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Sustainability analysis of the electric vehicle use in Europe for CO2 emissions reduction.

Word count: 7951 words

Abstract:

Electric vehicles are considered the most promising alternative to internal combustion engine vehicles towards a cleaner transportation sector. Having null tailpipe emissions, electric vehicles contribute to fight localized pollution, which is particularly important in overpopulated urban areas. However, the electric vehicle implies greenhouse gas emissions related to its production and to the electricity generation needed to charge its batteries. This study focuses the analysis on how the electric vehicle emissions vary when compared to internal combustion engine vehicles, depending on the electric power plant fleet and the efficiency during the use-phase. For this to be done, the GWP associated to the electricity generation on the electric vehicle most selling European countries are calculated. Similarly, electric vehicle's use-phase energy efficiency is calculated under a wide range of driving conditions using the Monte Carlo method. The results from energy production and energy use-phases are compared to the GWP calculated for internal combustion engine vehicles for six different driving cycles, to obtain the threshold values for which electric vehicles provide GWP reduction. These threshold values are then matched with the current electricity power plant fleet and the electric vehicle promotion incentives of the European countries considered in the study, showing that some countries (*e.g.* France or Norway) are better-suited for electric vehicles adoption, while countries like Spain or Portugal should boost electric vehicle promotion policies. Furthermore, other countries in Europe, such as Germany or the UK that are doing an effort on decarbonizing their power plant fleet, do not offer immediate greenhouse gas emission reductions for the uptake of electric vehicles instead of conventional cars.

Keywords:

Electric vehicle; Carbon emissions; Well-to-wheel analysis; Monte Carlo simulation; Energy efficiency;

Introduction:

During the last century, the automotive industry and the electric energy generation sector revolutionized the society, bringing motorized mobility to the layman and powering up their homes. However, nowadays both transportation and energy generation sectors are key actors in the greenhouse gas (GHG) emissions scene, gathering about 14% and 25% of total GHG emissions worldwide, respectively (Pachauri et al., 2014).

European directives concerning the transportation emissions (from Euro 1 to the Euro 6) (Dieselnet, 2015; Official, 2007) have pushed automaker companies to continuously improve their internal combustion engines vehicles (ICEV). However, ICEVs seem to be reaching their techno-economical limits, pushing forward alternative mobility solutions, powered by less pollutant energy sources. Among those solutions, the electrification of vehicles powered by Lithium-Ion batteries (Li-Ion) is probably the most popular (Sierzchula et al., 2012). Considering the many Hybrid and Plug-in-hybrid vehicle powertrain configurations, this study is only focused on the full Electric Vehicle (EV), whose penetration in the automotive market is steadily increasing in the last years (Mock and Yang, 2014), as shown in Fig. 1.

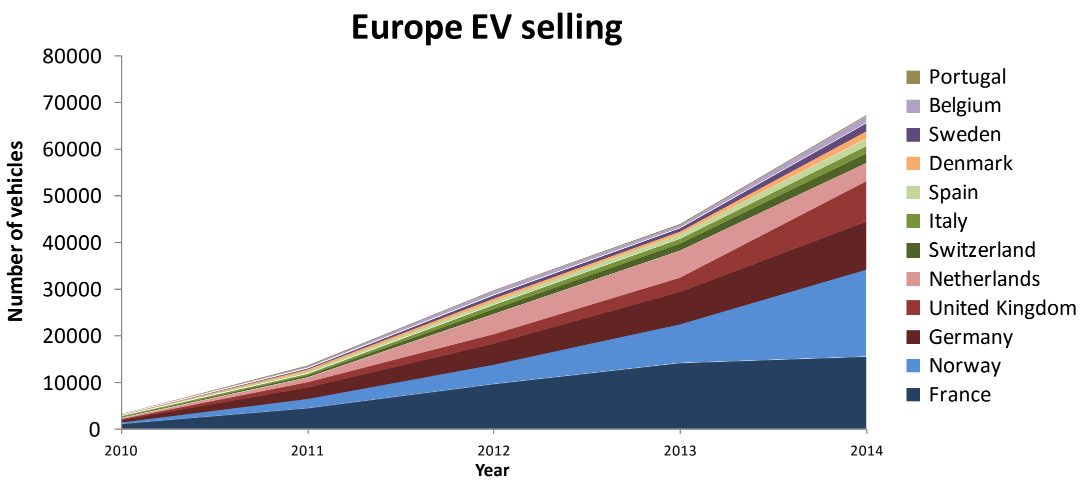

Fig. 1: Full EVs sold in European countries from 2010 to 2014. Source: (ACEA, 2015)

From an environmental point of view, EV has null tailpipe emissions, which helps fighting localized pollution, an especially important fact in urban concentrations. Nevertheless, this does not mean that EVs have no environmental burdens at all (Hawkins et al., 2013). The manufacturing of an EV entails higher environmental impact than that of an ICEV, being battery production one of the main contributors on the production phase GHG emissions (Notter et al., 2010; Patterson et al., 2011). Similarly, electricity consumed during the use-phase for charging the EV mostly comes from the existing electricity grid. Additionally, as mentioned before, being the energy generation sector one of the most pollutant sectors worldwide, this also supposes an implicit carbon footprint that cannot be neglected.

Thus, the environmental analysis of a vehicle entails studying the different energy needs involved in the vehicle lifetime, from vehicle fabrication to use phases. For the use phase, the Well-to-Wheel (WTW) methodology is commonly adopted to estimate complete fuel efficiency of a vehicles, which can be separated in two phases: the Well-to-Tank (WTT) and the Tank-to-Wheel (TTW). Considering the energy transformation and transportation stages on each of these two phases, the environmental impact implied on the vehicle use can be obtained (Campanari et al., 2009a; Hawkins et al., 2012). The WTT emissions analysis, calculates the emissions derived from fuel extraction, refining and distribution activities needed to fill the vehicle tank. TTW emissions are calculated translating the power train energy efficiency of the vehicle into the environmental impact produced by fuel combustion to generate traction power. The environmental impact of ICEV is most dependent on the TTW phase.

In the case of EVs, the carbon footprint assessment is calculated following the same WTW methodology. Nevertheless, being null the tailpipe emissions of such vehicles, the electricity generation process has a significant influence on the final EV emissions' results (Nicolay, 2000). Divergent results have been reported in literature when evaluating the TTW phase, showing a wide range of energy consumption values going from 0.10 kWh/km to 0.24 kWh/km, (Campanari et al., 2009a); (De Vroey et al., 2013); (Hawkins et al., 2012); (Helms et al., 2010); (Strecker et al., 2014). Moreover, EV energy consumption does not only depend on technological aspects, but also on driving habits, use of auxiliaries (such as air conditioning and heating system, defroster, power brakes, radio...) and weather conditions (Badin et al., 2013; De Vroey et al., 2013). In addition to this large consumption variability, the emissions created from electricity generation and distribution to charge the EVs (WTT), have also been studied to determine the Global Warming Potential (GWP) of these vehicles (Helms et al., 2010).

The whole assembly of these two steps (WTW emissions) provides the environmental impact results for a single vehicle and it shows up that, unlike ICEVs, it may substantially change depending on the electric energy source and EV consumption in the use-phase (Campanari et al., 2009a). The Life Cycle Analysis (LCA) of EVs review written by Hawkins et al (Hawkins et al., 2012), showed that most of these studies include fuel and electricity generation in their calculations, and that the GWP is the most widespread parameter to evaluate the environmental impact. However, usually the impacts of different fuel sources are calculated and then compared with the electricity generation plant fleet of a specific country – herein referred as the 'energy MIX' or 'energy generation MIX', which describes how final energy consumption in a given geographical region is distributed by primary energy sources –.

This paper focuses on the calculation of the maximum electricity generation MIX GHG emissions during the energy generation phase that keep the EV GWP below ICEVs. For this to be done, the electricity energy generation systems of many European countries are analyzed, taking into account their different energy strategies, different electricity MIX, and thus, different GHG emissions produced during the energy generation phase (Eiber and Grassmann, 2012); (Held and Baumann, 2011); (Helms et al., 2010); (Messagie et al., 2014).

