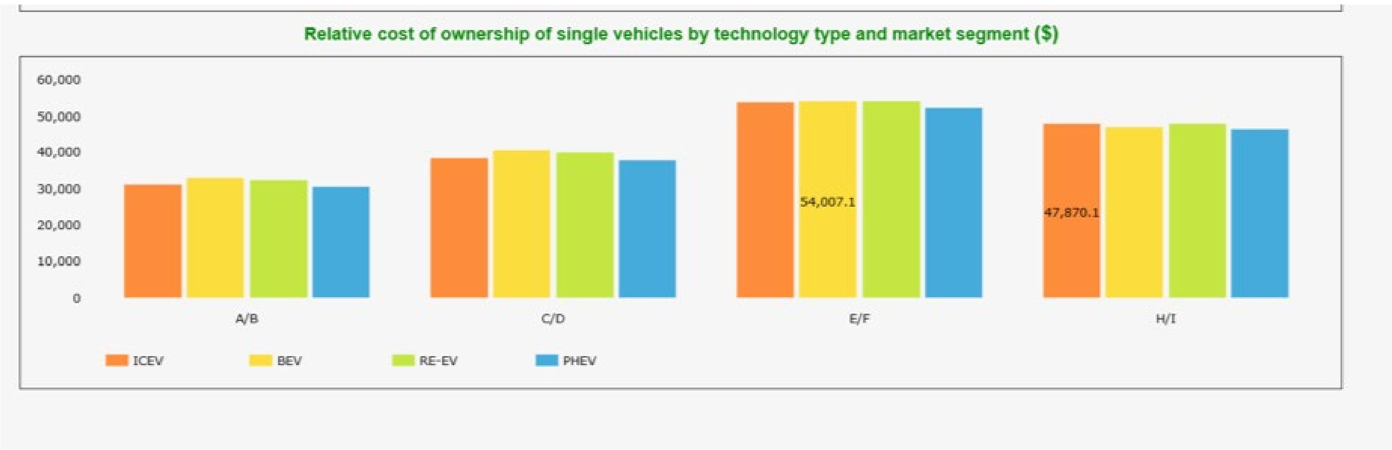

Figure 8. Discounted lifetime relative cost of ownership of different powertrain options across market segments: small, medium, luxury and SUV.

Source: KAPSARC.

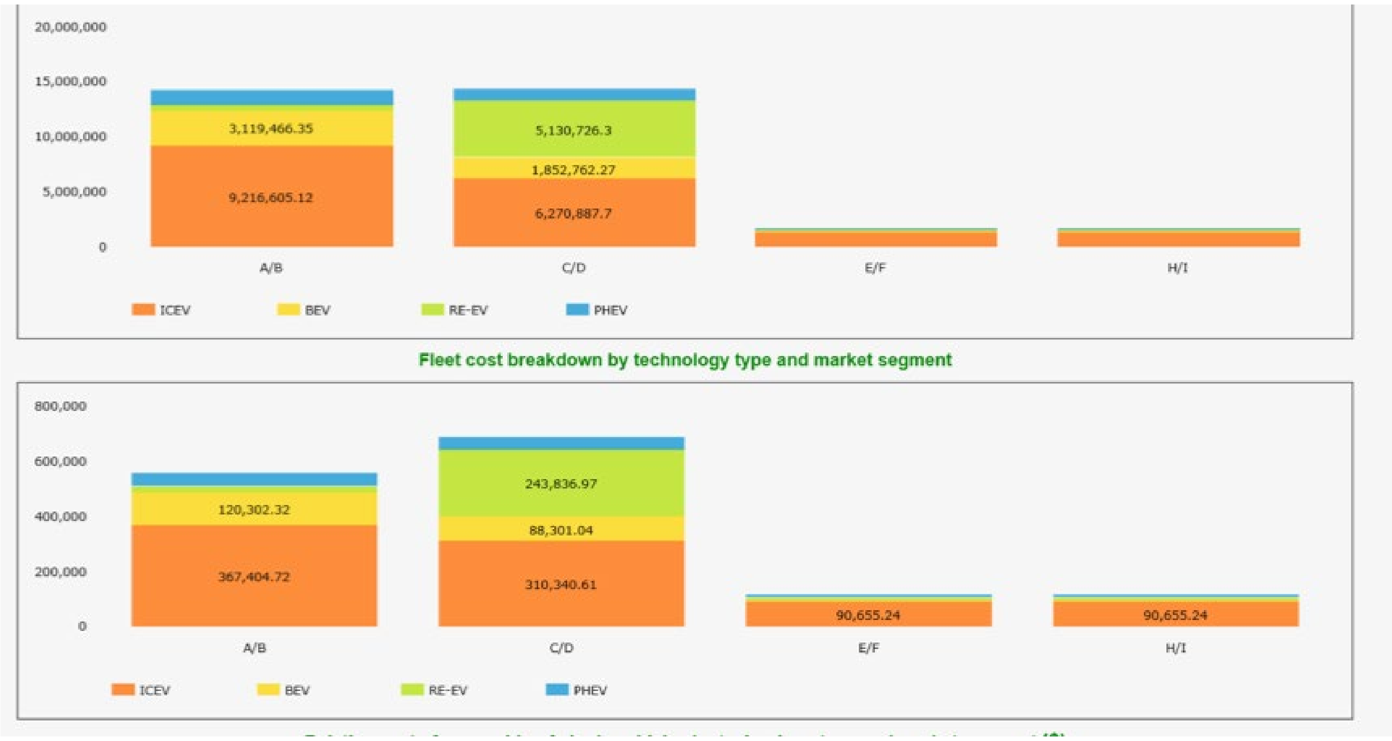

Figure 9. Visual representation of the chosen powertrain stock levels: number of vehicles by segment (above) and their relative contributions to the overall cost (in M$) of the passenger car fleet.

