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Citation: Noshadravan, Arash, Lynette Cheah, Richard Roth, Fausto Freire, Luis Dias, and Jeremy Gregory. "Stochastic Comparative Assessment of Life-Cycle Greenhouse Gas Emissions from Conventional and Electric Vehicles." *The International Journal of Life Cycle Assessment* 20, no. 6 (March 18, 2015): 854–864.

As Published: <http://dx.doi.org/10.1007/s11367-015-0866-y>

Publisher: Springer Berlin Heidelberg

Persistent URL: <http://hdl.handle.net/1721.1/103107>

Version: Author's final manuscript: final author's manuscript post peer review, without publisher's formatting or copy editing

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Stochastic comparative assessment of life-cycle greenhouse gas emissions from conventional and electric vehicles

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Received: 19 December 2013 / Accepted: 16 February 2015

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Responsible editor: Hans-Joerg Althaus

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Abstract

Purpose Electric vehicles (EVs) are promoted due to their potential for reducing fuel consumption and greenhouse gas (GHG) emissions. A comparative LCA between different technologies should account for variation in the scenarios under which vehicles are operated in order to facilitate decision-making regarding the adoption and promotion of EVs. In this study we compare life-cycle GHG emissions, in terms of CO₂eq, of EVs and conventional internal combustion engine vehicles (ICEV) over a wide range of use-phase scenarios in the US, aiming to identify the vehicles with lower GHG emissions and the key uncertainties regarding this impact.

Methods An LCA model is used to propagate the uncertainty in the use phase into the greenhouse gas emissions of different powertrains available today for compact and midsize vehicles in the US market. Monte-Carlo simulation is used to explore the parameter space and gather statistics about GHG emissions of those powertrains. Spearman's partial rank correlation coefficient is used to assess the level of contribution of each input parameter to the variance of GHG intensity.

Results and discussion Within the scenario space under study, battery electric vehicles are more likely to have the lowest GHG emissions when compared with other powertrains. The main drivers of variation in the GHG impact are driver aggressiveness (for all vehicles), charging location (for EVs) and fuel economy (for ICEVs).

Conclusions The probabilistic approach developed and applied in this study enables an understanding of the overall variation in GHG footprint for different technologies currently available in the US market and can be used for a comparative assessment. Results identify the main drivers of variation and shed light on scenarios under which the adoption of current EVs can be environmentally beneficial from a GHG emissions standpoint.

Keywords Electric vehicles • Greenhouse gas emissions • Life-cycle assessment • Uncertainty analysis

1 Introduction

The electrification of the global vehicle fleet is gradually underway. Sales projections vary, and one estimate puts the penetration of electric vehicles (EVs) at 7 % of the global market by the year 2020 (JD Power 2010). EVs are being promoted because they emit less tailpipe emissions. They also have the potential to reduce greenhouse gas (GHG) emissions to mitigate the global warming impact of road vehicle transport. There are various types of EVs (here understood as vehicles with some type of electric powertrain), including hybrid-electric vehicles (HEVs), plug-in hybrid-electric vehicles (PHEVs), and battery electric vehicles (BEVs). HEVs provide the ability to store energy, when decelerating, in a battery and operate the vehicle using both an internal combustion engine (ICE) and an electric motor. In PHEVs, the battery packs are larger and they can be charged using electricity from the grid. In BEVs, a battery and an electric motor replace the engine entirely and are likewise charged from the grid. Fuel-cell vehicles (FCVs), which also use an electric powertrain, but produce electricity from hydrogen stored in fuel cells rather than an electric battery, are not considered in the scope of this work.

Increasing sustainability and energy policy concerns have promoted the adoption of EVs due to their potential for reducing fuel consumption and global warming potential. The common perception regarding the environmental superiority of EVs, as compared to conventional internal combustion engine vehicles (ICEVs), relies on considering the direct tailpipe emissions, which constitute only one element of the overall environmental footprint. Prior studies suggest that a comprehensive environmental impact assessment of the entire vehicle life is crucial in making a robust comparison among different technologies (Lave et al. 1995; Hawkins et al. 2013). It remains debatable whether PHEVs and BEVs offer significant savings in GHG intensity over their predecessor technologies on a life-cycle basis. Given the larger battery packs and electric motor components, PHEVs and BEVs typically require more resources and energy during their material processing and manufacturing phases to produce (Hawkins et al. 2012). Moreover, the GHG emissions associated with driving and charging EVs depend on a variety of factors defining different aspects of vehicle use. Some of the major factors that can influence the results of comparative assessments among different vehicle types include:

- What is being driven - type of EV, vehicle size, payload;
- How they are driven - trip characteristics, driver behavior, EV operational parameters;
- Where they are driven - traffic conditions, road type and grade, weather conditions;
- When they are charged - peak vs. off-peak charging; and
- Where they are charged - emissions intensity of electricity.

Over the past two decades, life-cycle assessment (LCA) has been utilized as a tool for comparing the environmental impacts of vehicles (Wang et al. 1997; Singh 1998; Bandivadekar 2008; Baptista et al. 2009; Hawkins et al. 2013) (see Hawkins et al. 2012) for a general review). For EVs in particular,

there have been a number of studies examining their GHG intensity (Silva et al. 2009; Elgowainy et al. 2010; Freire and Marques 2012). Assumptions were made or scenarios created for the driving and charging profiles, usually based on travel survey data. These analyses are often deterministic: the average GHG emissions were reported, rather than probabilistic distributions. Some exclude materials production impacts and examine the “well-to-wheel” impact only. Reports that analyzed the variation in emissions due to different factors tend to focus on the GHG intensity of the grids. Doucette and McCulloch (2013) compared CO₂ emissions from BEVs in the U.S., France, India and China. BEVs were found to emit more CO₂ than conventional ICE vehicles in countries like China and India, where the average CO₂ intensity of power generation is high. Nansai et al. (2002) found that the life-cycle CO₂ emissions of BEVs driven in Japan ranged widely mainly due to regional differences in the energy mix used for electric power generation in the country. Ma et al. (2012) accounted for real-world driving conditions and the burden of marginal electricity to assess the impact of BEVs in the UK and California. They concluded that GHG intensity of BEVs is context-specific, and BEVs do not always outperform ICE vehicles or HEVs. Anair and Mahmassani (2012) did not consider the complete life-cycle impact, but instead studied the impact of charging BEVs only. They found variation in EV charging-related emissions across the U.S., due to the regional variation in grid emissions intensity.