Further, an analysis of the effect of driving patterns upon the efficiency of EV is carried out. Knowing that the use-phase leads to high variability in the final emissions result (Hawkins et al., 2013), the energy consumption is evaluated under various EV standard driving profiles. Then, the analysis is extended via Monte Carlo method to take into account differences among several EV and driving conditions –in terms of vehicle mass, drag area, drivetrain efficiency, regenerative braking and auxiliaries' consumption –. Including EV design and driving conditions variability, this study offers a deeper view of the effect of several parameters upon EV efficiency.

Finally, the impacts calculated in the energy generation phase and during the use-phase are cross checked, to evaluate the coupled impact between energy generation emissions and energy use efficiency. Studies in literature showed that EV incentives have a positive response in the automotive market share (Sierzchula et al., 2014). Hence, the results obtained in this paper are used to further conclude, depending on their current electricity MIX emissions, in which European countries it makes more sense to boost the use of EVs, if it corresponds to its reality and to determine if there are incoherent strategies between the electricity and transportation environmental policies.

The present work is divided in five sections. After the introduction section, the methodology section describes calculations and data sources for the energy generation GWP, the EV energy consumption and the total emissions of an EV. Additionally, it describes how the obtained results are compared to ICEV average emissions. Then, the WTT, TTW and WTW emissions calculated for higher selling European countries, which are more representative of the EV reality, are presented in the results sections. Next, a discussion section analyzes all the presented results and evaluates the suitability of introducing EV promoting policies on some of the countries included in the study. Finally, the main conclusions and future works are outlined.

Methodology:

The methodology followed for the calculation of the GHG emissions associated to EV and ICEVs is described in this section, which is divided in different parts for the energy generation phase, use-phase and total EV emissions comparison against ICEV.

Energy generation phase:

WTT emissions analysis take into account many steps from the extraction of energy source material to the electricity power distribution (Odeh and Cockerill, 2008; To et al., 2012). For this to be done, this study takes advantage of the information about the electricity generation MIX in the selected European countries, available in Eurostat databases from 2013 and the FP7 funded project LCA2GO (EUROSTAT, 2013). These databases present the GHG emissions caused by the electricity generation power plant fleet on each country. To complete the analysis, the upstream and downstream emissions have been incorporated. In this way, the upstream emissions correspond to raw energy sources mining or acquisition and transportation to the power plant, while the downstream emissions are caused by the inefficiency of energy transportation and distribution infrastructure from the power plant to the home plug and the losses of the EV charging system.

The calculation of GWP associated to raw materials acquisition depends on the type of energy source considered. Based on the ECOINVENT Life Cycle Inventory Data, emissions coming from raw materials' acquisition for thermal, combined cycle and nuclear power plants per country were included. However, this inventory database does not contemplate uncertainty on the values provided, which has been reported as a key factor on LCAs of EV to facilitate policy decision making (Noori et al., 2015). The uncertainty analysis was incorporated in this study by using previous works from Dones et al. (Dones et al., 2005), who determined the uncertainty values from these databases taking into account the different technologies of Nuclear and Natural Gas power plants on each European country. Coal fired power plants uncertainty is incorporated from the multiregional environmental comparison by Bouman et al. (Bouman et al., 2015).

Downstream emissions calculation is based on the electric power transmission and distribution infrastructure efficiency evaluation, which is incorporated in the study from the Worldbank database (Worldbank, 2014) based on the IEA Statistics from 2014 and the ERGEG report (Ergeg, 2008).

To complete the WTT emissions analysis, the EV charging efficiency represents the energy losses caused by the EV charger and the battery charging efficiency. According to literature, the whole efficiency is typically around 80-95%. The EV charging efficiency is mainly affected by three factors: First, The instant charger efficiency, which depends on the current intensity, being normally above 95% (Musavi et al., 2012). Secondly, battery efficiency, which also depends on current intensity, being above 95% under normal charging conditions but reaching lower values during fast charges (Kang et al., 2014). Finally, there is a residual, but not negligible, energy loss during the standby mode of EV chargers, which may occur during long time spaces as home chargers are expected to work once per day or less. Thus, the EV charging efficiency depends not only on the charger system, but also on the electricity consumption between charges and the current intensity during charges (Åhman, 2001; De Vroey et al., 2013; Du et al., 2010). For this study, the 90% average efficiency will be accounted as baseline and the uncertainty analysis will go from a minimum 80% to a maximum 95% efficiency.

Energy use-phase:

Once the emissions per kWh from the energy generation phase are calculated, it is necessary to find out the kWh per km, *i.e.* the efficiency of EVs. The TTW efficiency represents how the energy charged to the vehicle is transformed into movement, which entails an important effect over the final WTW emissions.

It is important to evaluate the use-phase (or TTW efficiency) under different scenarios to notice how relevant the emissions per country are when taking into account the total WTW emissions.

For the evaluation of the TTW efficiency, an approach similar to that reported by Peterson et al. has been followed (Peterson et al., 2010). In this way, the power consumption for a certain driving cycle can be calculated according to equations (1) and (2). When deceleration is large enough to exceed the effect of air resistance and rolling resistance, power is fed back from the wheels to the batteries (*i.e.* regenerative braking), according to equation (1). On the contrary, equation (2) describes the power consumption for the cases when no regenerative braking energy is fed to the batteries:

$$P = \left[\left(m \cdot a + \frac{1}{2} \cdot \rho \cdot v^2 \cdot C_d A + C_{rr} \cdot m \cdot g\right) \cdot \zeta\right] \cdot \eta_{Pt} \cdot v + P_{aux} \tag{1}$$

$$P = \frac{\left(m \cdot a + \frac{1}{2} \cdot \rho \cdot v^2 \cdot C_d A + C_{rr} \cdot m \cdot g\right) \cdot v}{\eta_{Pt}} + P_{aux} \tag{2}$$

Where a and v are the acceleration and the speed of the vehicle, respectively; $C_d A$, m and C_{rr} are the drag area of the car – representing the area of the car multiplied by the drag coefficient of the car – the mass of the vehicle and the rolling resistance, respectively; g is the gravitational acceleration and ρ is the density of the air.

In addition, it is assumed that when negative accelerations are registered, the regenerative braking contributes to recharging the batteries, thus reducing the total energy consumption. In general terms, the amount of energy that can be recovered during the regenerative braking depends on the instantaneous speed, deceleration of the vehicle and the State of Charge of batteries (Gantt et al., 2011; Gao et al., 1999; Ma et al., 2012; Wang et al., 2014; Xu et al., 2011). For this reason, different strategies are implemented to determine the braking force to be applied by the regenerative braking system and the mechanically frictional braking system (Gao et al., 2007; Guo et al., 2009; Sangtarash et al., 2008). In consequence, only a fraction of the total braking energy can be recovered by the regenerative braking system. The coefficient ζ introduced in equations (1) and (2) accounts for the average fraction of the regenerative braking energy recovered for battery recharge during a single trip.

The total powertrain efficiency, η_{Pt}, is calculated in equation (3) as the multiplication of the efficiency of the various parts connected in the powertrain of EVs from batteries to wheels, described as follows according to (Campanari et al., 2009a; De Vroey et al., 2013; Gantt et al., 2011; Park et al., 2014; Wu et al., 2014):

$$\eta_{Pt} = \eta_{Batt} \cdot \eta_{inv} \cdot \eta_m \cdot \eta_{tr} \tag{3}$$

Where $\eta_{Batt}, \eta_{inv}, \eta_m$, and η_{tr} are the efficiencies of the battery pack, the inverter, the electric motor and the transmission system (transmission shaft, gear, differential, etc.), respectively.

Finally, the variable P_{aux} in equations (1) and (2) represents the power required by the auxiliaries in the EV, including air conditioning, cooling and heating system, radio, light or any other accessories.

The parameters involved in the energy use-phase, imply significant variability depending on the EV and the driving conditions considered. For this reason, and with the purpose of increasing the representativeness of the study presented, a Monte Carlo analysis was performed. In this way, distributions shown in Table 1 were assigned to some of the most relevant parameters in equations (1) and (2).