Source: KAPSARC.

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Appendix

Previous studies have sought to investigate the economics of electric vehicles. Extensive reviews can be found in a number of papers; see for example (Al-Alawi and Bradley 2013, Wu, Inderbitzin and Bening 2015). We have not, therefore, sought to conduct a comprehensive review so much as to position our model in the previous literature and to help bridge some of the gaps that may exist in turning the insights of these studies into usable models. In this Appendix we briefly discuss selected relevant studies to identify the most appropriate methods for doing so.

We find studies that cover the whole spectrum of economic assessments of electric vehicles, from detailed powertrain cost and performance modelling aimed at guiding the design of systems or components, to studies comparing the lifetime cost and emissions of different EV types in order to inform policymaking. Common to most of these studies is the use of the Relative Cost of Ownership (RCO) metrics that allows estimating the cost of individual EVs over their lifetime and comparing across different powertrain types; as the name suggests, RCO does not consider all costs but only those that are relevant to the comparison being made. It is on studies that use this method, alone or in combination with others, that we focus our attention.

Let us start from the technical end of the spectrum of these studies. Here we are not concerned with engineering-economic studies aimed at powertrain optimization and R&D, the sophisticated vehicle simulation tools on which they are based. These have sometimes also been used to perform comparative RCO analysis of different powertrain types such as the work done at Argonne National Laboratory (Moawad and Rousseau 2014), where powertrain sizing and the effect of lightweighting on vehicle cost and performance are accurately modelled for different electric powertrain types over specific segments of the passenger car market. Another example is the study done at the National Renewable Energy Laboratory where their vehicle simulation tool is combined with a battery degradation model in order to assess the effect of battery size and driving / charging patterns on the RCO of a particular PHEV model (Neubauer, Brooker and Wood 2013). A number of other technical studies comparing costs of ICEVs and EVs using detailed economic-engineering analysis and sophisticated vehicle simulation tools have been recently conducted in order to inform post-2020 fleet-average CO2 emission standards for passenger cars in the European Union; see for example (Ernst, Olschewski and Eckstein 2014).

Several RCO studies of a less technical nature have also been carried out, which compare the cost of different types of electric powertrains among themselves and against ICE powertrains. These studies generally aim at improving the understanding of EV economics for the benefit of policymakers and other stakeholders; examples of such studies published in the last five years are the following (Bishop, Martin, and Boies 2014, Contestabile et al. 2011, Element Energy 2011, González Palencia et al. 2015, Le Duigou, Guan, and Amalric 2014, Thiel et al. 2014, Wu, Inderbitzin, and Bening 2015, Kihm 2014). Some of these studies make use of a vehicle simulation software, while others use fuel economy values from literature. These studies, although generally less accurate than the more technical ones in the way they model powertrains and vehicle capital costs, better account for the multiple segments that compose the passenger car market and for real-life drive patterns.

Both of these groups of studies address, albeit in different ways, the question as to what type of EVs are most economical under different technology development and market scenarios. They have generated a large amount of knowledge on the economics of EVs, both present and future, and the important factors that should be included when assessing it. In particular, several studies consider the effect of vehicle weight reduction through the use of lightweight materials, improvements in vehicle aerodynamics and reduction of tire rolling resistance (Contestabile et al. 2011, González Palencia et al. 2015, Moawad and Rousseau 2014, Bishop, Martin, and Boies 2014). Several studies also analyze the passenger car market by dividing it into segments, which is important particularly when comparing the relative economics of different EV types (Ernst, Olschewski, and Eckstein 2014, Bishop, Martin, and Boies 2014, Contestabile et al. 2011, Element Energy 2011, Thiel et al. 2014, Wu, Inderbitzin, and Bening 2015). Some studies also consider the distribution of daily driving distances and its variation across vehicle segments, which matters particularly in the case of PHEVs and RE-EVs (Le Duigou, Guan, and Amalric 2014, Contestabile et al. 2011, Element Energy 2011). However, few studies go beyond the cost comparison of individual vehicles and also assess the total cost of the passenger car stock, including market structure effects (Ernst, Olschewski, and Eckstein 2014, González Palencia et al. 2015). Moreover, charging / fueling infrastructure costs are generally either ignored or subjected to simplifying assumptions: with the exception of (Neubauer, Brooker and Wood 2013), the different types of chargers (slow vs rapid) and their utilization levels are not accounted for. It could be argued that these studies tend to focus on a particular part of the problem and don't give the same attention to all the main variables. Moreover, due to the presence of country-specific inputs such as market structure and drive patterns, RCO studies typically focus a single country or region. Our objective is to allow comparisons between countries and to allow trade-offs among all the variables, rather than constraining the problem.

Perhaps most importantly, our intention is to make models that are entirely transparent and simple enough that they can be modified by analysts seeking to use them as a starting point for their studies. This help avoid the risk that RCO models used in specific studies can be somewhat complex and, as far as we are aware, not publicly available for direct use by stakeholders.

Notes

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About the Project

After decades of development and false starts, electric vehicles have now become commercial. However, they still rely on strong policy support for their further development and adoption.

The project assesses the effectiveness of current electric vehicle policy in leading the technology toward self sustained market competitiveness. The multi-method approach chosen involves techno-economic, strategy and innovation systems analysis. In particular, we have developed a bottom-up electric vehicle fleet cost model in order to assess the economic implications of electric vehicle policy.

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