Another set of studies focused on the effect of driving patterns, local traffic, and road conditions on the fuel consumption or energy use in both conventional as well as electric powertrains. Real-world fuel consumption and corresponding GHG emissions always varied from the vehicle’s rated values, which is based on standardized emissions test drive cycles. Earleywine et al. (2010) tracked 783 vehicles in Texas using Global Positioning System technology to gain an understanding of in-use travel profiles. More aggressive driving and higher accelerations were observed in the real world than compared with standard test cycles. Based on a survey of more than 28,000 drivers in Germany, Mock et al. (2012) reported that the real-world fuel consumption experienced in conventional vehicles were on average 21 % higher than the value based on the New European Driving Cycle (NEDC) standard. In Michigan, LeBlanc et al. (2010) tracked 117 identical conventional gasoline vehicles driven by different drivers, and observed that fuel consumption ranged from 8 to 13 liters/100 km. Finally, Raykin et al. (2012) simulated PHEVs over different drive cycles (vehicle speed profiles) and also found substantial variation in tank-to-wheel energy use across driving patterns. Their study shows that, for PHEVs, energy use per unit distance traveled over highway driving can be almost twice that over city driving.

Considering that the variation of the aforementioned factors can greatly influence the GHG intensity of EVs, using average values to assess the global warming impact can be misleading. A challenge arises in characterizing the overall variation in emissions due to different scenarios under which the vehicles are operating. This is clearly a challenging task since an exhaustive examination of

all possible scenarios is prohibitive. An efficient methodology is required to explore a scenario space that is sufficiently representative. The other important issue is the way the environmental impacts are compared across a range of scenarios for different powertrains. Finally, it is valuable to identify the key drivers of vehicle environmental impacts.

The present paper aims to address the challenges identified above. We propose a probabilistic approach to characterize the uncertainty in scenario parameters and propagate the consequences into the GHG emissions in terms of CO₂ equivalent. This allows us to obtain probabilistic conclusions about CO₂ intensity for each powertrain under study. Given the probabilistic description of the impact quantity, frequency assessments are conducted to quantify the overall superiority of different types of powertrains over the entire scenario space. Moreover, the method of sensitivity analysis is employed to characterize the relative contribution of different factors in the variation of GHG intensity. The probabilistic approach developed and applied in this study enables an understanding of the overall variation in GHG footprint for different technologies currently available in the US market and can be used for a comparative assessment. Results identify the main drivers for variation and shed light on scenarios under which the adoption of current EVs can be environmentally beneficial from a GHG emissions standpoint. Although the methodology can be generalized to other contexts, we consider in particular the current situation in the US and the class of compact/midsize vehicles currently available in the market.

It is worth emphasizing that the results of uncertainty analysis rely on the assumptions regarding the probabilistic descriptions of uncertain input parameters. These assumptions are affected by limitations on the availability and the quality of data sources. We acknowledge these limitations despite of thorough review of different data sources that we have conducted to improve the characterization of distributions for the relevant input parameters. Furthermore, the degree by which these assumptions affect the robustness of the results depends on the functional relationship between the input parameters and the modeled quantity of interest. The sensitivity analysis presented in this work provides useful insight about the level of contributions of different input on the overall variation of the global warming potential.

2 Life-cycle assessment model

In this section we present the main components of the life-cycle assessment model that is developed in order to assess the global warming potential of ICEVs and EVs. The goal of the analysis, system definition, and functional unit are discussed, along with the key parameters considered. This is followed by a description on the uncertainty analysis method, the data used in the analysis, and the results.

2.1 System definition

The goal of this study is to provide a comparative assessment of the life-cycle GHG emissions for conventional and electric vehicles. In particular, we consider compact and midsize cars (according to the classification of (EPA 2014)) operated in the United States (US) with five types of powertrain: gasoline, diesel, HEV, PHEV10, PHEV40 (both PHEVs having an ICE as a range extender) and BEV80, where the numbers after PHEV and BEV denote the maximum range in miles they could travel under solely battery power until recharging is needed (or until a range extender ICE must intervene, in the case of PHEV). Only a subset of the vehicles on sale in the US is considered, to increase comparability: cars with more than 150 kW of power were excluded, as well as cars that were significantly smaller (<4.10 m) or larger (>4.80 m) than the compact and midsize BEV80s. In some cases this means there is only one car in a category, which is a reflection of the state of the current US automotive market.

The system boundary of the LCA consists of the well-to-wheel impacts of generating, transmitting, and distributing electricity used to charge the vehicles, and processing and using fuel, if applicable. It also includes the impacts arising from automotive materials extraction, processing and vehicle manufacturing. Fig. 1 shows the main stages of a vehicle life-cycle. The end-of-life treatment is not considered in this study due to its negligible effect on greenhouse gas emissions as compared with the use phase and vehicle production (Samaras and Meisterling 2008). In addition, we focus solely on pure fossil fuels, thereby neglecting the use of ethanol and gasoline fuel blends, or the use of biodiesel. The functional unit is one kilometer (km) driven.