Table 1: Distributions associated to each of the variables included in the Monte Carlo analysis.

Variable		Distribution type	Parameters	References
Vehicle mass (m)	[kg]	Triangular	Lower = 450 Peak = 1518.97 Upper = 3070	(Shmuel De-Leon Energy Ltd., 2014)
Drag Area ($C_d A$)	[m^2]	Lognormal	μ = -0.446 σ = 0.105	(EcoModder, 2013; Sherman, 2014)
Powertrain efficiency (η_{Pt})	[-]	Normal	μ =0.8 σ = 0.035	(de Santiago et al., 2012; Rabiei, 2013)
Average regenerative braking energy fraction (ζ)	[-]	Normal	μ =0.75 σ = 0.1	(Guo et al., 2009; Wang et al., 2014)
Auxiliary load (P_{aux})	[W]	Lognormal	μ = 6.6120 σ = 0.381	(Farrington and Rugh, 2000; Greaves et al., 2014; Peterson et al., 2010)

To define the vehicle mass distribution (m) [kg], data of more than 40 vehicles was considered. A triangular distribution was assigned, as vehicles in the range of 1100-1700 kg are more likely to be driven – that is the vehicle mass range of the most sold electric vehicles like the Nissan Leaf, Tesla model S or the BMW i3 – than models out of that same range. However, the lower limit was established by small vehicles like the Renault Twizy (*c.a.* 450 kg), while the upper limit was set by larger vehicles like the Tesla model X (*c.a.* 2500 kg), (Shmuel De-Leon Energy Ltd., 2014). In a similar manner, data from about 240 vehicles was considered to adjust drag area distribution ($C_d A$) [m^2]. However, considering that such parameter slightly varies for the same vehicle depending on the wind tunnel in which the drag coefficient is calculated, a lognormal distribution was more appropriate to fit the available data.

In order to assign a probability distribution function to the EV powertrain efficiency (η_{Pt}), the typical efficiency range of the elements depicted in equation (1) has to be considered. Thereby, considering battery, inverter and electric motor efficiencies typically ranging from 90% to 98% depending on the technology implemented and the operation window (Campanari et al., 2009a; de Santiago et al., 2012; Rabiei, 2013), and also considering an efficiency of *c.a.* 97-98% for the transmission system, a normal distribution was defined.

As it has already been explained, the fraction of braking energy recovered depends on the strategy implemented to divide the braking force between the regenerative braking system and the mechanic frictional braking system. This strategy varies according to the EV model considered. On the other hand, battery SOC, and vehicle speed affect the total energy that can be recovered from regenerative braking. With the purpose of extending the applicability of the considered model, the average fraction of the braking force that is recovered on a trip was modeled with the factor ζ. In this way, a regenerative braking force fraction ranging from *c.a.* 0.4 to 0.95 was modeled with a Gaussian distribution. The shape of the distribution was defined considering that contextual driving conditions affect in a random way the probability distribution of the average fraction of the braking energy recovered.

The auxiliary load considered for each trip P_{aux} [W] was modeled with a lognormal distribution describing auxiliaries consumption from very low values of *c.a.* 200 W to larger values in the range of 3000 W. However, it is considered that lower values are more likely to be common on modern EVs, and that only under extreme weather conditions auxiliary load would go above *c.a.* 1500 W (Allen, 2014; Kambly and Bradley, 2015).

To complete all the parameters shown in equations (1) and (2), the constant values shown in Table 1 were assigned. The rolling resistance may vary depending on weather, road conditions or even the degradation status of vehicle tires. Similarly, air density changes also depends on weather conditions and geographical location of the vehicle considered (Shelquist, 2016). Nevertheless, their strong location and weather dependence complicate implementing such variability under a Monte Carlo analysis framework, as the distribution to be adjusted is dependent on the weather and the country considered. With the purpose of simplifying the interpretation of the results obtained, while preserving the representativeness of the study, a constant value of 0.01 for the rolling resistance (Gillespie, 1992) and an air density of 1.225 kg/m^3 were considered.

Table 2: Parameters considered constant in the Monte Carlo analysis and their values.

Parameter		Constant Value
Rolling resistance (C_{rr})	[-]	0.01
Air density (ρ)	[kg/m^3]	1.225
Gravitational acceleration (g)	[m/s^2]	9.81

Driving cycles considered:

Several standard driving cycles were used to extend the representativeness of the evaluation of the TTW efficiency. Although it has been reported in literature that standard driving profiles do not usually represent real EV performance (Dings, 2013; Kühlwein et al., 2014; Mock et al., 2013), it is assumed that the aggregation of the results obtained with various profiles would enhance the representativeness of the analysis in a cost-effective way.

Six standard driving profiles have been considered, covering a wide range of driving scenarios. The New European Driving Cycle (NEDC) and the Worldwide harmonized Light duty driving Test Cycle (WLTC) have been selected as baseline cycles to evaluate the EV performance (Kühlwein et al., 2014). NEDC is the standard driving cycle used in Europe for the environmental impact evaluation and range quotation. However, WLTC is the standard driving cycle called to substitute the NEDC and prevail over other standard cycles for the performance assessment of EVs on the EU in the near future.

Additionally, the US06 and the Highway Fuel Economy Test Cycle (HWFET) American standards have also been included in the analysis, as representatives of different kinds of highway driving patterns.

Finally, the Urban Dynamometer Driving Schedule (UDDS) and the New York City Cycle (NYCC) have been also included to analyze the effect of urban driving patterns and stop-and-go driving conditions over the energy consumption of an EV.

Table 3 summarizes the main characteristics of each of the driving cycles considered.

Table 3: Main characteristics of each driving cycle considered

		NEDC	WLTC	US06	HWFET	UDDS	NYCC
Total Distance	[km]	10.93	23.26	12.89	16.51	11.99	1.90
Total time	[s]	1185	1801	593	766	1370	599
Time standing	[%]	24	13	6	1	19	35
Average Speed	[km/h]	33.24	46.50	78.24	77.58	31.51	11.41
Maximum Speed	[km/h]	120	132	130	97	92	45
Average acceleration	[m/s^2]	0.54	0.42	0.49	0.31	0.46	0.48
Average deceleration	[m/s^2]	-0.79	-0.44	-0.53	-0.34	-0.53	-0.54

Total GWP calculation and comparison:

The total GWP calculation analysis is the bond of energy generation and energy use-phase analysis, which in this case is focused on the GWP of EVs in many European countries, measured in kg of CO_2e. Moreover, the analysis permits finding out the energy MIX GHG emissions for which EV and ICEV emissions equalize, and thus evaluating the convenience or not of EV use enhancement in function of the electricity generation GWP.

Following Equation (4), the GWP of EV is calculated per country (GWP_i in Equation (4) where $_i$ identifies the country). Considering the electricity MIX emissions calculated in the energy generation phase (MIX_i) [kgCO2e./kWh], multiplyed it by the distance (D) [km] covered by the EV and the energy consumption (E) [kWh/km] of the EV per kilometer, the GWP of an EV related to its whole-life use-phase is calculated. Moreover, as mentioned in the introduction section, the EV fabrication entails higher environmental impact than the fabrication of ICEV. This fabrication impact is stated in the literature and in different projects such as CCEM, FSEM or EVREST, (Helms et al., 2010; N.Genikomakis et al., 2013; Eiber and Grassmann, 2012; Held and Baumann, 2011; Messagie et al., 2014) to be *c.a.* 11000 kgCO_2e., which is added for the calculation of the total GWP. Being the EV impact calculated on a yearly basis, it has been considered an average of 12000 km (D) and the EV fabrication impact is divided by the expected EV lifetime (GWP_{fabEV}), which is considered to be 10 years according to the warranty offered by car manufacturers (Sierzchula et al., 2014). This timeframe might seem short compared to other studies, that normally go from 100000 to 300000 km ((Hawkins et al., 2012). However, considering that the average age of ICEVs in the analyzed European countries is around 6-8 years (Eurostat) and that EV batteries are considered not useful for traction purposes when they have lost a 20% of its capacity, which most Li-ion batteries aging studies indicate that is achieved around 10 years (Lunz et al., 2012), (Messagie et al., 2014), (Neubauer and Pesaran, 2011), a conservative value was preferred.

$$GWP_i = MIX_i \cdot E \ \cdot D + GWP_{fabEV} \qquad (4)$$

This value, multiplied by the number of cars sold in each country, shows the GWP or CO_2 equivalent emissions of EVs and allows comparing their effect in several European Countries.