Figure 1 goes here

2.2 Vehicle production

Vehicle and battery production are the second major contributor to life-cycle GHG emissions and could vary for different powertrains (Hawkins et al. 2013). As such, it is important to account for the impact of vehicle production phase in a comparative assessment of conventional and electric vehicles. This includes a full life-cycle inventory analysis of all the upstream processes related to the vehicle production. A complete LCA of vehicle production is beyond the scope of this study and is not discussed here in detail. Readers are referred to the relevant studies in the literature for detailed analyses (Sullivan et al. 1998; Burnham et al. 2006, Bandivadekar 2008; Samaras and Meisterling 2008; Baptista et al. 2009). Hawkins et al. (2012) reported the results of several studies on comparing GHG emissions from vehicle and battery production for both conventional and electric vehicles adjusted for the life standard lifetime mileage of 200,000 km. The reported values in (Hawkins et al. 2012) are averaged over different studies and are used here as an estimation of the baseline upstream

GHG emissions due to vehicle and battery productions for the powertrains considered in this study (Fig. A.1, Electronic Supplementary Material).

2.3 Use phase

In the life-cycle assessment of vehicles, the use phase accounts for the majority of GHG emissions through fuel combustion and/or electricity production. An LCA model is developed in this work to evaluate the use phase GHG impact. The model relies on four main input moduli characterizing charging location, trip profile, driving profile, and charging pattern. These moduli are described in more detail below.

2.3.1 Charging location

Charging location influences the GHG impact of EVs through the GHG intensity of electricity grids. Within the U.S., the fuel mix used to generate electricity varies by region and, as such, the GHG emissions due to charging of EVs are heavily dependent upon the location where the vehicles are being used. Thus, the spatial variation in the electricity grid must be taken into account to capture a full range of scenarios regarding the charging locations. The U.S. Environmental Protection Agency (EPA) provides comprehensive data on the emissions intensity of almost all electric power generated in the United States (EPA 2012). Fig. 2 shows GHG emissions of the average US electricity grid and the overall variation based on 2009 data.

Figure 2 goes here

2.3.2 Trip profile

Trip profile consists of the number and distance of weekday and weekend trips as well as long distance trips. There is a considerable variation in trip statistics across different states. The National Household Travel Survey (NHTS) (Santos et al. 2011) provides a rich nationwide inventory of travel trends. NHTS includes detailed information on daily and longer-distance travel. This information is used to estimate a reasonable range of values for trip profile parameters (see Table 1).

2.3.3 Driving profile

A driving profile includes traffic conditions encountered (i.e. traffic congestion) and driving style (i.e. driver aggressiveness), which would determine the speed vs. time profiles of trips undertaken by the

vehicles considered. In this work we account for traffic congestion, which varies by locations and time of day, by splitting city versus highway driving and assuming that congestion only happens during the daily commute. The Urban Mobility Report by the Texas Transportation Institute provides information on congestion across the U.S. (Schrang et al. 2011). This information is used to estimate lower and upper bounds for the travel time spent idling. The idling is implicitly taken into account in our analysis by considering the fraction of distance split between city driving versus highway driving and EPA's Urban Dynamometer Driving Schedule (UDDS) and Highway Fuel Economy Driving Schedule (HWFET), respectively.

The driving aggressiveness, defined as driver performance in speed and acceleration of vehicles, is another factor that influences the fuel economy and consequently impacts the use phase of the vehicle LCA. Studies on the effect of aggressive driving on fuel and battery power consumption show that the electric vehicles can potentially be more sensitive to driving aggressiveness (Duoba et al. 2005; Carlson et al. 2009). Thus, the variation in the fuel consumption due to different driving behavior needs to be adequately addressed in a comparative LCA of different powertrains. Carlson et al. (2009) conducted an experimental study to examine the impact of aggressive driving on PHEV fuel and electrical energy consumption. The results of their study were presented in the form of the percentage change in fuel consumption/battery depletion for different driving cycles. We make use of these results to take into account the variation in driving aggressiveness in our LCA model for the use phase. For this purpose the percentage change in fuel efficiency due to increase in driving cycles are applied to the baseline on-road fuel consumption/battery depletion (see Table A.1, Electronic Supplementary Material for baseline values). Well to wheel GHG emissions and other fuel parameters used in this study are extracted from Bandivadekar (2008) and reported in Table A.2 (Electronic Supplementary Material).

2.3.4 Charging pattern

The GHG impact of PHEVs is further complicated by charging pattern, which encompasses the distances driven between charging. This can vary depending on the user as well as availability of charging infrastructure. It affects the fraction of time the vehicle is driven on battery charge-depleting mode, versus relying on combusting fuel within the engine (charge-sustaining mode). Often, an aggregated utility factor, or the fraction of travel on battery charge-depleting mode, is interpreted from travel survey data and used. Whether EVs are charged only during the night or also charged during the day can impact GHG emissions through the intensity of the electricity grid that is being used while charging. In our LCA model the charging habit is parameterized by a bimodal variable that specifies whether the electric vehicle is charged only during the night or also charged during the day, with the associated percentage of the charging time during the day. We assume that charging during the day corresponds to the peak electricity demand with non-baseload output emission rates are being used

(EPA 2012). It should be noted that our current model does not account for the differences in charging modes or location-related losses, which could be another source of variation.

3 Uncertainty analysis method

In section 2.3 we described the main parameters defining the scenarios under which the vehicles are used (trip nature, driving pattern, charging profile and charging location). These parameters directly affect the GHG intensity of the use phase. There is a significant variation in scenarios stemming from the uncertainty in these parameters. The consequence of these uncertainties is reflected in the results of LCAs in the form of variation in GHG emissions. In order to obtain robust conclusions about LCA results, these uncertainties need to be sufficiently accommodated. The propagation of uncertainty in comparative LCA of different alternative products requires generating sufficiently representative subsets of the scenario space.

In general, exploring the scenario space can be carried out using two different strategies. In one strategy the domain parameters can be discretized and the scenario space is analyzed in a *parametric* way by changing one parameter a time. Alternatively one can explore the scenario space in a *probabilistic* manner. In this method each scenario parameter is described as a random variable with an appropriate probability distribution. Then a sampling method, such as Monte Carlo simulation, is utilized to generate a large number of random samples of the scenario space. These samples are in turn used to compute the corresponding realizations of impact quantities making use of the LCA model. The overall variation on GHG intensity of each powertrain can then be represented by a probability distribution estimated from computed realizations. For a large scenario space an exhaustive examination of all possible scenarios in a parametric way is prohibitive. As such, in this work the latter method is used to characterize the uncertainty in a large scenario space in an efficient way. This leads to the estimation of complete probabilistic descriptions for GHG intensity, which in turn can be well adapted to conduct the comparative assessment in a statistical manner.

Fig. 3 schematically presents the stochastic LCA procedure, using a Monte Carlo simulation, to propagate use phase uncertainty into the global warming potential of alternative powertrains. The probabilistic analysis of the scenario space sets up a framework for performing a global (versus one-factor-at-a-time) sensitivity analysis to find the key drivers of GHG impact. We use Spearman's partial rank correlation coefficient (PRCC) (Hamby 1994) for the sensitivity analysis. This method measures the sensitivity as the relative correlation between the output and each uncertain input parameter. The square of PRCCs are normalized and represented as the percentage of variation in GHG intensity accounted for by variability in each input. This allows us to rank the input parameters based on their level of contribution to the variance of GHG intensity.

Figure 3 goes here

4 Results and discussion

4.1 Uncertainty characterization and propagation

The range of values and probability distributions used for the parameters that define use phase scenarios are presented in Table 1. Most of the values characterizing the trip profile are estimated from the data available through the National Household Travel Survey (Santos et al. 2011). For parameters without information on their underlying distribution, a uniform distribution is used within appropriate lower and upper bounds estimated from NHTS data. This is an attempt to uniformly explore the parameter space, in this situation where the true distributions are unknown due to a lack of data. The only exception is for long distance trips, where the choice of a lognormal distribution seems to be more pertinent since the trips with longer distance are less frequent. A lognormal distribution is estimated from the long distance trip data available in NHTS 2001 (Hu and Reuscher 2004). A probabilistic analysis using the Monte Carlo simulation has been performed based on the methodology described in Section 3 and depicted in Fig. 3 to propagate the uncertainty in scenario parameters into GHG use phase impacts. The Monte-Carlo simulations take into account the different nature of the variables in groups A to D in Table 1. The ranges chosen for the variables in Table 1 intend to represent the current situation in the U.S., reflecting the variation among different locations (x_1), different trip characteristics ($x_2 - x_8$), and among different individual behaviors, (x_9 and x_{10}), based on official surveys. The exceptions are x_9 , x_{12} , and x_{13} , for which a full range of 0 % to 100 % was considered reflecting all the possibilities that may occur.

Fuel economy of vehicles is another important source of uncertainty that propagates into the use phase GHG intensity (Cheah 2013). The uncertainty in the vehicles' fuel economy mostly stems from the variation in the technology and performance of vehicles. The Environmental Protection Agency's National Vehicle and Fuel Emissions database provides data on the rated fuel consumption for different vehicle types and different powertrains (EPA 2014). The year 2014 data for different types of midsize/compact vehicles are used to characterize the uncertainty in the fuel consumption for gasoline, diesel, and hybrid vehicles. Considering only midsize and compact class vehicles, there are two BEV80s, one PHEV40, and two PHEV10 in the EPA 2014 database. For the sake of comparability, one of the PHEV10 vehicles is excluded, since it is much larger (4.90 m) in length than the remaining PHEVs and BEV80s (ranging from 4.39 m to 4.50 m). In the same spirit, HEV, Gas and Diesel vehicles longer than 4.80m or shorter than 4.10m are excluded. Another filter applied concerns power, since there are several very high performance HEVs and Gas vehicles incomparable with the BEV and PHEVs. An upper limit of 150 kW is considered.

We used data on over 100 vehicles for the gasoline, eight for the diesel vehicles, and eight for the HEVs to estimate the variability of fuel economy. Uniform distributions are estimated to represent the variation, considering the minimum and maximum observed values. For the PHEV10, PHEV40 and BEV80 powertrains, this information is only based on one or two types of vehicle and as such only the baseline values are considered. This information is summarized in Table A.1 (Electronic Supplementary Material).

It is important to note the disparity in the number of vehicles used as data sources for fuel economy across the different categories (over 100 for gasoline vehicles, compared with eight for the diesel vehicles and HEVs, two for the BEV80s, and one each for the PHEV10 and PHEV40). While it would certainly be preferable to have a significant sample size for data sources in each category, our analysis is a realistic assessment of the current market. The introduction of a few vehicles in all categories except for gasoline vehicles would impact the results.

Fig. 4 shows the average values as well as 5th and 95th percentiles of life cycle GHG intensity in g CO₂eq/km for different powertrains estimated using 20,000 Monte Carlo samples. It is important to note that these GHG intensity results include vehicle production, although the scenario variation only concerns the use phase. The gasoline powertrain shows the largest variation in the impact whereas the variation is lowest for the case of PHEV10, as can be seen in Fig. 4.

Table 1 goes here

Figure 4 goes here

Figure 5 goes here

4.2 Comparative assessment

The results of an LCA are often represented in a comparative manner in order to allow analysis to comment on the superiority of different alternatives. When the LCA is conducted under uncertainty, the results are not deterministic values but rather a range of possible outcomes with their associated probabilities. As described in Section 3, we use Monte Carlo simulation to explore the variation in the scenario space and propagate this variation into GHG emissions. This provides the ingredients for conducting the comparative assessment in a statistical manner.

One straightforward comparison can be made observing the GHG intensity cumulative distribution functions (CDF) for the different powertrains, depicted in Fig. 5. The comparison of CDFs shows that among all the powertrains, it is more likely that the BEV80s and the PHEV10 yield lower GHG intensity among all. This implies a first order stochastic dominance of the BEV80s and the

PHEV10 over the other powertrains (the cumulative probability of having less than any given GHG intensity level is higher for the BEV80s and the PHEV10 than for other powertrains).