The same approach used to obtain the GWP of the EV is used to calculate ICEV impact by means of Equation (5).

$$GWP_{ICE} = D \ \cdot \ GWP_{km} + GWP_{fabICE} \qquad (5)$$

In this case, the FSEM project assumed that the GWP of the ICEV's fabrication phase ($GWP_{fabICEV}$) is 6500 kgCO_2e., almost half of that of an EV (Held and Baumann, 2011). The GWP_{km}, presented in Table 4, depends on the driving cycle studied. The base case, using NEDC, is extracted from (Nordelöf et al., 2014) and all the other emissions per kilometer are extracted from literature and related to the NEDC (Karabasoglu and Michalek, 2013; Myung et al., 2012) and (Kühlwein et al., 2014) for the WLTC.

Table 4: WTW emissions (in gCO_2e./km) under different driving cycles for the ICEV.

Cycle	Emissions (gCO_2e./km)	Variation vs. WLTC
NEDC	132	92%
WLTC	144.15	100%
US06	146.02	101%
HWFET	82.41	57%
NYCC	265.33	184%
UDDS	128.53	89%

Equation (5) does not depend on any specific country characteristic. It is herein used as the baseline to observe the convenience or not of EV market enhancement around Europe. If the calculated EV impact (for each of the driving cycles and for the whole range of auxiliaries' consumption values) is lower than this baseline, it means that the use of EV supposes a GWP benefit. On the contrary, if the calculated EV impact is higher or equal to the baseline ICEV impact, it would imply no benefits by the use of EV.

A similar approach can be followed to obtain the electricity MIX that equals the emissions of EV and ICEV. This threshold value is calculated according to equation (6), which was obtained by equalizing equation by equalizing equations (4) and (5) and isolating the MIX [gCO_2e./kWh] variable. An electricity MIX GWP value above this limit would incur into more emissions from an EV than an ICEV, while a lower electricity MIX value (meaning less emissions produced during the electricity generation phase) would lead to fewer emissions when driving EV instead of ICEV.

$$MIX = \frac{D \cdot GWP_{km} + GWP_{fabICE} - GWP_{fabEV}}{E \cdot D} \quad (6)$$

This value can be easily compared to the current energy generation MIX of each country, to assess the convenience of EV use from an environmental point of view.

Results:

The main results obtained in the different phases are described in this section, along with the most representative results obtained when comparing ICEV and EV emissions.

Energy generation phase:

The GWP/kWh of electricity used when charging an EV is shown in Fig. 2 for the European countries that sold more EVs during the last decade. Fig. 2 summarizes the results of the WTT emissions phase, showing a wide range of emissions per country and their uncertainty range. The results depend on the electricity generation MIX, the emissions associated to power source acquisition, transportation and transformation and the EV charging system efficiency. The uncertainty of these results is represented by an error bar on the edge of the accumulated emissions bar per country.

In Fig. 2, countries are ordered according to the number of EV sold (from left to right). Additionally, this figure shows the relevance of the upstream and downstream emissions on the final GWP per kWh, i.e. the final Italian GWP/kWh is similar to the German while the electricity generation MIX from EUROSTAT database (MIX in Fig. 2) indicates that the production of electricity in German power plants has higher GWP than in Italy.

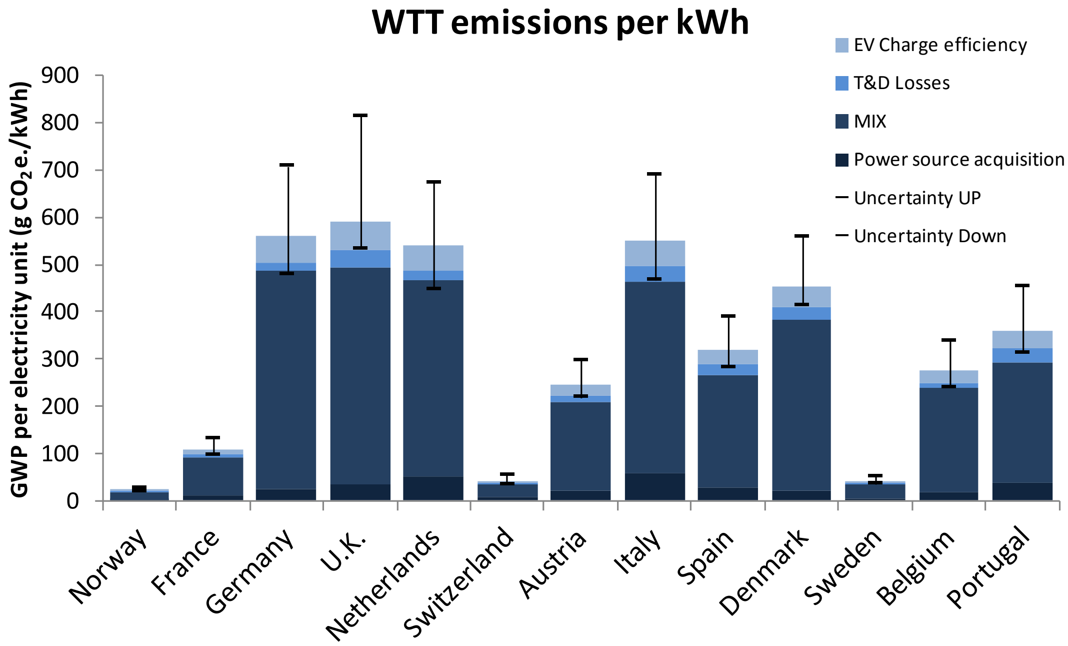

Fig. 2: GWP/kWh derived from EV charging (WTT) considering electricity MIX, upstream and downstream emissions from power plants and the effect of the EV charge efficiency system.

These results show large differences in the GHG emissions between the different countries in Europe, going from the 20 to 27 $gCO_2e./kWh$ uncertainty range from Norway (where the base calculation is 23 $gCO_2e./kWh$) until the 534 to 815 $gCO_2e./kWh$ range (black error bar) in the United Kingdom (where the base calculation is 591 $gCO_2e./kWh$, represented by the stacked blue bars).

Energy use-phase:

With the objective of extending the WTT analysis, the TTW efficiency and energy consumption of an EV has been analyzed under a wide range of conditions, as previously mentioned in the methodology section. The Monte Carlo analysis performed running 10.000 iterations. Fig. 3 shows the distributions obtained for the variables listed in Table 1.

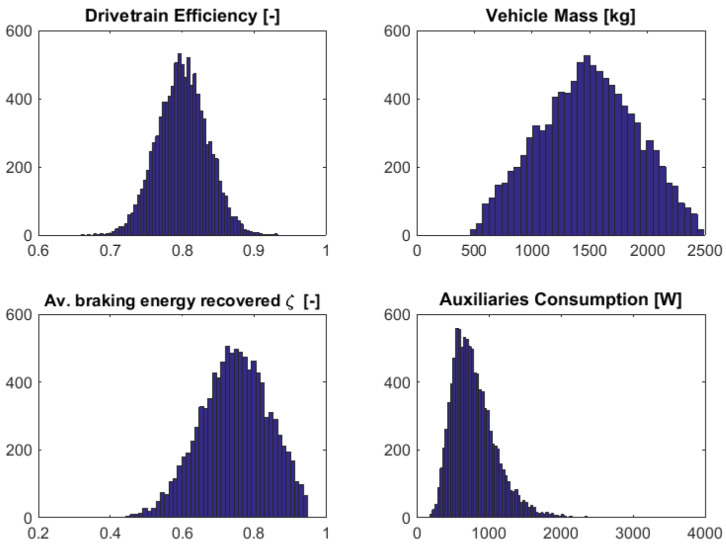

Fig. 3: Distributions defined for each of the input variables considered in the Monte Carlo analysis.

The EV performance analysis shows, for one of the iterations of the Monte Carlo analysis, a wide range of energy consumption values depending on the driving profile considered, as it can be observed in Fig. 4:

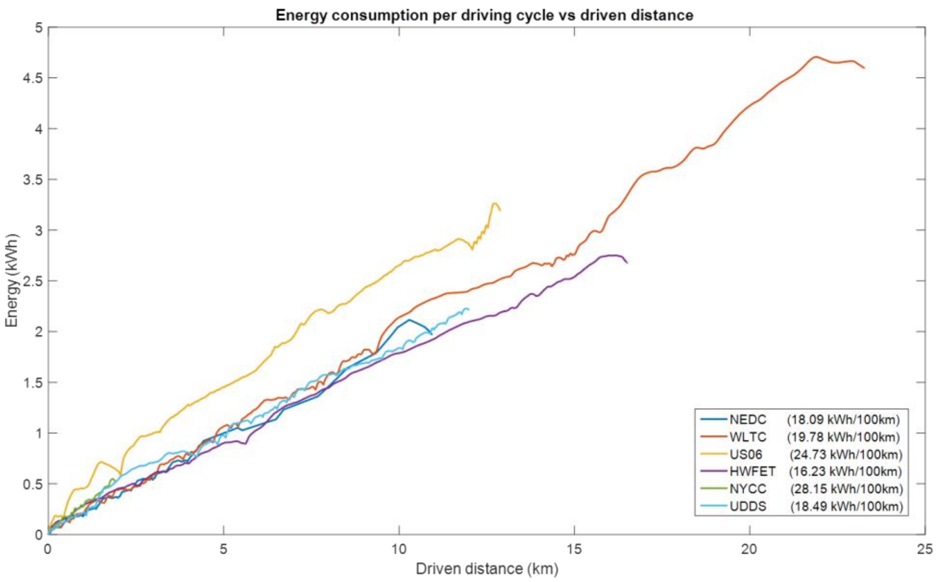

Fig. 4: Energy consumption versus driven distance calculated on one of the iterations analyzed in the Monte Carlo analysis.
Note: the same color identification for each driving cycle is followed all through the study.

Similarly to ICEV, most EV find their optimal efficiency range in speed values from 20 km/h to 80 km/h (Argonne National Laboratory, 2015; Badin et al., 2013; ; Sokolov, 2016; U.S. Department of Energy (DOE), 2015). Besides that, start-stop driving conditions imply large high energy consumption, especially considering that most EVs are unable of recovering regenerative braking energy when running at low speeds (Guo et al., 2009). In consequence, most EV have optimal efficiency under sub-urban driving conditions, where high-speed or start-stop driving conditions are less frequent. Fig. 4 supports this statement by showing larger energy consumption values for the NYCC driving cycle – with large stop periods and frequent acceleration and deceleration events – and the US06 driving cycle – which has the largest average speed among the profiles analyzed –. In a similar way, when evaluating the results obtained from the whole set of iteration in the Monte Carlo analysis, similar conclusions can be obtained. As it can be observed in Fig. 5, both the US06 and the NYCC driving profiles show the largest energy consumption mean values. In addition, both profiles also have larger standard deviations in the energy consumption distributions, which suggests a larger sensitivity to the parameters studied in the Monte Carlo analysis. As a matter of convenience, both the 10th and the 90th percentile have also been included in Fig. 5 for each of the driving profiles.

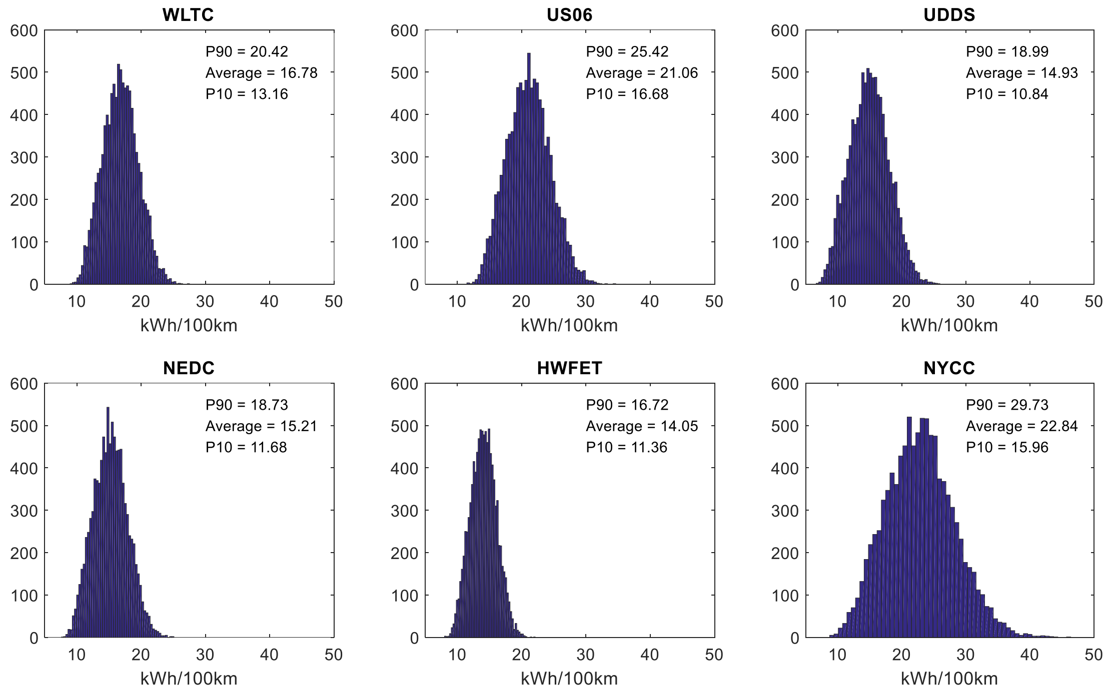

Fig. 5: Energy consumption distributions obtained in the Monte Carlo analysis for each driving cycle.

A sensitivity analysis was also performed with the objective of evaluating the sources of differences among profiles, besides obtaining a ranking of which parameters affect most the final energy consumption result. Fig. 6 shows the variation on energy consumption [kWh/100km] when varying each of the parameters considered in the Monte Carlo analysis on ±25% range over the mean value of each parameter distribution. In all six cases, EV power train efficiency results the factor with largest impact on final energy consumption, while vehicle mass is the second most important factor for every driving cycle considered. However, the effect of each parameter over total energy consumption varies depending on the driving cycle considered. Thus, for faster driving cycles, such as the US06, HWFET, WLTC or NEDC, vehicle drag area ($C_d A$) [m^2] has considerable impact over total energy consumption, while for urban driving cycles it has little effect over energy consumption. On the other hand, in urban areas, where the vehicle speed is lower, a greater time is needed to cover the same distance, which also aggravates the effect of energy consumption due to the auxiliary loads. This effect is especially noticeable in the case of the NYCC cycle, in which the effect of auxiliary loads is almost as important as vehicle mass. Finally, the factor ζ shows minor effects over total energy consumption for most of the driving cycles analyzed, and only under urban driving conditions reaches *c.a.* 5% reduction on energy consumption when elevated up 25% over the its average value.