A more detailed analysis can be made based on pair-wise comparisons. Let S be the scenario space and $s \in S$ denote each element of the set defining a use phase scenario. Let $G_X(s)$ denote the random variable associated with the GHG intensity for powertrain X , where X can be any of the powertrains being compared, that is $X \in \mathbf{PT} = \{\text{Gas, Diesel, HEV, PHEV10, PHEV40, BEV80}\}$. As a basic statistical indicator, one can look at the frequency of the cases that a product X has less GHG intensity than an alternative product Y among all the scenarios under study. This frequency is mathematically defined as

$$p_{XY} = P(G_X(s) < G_Y(s)), X, Y \in \mathbf{PT} \quad (1)$$

in which $P(\cdot)$ denotes the probability or the likelihood. Table 2 reports the likelihoods, p_{XY} , in percentage terms for different pairs of powertrains. For instance, the first row indicates that the diesel vehicle had less GHG intensity than the gasoline vehicle in 66.9 % of the randomly generated cases.

As another measure of comparison, we also look at the likelihood that each powertrain has the lowest GHG impact among all the powertrains, that is

$$p_X = P(G_X(s) = \min\{G_i(s) \mid i \in \mathbf{PT}\}). \quad (2)$$

These quantities are estimated from the results of Monte Carlo simulation and compared in Fig. 6. Gas vehicles, diesel vehicles, and the PHEV40 were never the best in terms of GHG impacts, and HEVs performed better than all other vehicles in only 0.9 % of the cases. Most of the times, the BEV80s had lower emissions.

Table 2 goes here

Figure 6 goes here

Based on the results of comparative assessment demonstrated in Fig. 6, the BEV80s and PHEV10 are the two contenders with a likelihood of having the lowest emission of 68.9 % and 30.2 %, respectively. In order to statistically quantify the difference between the two, we make use of a comparison indicator defined as the ratio of their associated GHG intensity as follows (Huijbregts et al. 2003):

$$\mathbf{CI} = G_{BEV80}/G_{PHEV10} \quad (5)$$

For each scenario, the BEV80s show lower GHG intensity than the PHEV10 if $\mathbf{CI} < 1$. The probability density function of the random variable \mathbf{CI} (Fig. 7) is estimated from the results of Monte Carlo simulation. This information is used to quantify the relative difference in the performance of two powertrains along with the associated likelihood. For instance, the probability that the BEV80s have lower GHG intensity than the PHEV10 is defined as $\beta = P(\mathbf{CI} < 1)$, which is estimated as $\beta \approx 0.69$ (Fig.

7). Furthermore, the results suggest that the GHG intensity of the BEV80s is almost surely at most $3/2$ of the competitor, the PHEV10; that is: $P(\text{CI} < 3/2) \approx 1$. On the contrary, the probability $P(\text{CI} < 2/3)$ is far from negligible (although $P(\text{CI} < 1/2) \approx 0$).

Figure 7 goes here

Looking into the scenarios under which the BEV80s have lower GHG intensity shows that these scenarios correspond to the situations where the vehicles are operating in low grid emission areas and the EVs are mostly charged during the night. Moreover, it is more likely that the BEV80s prevail over other powertrains for lower degrees of driving aggressiveness. This suggests that these parameters are the most critical factors when assessing whether the BEV80s have lower GHG intensity. Regarding the comparative assessment of BEVs, it should be pointed out that the range of this type of powertrain is often insufficient to allow the completion of the long distance trips. Thus it is worth noting that from this aspect, not all the vehicles that are analyzed are comparable.

In the following section we present a global sensitivity analysis in order to systematically identify the contribution of different uncertain factors in the variation of resulting CO₂ emissions for each vehicle type.

4.3 Sensitivity analysis

The use phase model for quantifying GHG intensity, as described in section 2.3, depends upon a variety of inputs, which influence the GHG impact of each powertrain to different extents. The influence of each parameter can be different for conventional and electric vehicles. It is important to identify the key drivers of impact in order to limit the burden and expense of data collection for a better characterization. Moreover, this information helps decision-makers to identify the area that causes the decision to change. To this end, we perform a sensitivity analysis to quantify the dependency of the impact to each uncertain parameter. As the measure of sensitivity we compute partial rank correlation between each input and the output, represented as the percentage of contribution to the variance of GHG intensity. The result of this sensitivity analysis is shown in Fig. 8. Driving aggressiveness is one of the top contributors to the GHG impact for all the powertrains. For the battery and plug-in hybrid electric vehicles (Fig. 8(a)) the charging location (grid) is one of most influential drivers of the uncertainty. For conventional and hybrid vehicles (Fig. 8(b)) other major factors include the fuel economy, percentage of city miles, and the average distance driven during the weekdays. The variation in the impact of the HEVs is almost entirely influenced by the uncertainty in the fuel consumption of these vehicles.

Figure 8 goes here

It is important to note the final results presented in this study and the subsequent outcome of comparative assessment hinge on the underlying assumptions regarding the range of input parameters and the associated distributions. The degree to which these assumptions influence the decision depends upon their level of contributions to the final results. The global sensitivity analysis presented in this section identifies the critical areas to focus on for a more detailed characterization.

5 Conclusions

In this paper we present a comparative assessment of GHG impacts for conventional and electric vehicles, while accounting for uncertainty in the use phase. A stochastic analysis using a Monte Carlo simulation has been adopted to propagate the uncertainty in the use phase into the greenhouse gas emissions of different powertrains. This procedure allows us to characterize overall variation in GHGs and conduct the comparative assessment in a statistical manner. Moreover, we present a global sensitivity analysis in order to identify the key drivers of impact that could cause the outcome to change.

The results suggest that the EVs currently available in the US market are preferable from a GHG standpoint only within certain contexts. Within the scenario space under study, the BEV80s are more likely to result in the lowest GHG impacts as compared to other powertrains. According to Table 2, only in rare circumstances do the BEV80s show higher CO₂ emissions than the PHEV40 (0.7 %), HEVs (7.4 %), gas vehicles (0.2 %), or diesel vehicles (0.5 %). Even acknowledging the use of uniform distribution and the absence of correlation modelling as limitations of this study, these are very robust conclusions that would not change (even if numbers would be different) if other statistical distributions were used. The close competitor is the PHEV10, which achieved lower GHG intensity in 30.2 % of the scenarios. But Fig. 7 shows that it is almost certain that the GHG intensity of BEV80s is at most 50 % higher than that of the PHEV10, whereas the reverse is not true.

If more precise results are sought, the sensitivity analysis provides clues on which parameters matter the most. GHG intensity of the PHEV40 and BEV80s depends heavily on the electricity grid used for charging the vehicles. Furthermore, driving aggressiveness can significantly affect the environmental footprint for both electric and conventional vehicles.

Concerning the limitations of this study, there are other sources of uncertainty that are not addressed. In particular, the uncertainty in vehicle production is not accounted and average values are used for these quantities. The uncertainty in the fuel production (see Kocoloski et al. 2012), for instance) is not discussed here since this is outside the scope of our LCA model. Other sources of variation such as the weight of the occupants or the use of air conditioning were not considered either. There is also temporal variation due to the technology dynamics, in particular in the electrical grid

emission factors, which can influence the results for the future scenarios. The focus of this paper is, however, on addressing uncertainty already present in the current situation of use phase. While we were able to characterize some sources of uncertainty in the use phase, several sources were not included due to a lack of data such as weather conditions and the loads of equipment and devices within the vehicle. This study is also limited by lack of information on the correlations between input parameters, which deserves further investigation. Finally, the scope of the analysis is limited by the small numbers of EVs currently available in the US market. Introduction of a few new EVs could potentially have a significant impact on outcomes.

Despite these limitations, the results of this study can inform decision-makers of the overall variation in environmental footprint for different technologies and shed light on the scenarios under which the adoption of EVs currently available in the US market can be environmentally beneficial from a GHG emissions standpoint.

Acknowledgments This work has been partly supported by the FEDER/COMPETE FCT projects MIT/MCA/0066/2009 and PTDC/SEN-TRA/117251/2010, the MIT Portugal Program, and EMSURE CENTRO 07-0224-FEDER-002004.

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Figure captions

Fig. 1 Study system boundary – the dotted lines indicate the life-cycle phases of vehicle included within the scope of this study

Fig. 2 Variation in GHG emissions intensity of electricity grids in the U.S. The non-baseload emission rates are a portion of the system total mix, with a greater weight given to plants that operate during the peak demand for electricity

Fig. 3 Monte Carlo simulations are used to propagate the uncertainty in the use phase into the life-cycle GHG intensity. Statistical distributions of GHG intensity are estimated and used to conduct a probabilistic comparative assessment

Fig. 4 Average values and uncertainty ranges for GHG intensity. The error bars represent the 5th and 95th percentiles

Fig. 5 Comparison of estimated cumulative distribution function of GHG intensity from vehicle production and use

Fig. 6 The likelihood that each powertrain achieves the lowest emission among all powertrains, p_x

Fig. 7 Statistical characterization of the difference in the performance of PHEV10 and BEV80. The plot shows the cumulative distribution function of the comparison indicator, CI, as the measure of comparison

Fig. 8 Sensitivity analysis: percentage of variation in GHG intensity accounted for by variability in each input parameter (see Table 1 and Table A.1 (Electronic Supplementary Material) for the descriptions of each parameter x_i): (a) Vehicles charged or partially charged from the grid; (b) Vehicles not charged from the grid