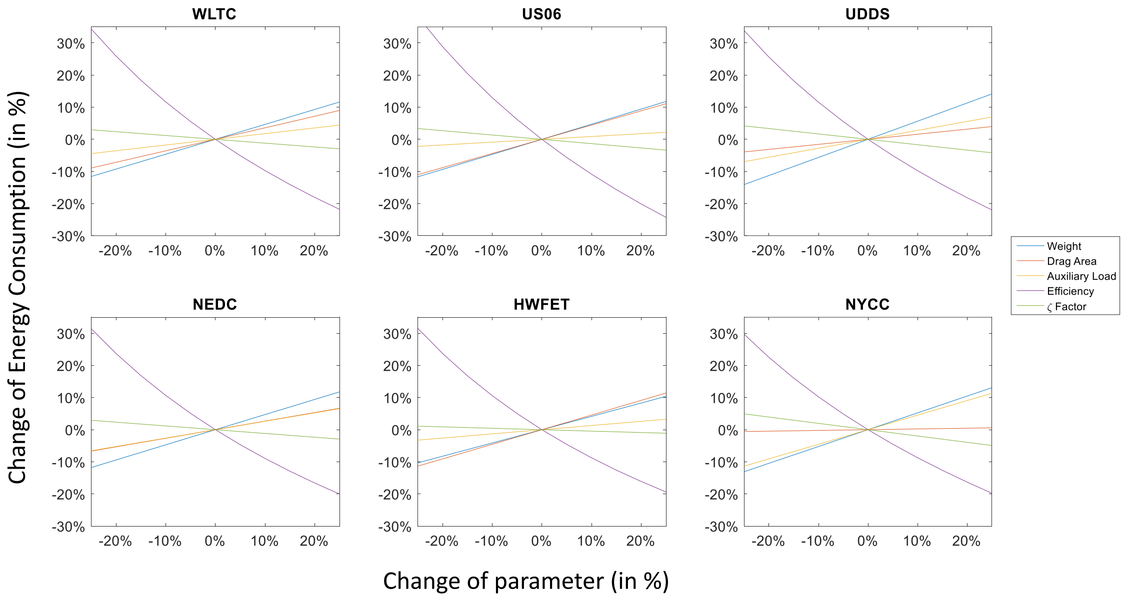

Fig. 6: Sensitivity analysis of the parameters considered in the Monte Carlo analysis and their effect over EV energy consumption

The EV consumption values calculated in kWh/100km from Fig. 5 – E in equation (6) –, for the different driving cycles analyzed consider the mean values from the distributions and the 10^{th} and 90^{th} percentile. These values are then combined with the WTT data to complete the WTW results of EV use. The 10^{th} and 90^{th} percentile values were considered as lower and upper energy consumption boundaries to neglect the effect of very pessimistic (or optimistic) parameter combinations, not likely to be realistic with the EV nowadays on the roads, and neither with future EV available in a near-term.

The values presented show good agreement with the results provided by other sources in literature, in which both the theoretical and experimental results are provided (Adriano et al., 2014; Badin et al., 2013; Gennaro et al., 2014; Laurikko et al., 2013).

Total emissions calculation and comparison:

From Equation (5), the baseline of the ICEV GWP that will be used to compare each different driving cycle is obtained. Similarly to the EV case, best results are found under highway driving conditions and worst results are reported under urban conditions. However, ICEV consumption show larger variations between urban and highway driving conditions. In fact, the consumption for the NYCC is 184% the consumption from WLTC and a 57% for the HWFET (Table 4), while in an EV, these differences in comparison to the WLTC consumption are 136% for NYCC and 84% for HWFET (Fig. 5).

The annual and total GWP of EVs under WLTC drive cycle, which is the driving cycle that better represents current driving conditions, were calculated to compare the results with those of the FSEM project and evaluate its robustness. Calculations were done considering the average energy consumption and the range defined by the 10th and the 90th percentiles. The results obtained strongly depend on the European Country analyzed, varying from 1136 $kgCO_2e$. to 2548 $kgCO_2e$ per year. Considering a 10 year EV life, the total GWP ranges from *c.a.* 11360 $kgCO_2e$. to 25480 $kgCO_2e$. However, these results consider the average electricity GWP calculated for each country, thus, the uncertainty range from Fig. 2 should be added. Including the uncertainty analysis, the total GWP of EV ranges from 11310 $kgCO_2e$ for the best case (Norway) to 30970 $kgCO_2e$ for the worst case (U.K.). These values are consistent compared to the results obtained within the FSEM project (Held and Baumann, 2011), where, using the German electricity MIX and considering 12 years EV lifetime and 14300 km per year, GWP reached up to 30000 $kgCO_2e$., or either 11000 $kgCO_2e$. when using only renewable energy sources.

The electricity MIX threshold values are calculated by means of Equation (6) in order to determine the electricity generation emission values for which EV and ICEV consumption are equalized.

These threshold values can be then compared with the current electricity generation MIX GWP of the European countries considered, as shown in Fig. 7. The colored background represents the EV consumption range and its tone identifies the driving cycle following the same classification from Fig. 4: NEDC (Blue), WDTC (Red), US06 (Orange), HWFET (purple), NYCC (green), UDDS (Cian). The lower limit corresponds to the electricity MIX GWP that equalizes EV and ICEV GWP for the worst performing EV (largest energy consumption value considered, *i.e.* 90th percentile) and the upper limit represents the best performing EV (smallest energy consumption value considered, *i.e.* 10th percentile), for each driving cycle. The colored line represents the results obtained for the average EV consumption value. This figure represents the allowable GWP range associated to the WTT phase, for the EV to be environmentally profitable against an ICEV; hence, the higher the energy consumption of an ICEV is, the lower the energy generation MIX emissions can be for the EV to represent GWP improvement, and vice versa.

In Fig. 7, electricity generation MIX emissions bars are represented as dark blue bars, together with the error bars represented as vertical thin black lines. Thereby, if the electricity generation MIX GWP and the error bars (in black) have an overlapping with the colored background, it means that some EV may produce greater GWP than ICEV, depending on the uncertainty parameters considered in the energy generation phase (*e.g.* EV charger infrastructure). Similarly, if the electricity MIX bar exceeds the colored background and the whole uncertainty range (black bars) is above such colored background, every EV would surely produce greater GWP than ICEV. On the contrary, if the bars do not reach the colored background and the whole uncertainty range is below such colored background, then every EV would produce fewer GWP than ICEV. In this way, Fig. 7 represents the convenience or not of using EV instead of ICEV on each country.