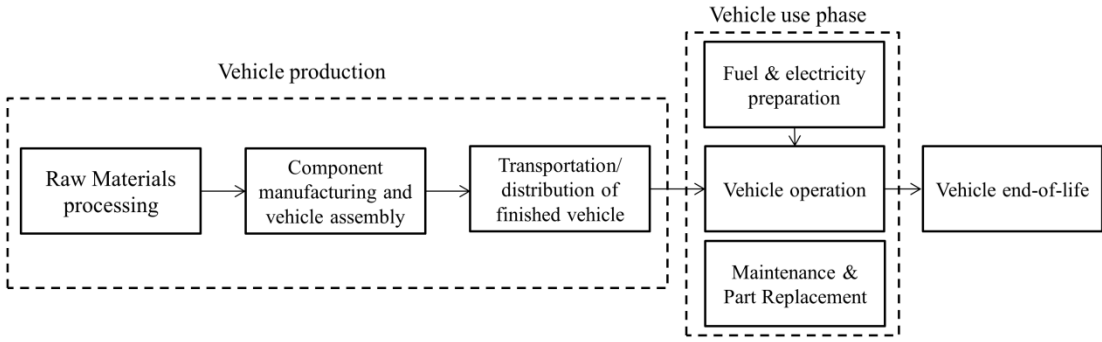


Figure 1

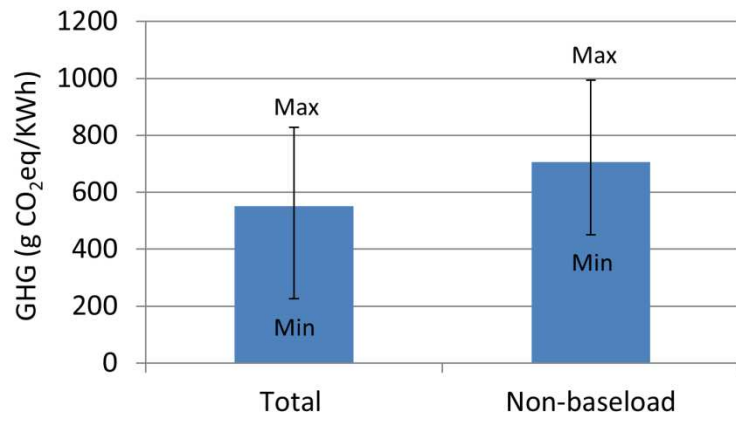


Figure 2

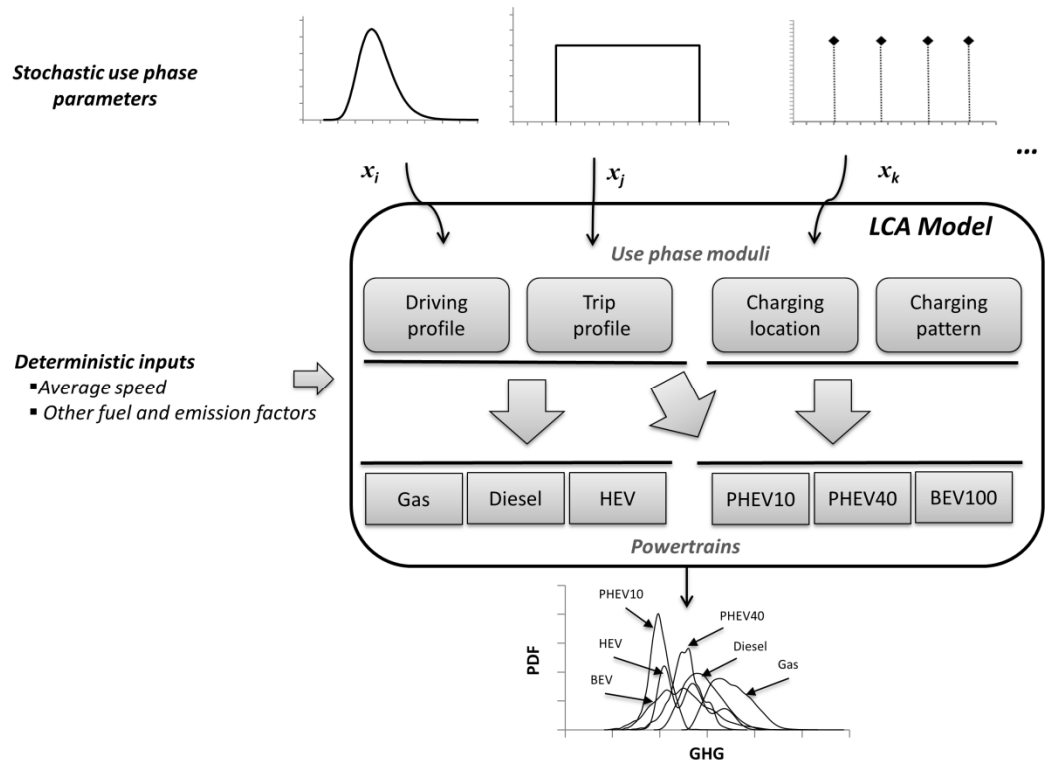


Figure 3

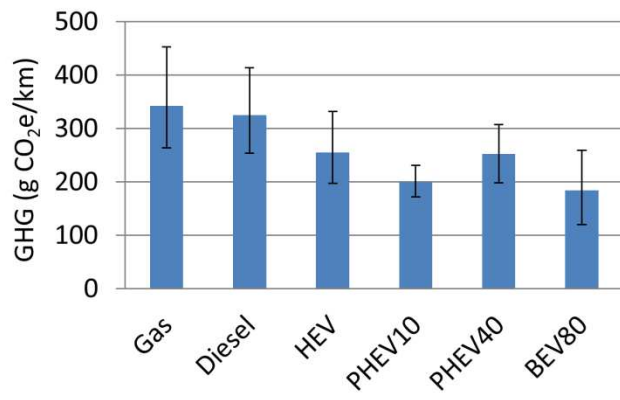


Figure 4

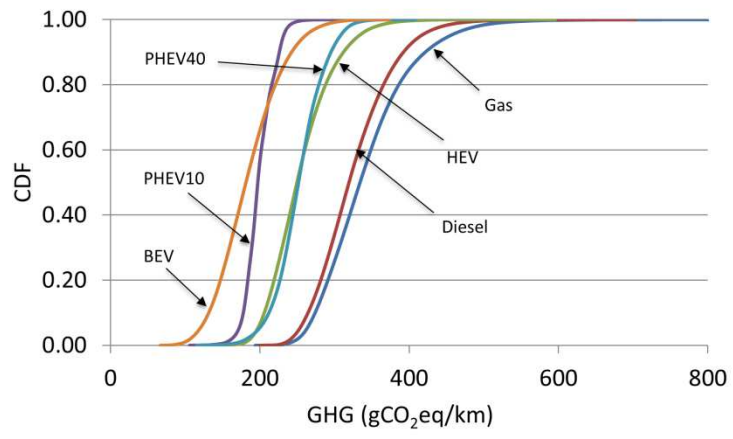


Figure 5

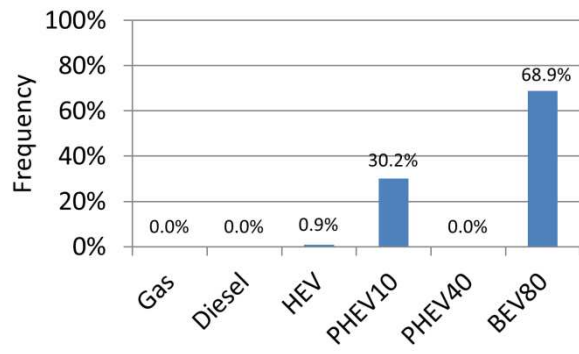


Figure 6

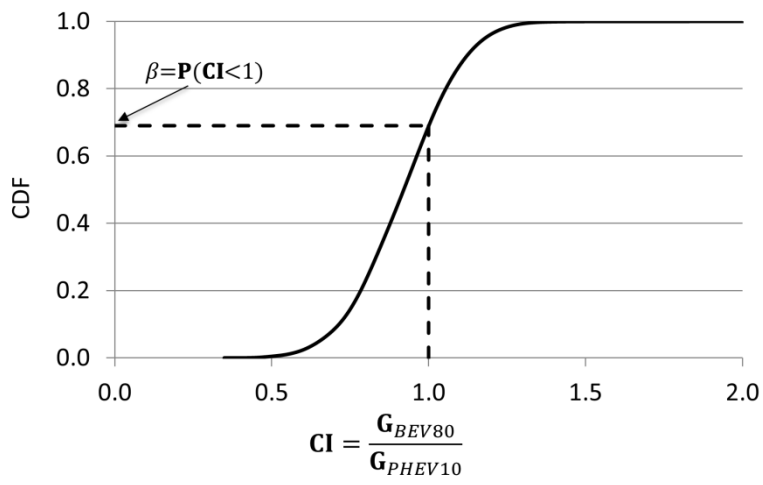


Figure 7

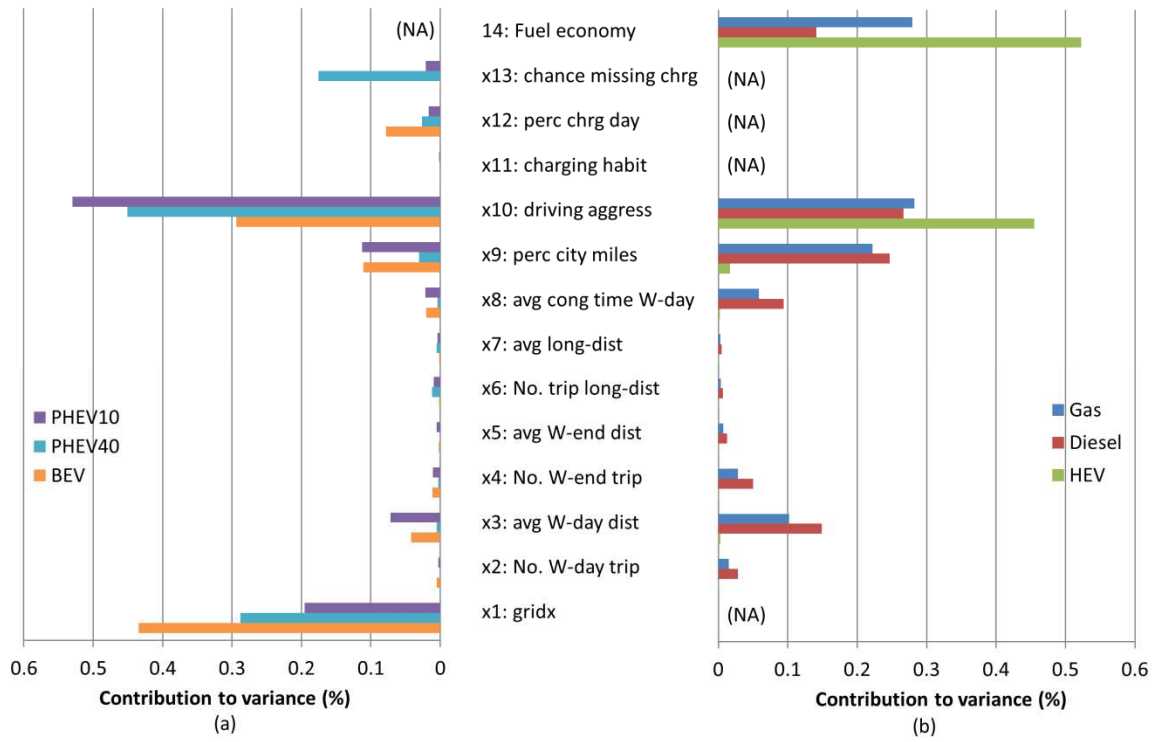


Figure 8

Table 1 Description of scenario parameters and the associated distributions used in uncertainty analysis

<i>Scenario Parameters</i>	<i>Min</i>	<i>Max</i>	<i>Distribution type</i>
A. Charging location			
• x_1 : Grid emission (g CO ₂ eq/KWh)	227.1	894.2 ^a	Uniform (discrete)
B. Trip profile			
• x_2 : Number of trips per weekday	1	4 ^b	Uniform (discrete)
• x_3 : Average weekday trip distance (km)	6.4	48 ^b	Uniform
• x_4 : Number of trips per weekend days	0	3 ^b	Uniform (discrete)
• x_5 : Average weekend trip distance (km)	6.4	48 ^b	Uniform
• x_6 : Number of long-distance trips per year	0	4	Uniform (discrete)
• x_7 : Average distance of long trips (km)	$\mu=425$	$\sigma=360$ ^c	Lognormal
• x_8 : Average trip congestion time for weekday commute (min)	7	20 ^d	Uniform
C. Driving profile			
• x_9 : Percentage of distance driven in city (vs. highway)	0 %	100 %	Uniform
• x_{10} : Driving aggressiveness (USDDS scaling factor)	1.0	1.6 ^e	Uniform (discrete)
D. Charging pattern			
• x_{11} : Charging habit night night\day			Binomial
• x_{12} : Percentage of charging time during the day	0 %	100 %	Uniform
• x_{13} : Chance missing a charge (percentage)	0 %	100 %	Uniform

References: ^a eGRID (EPA 2012), ^b NHTS 2009 (Santos et al. 2012),

^c NHTS 2001 (Hu and Reuscher 2004), ^d (Schrank et al. 2011), ^e (Carlson et al. 2009)

Table 2 The likelihood that a powertrain, X , has lower emission than an alternative one, Y , $p_{XY} = P(G_X < G_Y)$

$X \setminus Y$	Gas				
Diesel	66.9	Diesel			
HEV	97.1	97.1	HEV		
PHEV40	99.1	98.2	48.7	PHEV40	
PHEV10	100.0	100.0	98.4	99.0	PHEV10
BEV80	99.8	99.5	92.6	99.3	69.0