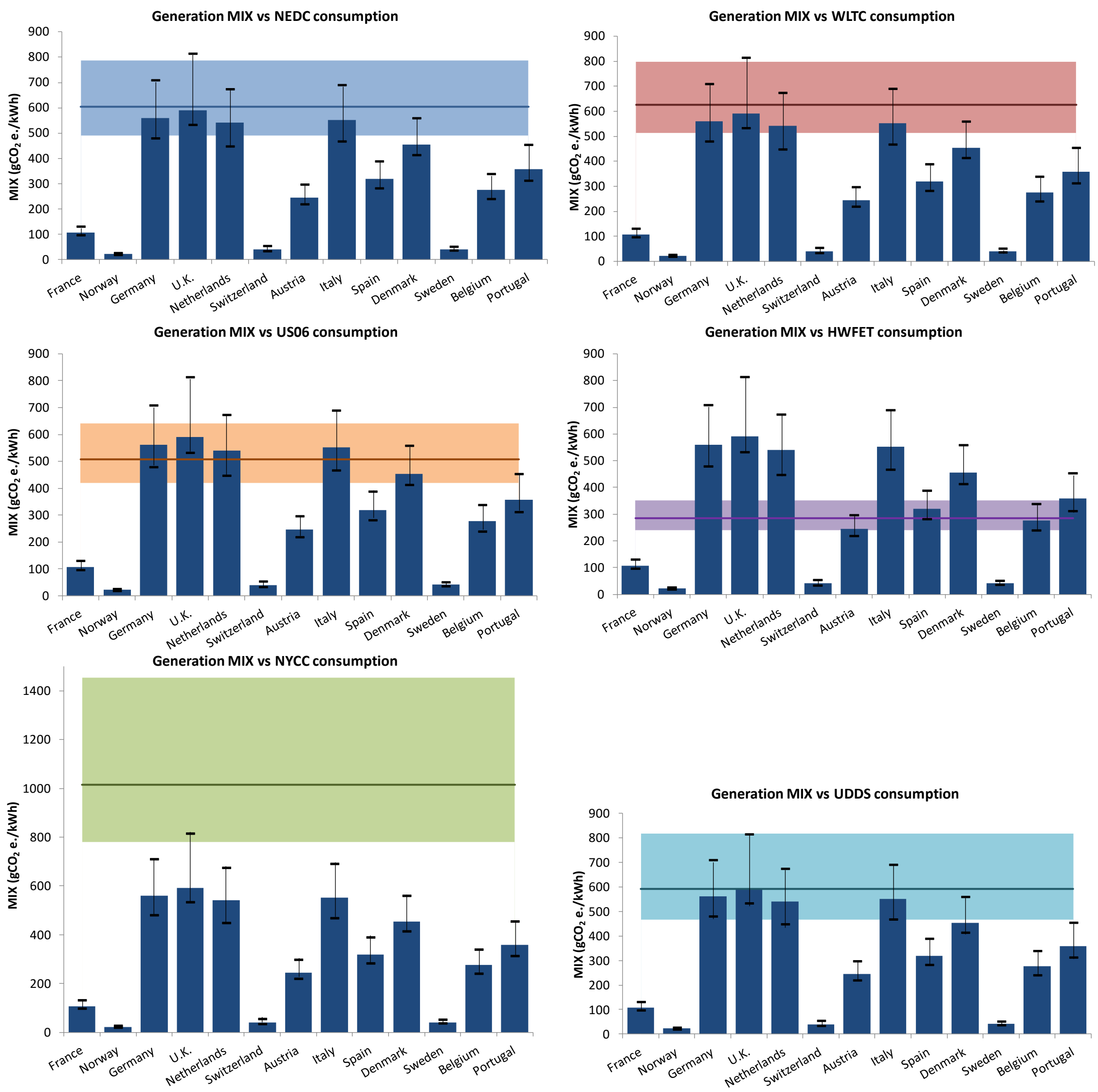

Fig. 7: Electricity MIX GWP/kWh threshold to obtain benefits from the use of the EV instead of ICEV and the corresponding WTT emissions per country.

In Fig. 7, the GWP per electricity unit threshold to charge the EV considering the NYCC (green background) goes from 781 to 1454 $gCO_2e./kWh$ while the electricity generation GWP per country (blue bars) are always below this range. Only in the U.K., the worse case of the uncertainty range (error bar) is overlapping with the threshold. On the contrary, for the HWFET driving cycle (purple background), the GWP per electricity unit threshold to charge the EV is thinner, ranging from 239 to 352 $gCO_2e./kWh$. For this driving cycle, the overall electricity generation GWP (blue bars) of Germany, U.K., Netherlands, Italy and Denmark (blue bars) exceed the EV charging GWP threshold even considering all the uncertainty range (black error lines).

From Fig. 7, the GWP per kWh on each driving profile was calculated. Thereby, considering the 10^{th} and 90^{th} percentile EV consumption range, Fig. 8 shows the GWP variations when driving EVs instead of ICEVs on each country, depending on the driving profile. In this case, these calculations do not incorporate the WTT uncertainty with the objective to clearly separate the effects from the EV performance and the effects from electricity generation emissions uncertainty.

In Fig. 8, it can be appreciated that the only driving cycle offering GWP reductions in all the EV consumption range is the NYCC (green), where the lower GWP reduction is found in U.K. (17%) and the higher benefits are found in Norway (71%). Again, the worse case is the highway driving cycle (HWFET in purple), where the maximal GWP reduction is found in Norway (28%), while the GWP is increased by 45% in the U.K.

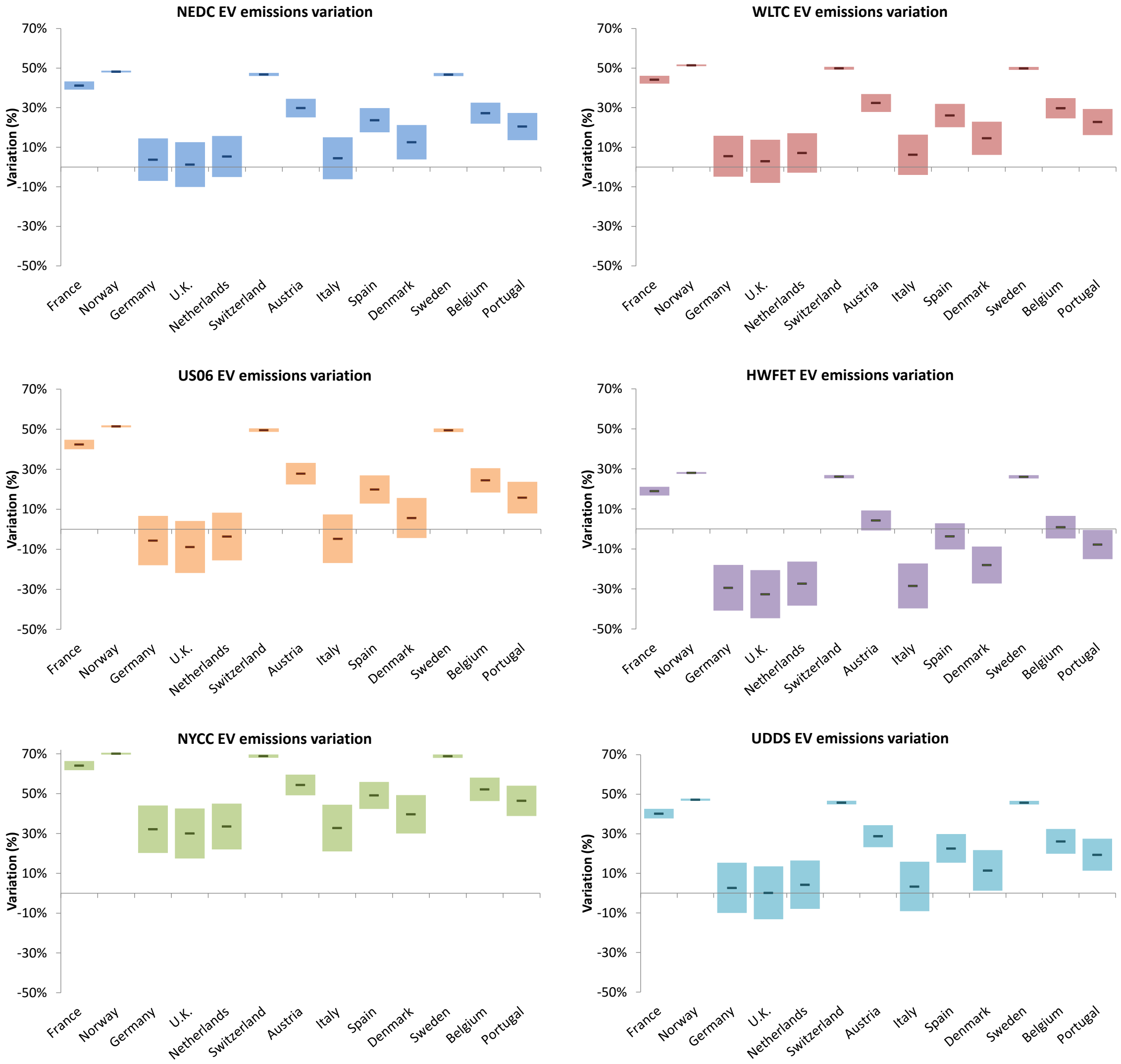

Fig. 8: EV use GWP range variation for each driving cycle per country taking the base electricity generation GWP.

Discussion:

Results shown in the previous section depict a controversial scenario about which European countries are better suited, considering their current power plant fleet, to face the potential penetration of EVs in the upcoming years.

The results clearly show the countries that are nowadays prepared to integrate the EV with immediate GWP reduction. However, all European countries are currently substantially decarbonizing their electricity generation sector, which implies that the boosting the EV penetration today will benefit from the forthcoming decarbonization, as reported by Jochem et al. when assessing the CO_2 emissions of EV in Germany in 2030 (Jochem et al., 2015). Additionally, the GWP reduction on transportation might also come from convenient driving patterns, which affects both ICEV and EV.

To facilitate the introduction of EVs, the European Union has provided incentives, plans, and strategies such as: European Commission 2010, Greater London Authority 2009, plan MOVELE, etc. (Hawkins et al., 2013; Sierzchula et al., 2014; Pasaoglu et al., 2012). However, only five countries in Europe (France, Norway, Germany, the U.K. and Netherlands) gather more than 80% of the EV sales in Europe. Despite all, economic incentives seem to be insufficient, and other factors like long charging periods, range-anxiety or the uncertainty about battery lifetime are important for end-users' acceptance, and are still hampering mass-market adoption of EV.

Similarly, after the Kyoto protocol and the European 20-20-20 initiative, incentives to enhance the introduction of renewable energy power plants and to promote cleaner electricity generation have been incorporated differently on each European country. Few examples of these strategies towards decarbonization of the electricity sector were highlighted by the last IEA Energy Policy report, such as, U.K. has done the largest reform since privatization to increase renewable share, while Denmark plans major investments to generate 50% of the energy from wind by 2020 and Netherlands increased the subsidies in renewables (IEA, 2013). Thus, the renewable energy penetration and the GHG emissions associated to electricity generation differ considerably from country to country, as shown in *Fig. 9* (a). In Fig. 9(b) the number of EV sold and the GHG emissions associated to electricity generation per country can be observed.

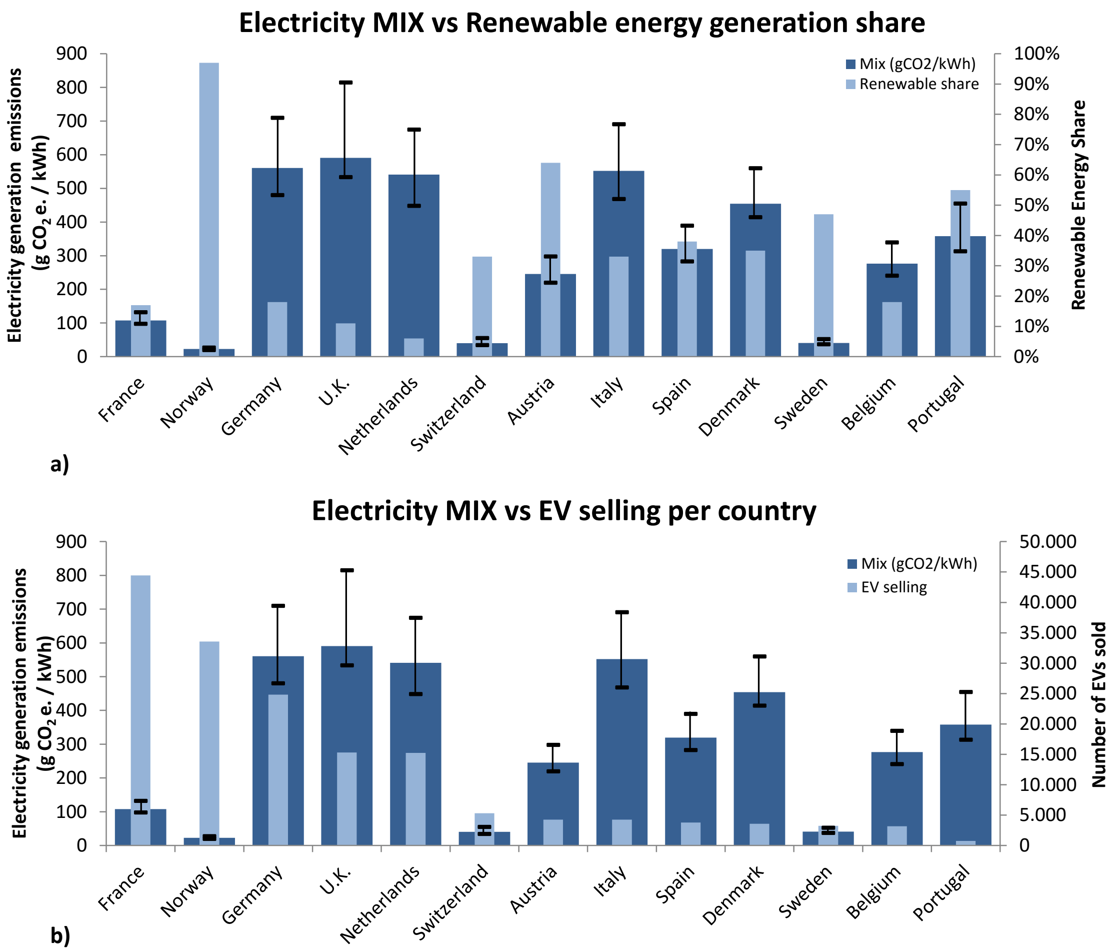

Fig. 9: GWP associated to electricity generation MIX vs renewable electricity generation share (a) and vs EV sales (b) per country. (EUROSTAT, 2013)

From Fig. 9, and considering the results obtained in Fig. 7 and Fig. 8, it can be derived that from the five EV most selling countries, only France and Norway have an electricity generation MIX that ensures GWP reductions for the whole EV energy consumption range. In the case of France though, low electricity generation GHG emissions are achieved through a high penetration of nuclear power, despite its low renewable share. Thus, when trying to evaluate the total environmental impact of electro-mobility solutions, it is important to consider additional environmental parameters rather than only GWP, which should be addressed in future studies.

Considering the number of registered EV on each country and the emissions from an average EV under WLTC cycle, the GWP of all EVs per country was calculated. Thus, France and Norway, which gather almost 50% of the EV sales in Europe, are responsible of *c.a.* 12% of the total GHG emissions directly imputed to the use of these vehicles. On the contrary, Germany, U.K. and Netherlands, having just 33% of the EV market share in Europe, are responsible of 71% of the total GWP coming from EVs use, Fig. 10.

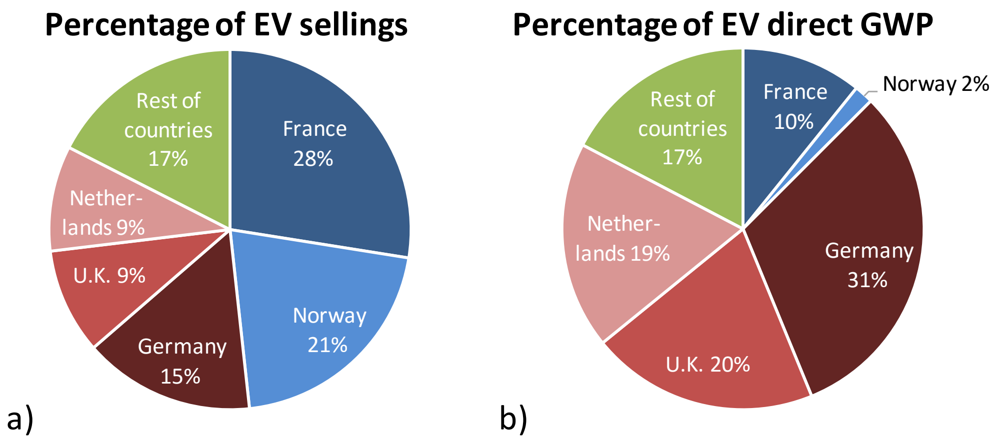

Fig. 10: Share of EV sales in EU (a) and GWP associated following the WLTC average consumption and the base electricity MIX (b).

Other countries like Switzerland, Austria, Spain, Sweden, Belgium or Portugal have big potential to accommodate EV penetration due to their low GHG emissions associated to electricity generation and their high renewable share (especially high in the case of Austria, Spain and Portugal). Those countries present reductions in the GWP under most of the analyzed driving cycles when using EV instead of ICEVs (Fig. 8) and the electricity MIX emissions are below the thresholds calculated for most driving cycles even considering the WTT emissions uncertainty (error bars from Fig. 7). In these countries, ICEVs present lower GHG emissions only under highway conditions. In fact, most EVs are oriented to urban and sub-urban use, where they achieve considerably lower emissions than ICEVs. This supposes direct benefits on the reduction of local air pollution and on the net GHG emissions of the country.

Fig. 7 shows that, despite the higher energy consumption calculated for most EVs under urban start-stop driving conditions (NYCC and US06 in Fig. 5), the EV is always beneficial in all countries and the worst case is found for highway driving (HWFET), where emissions are reduced in only 4 countries. This finding suggests that it might be convenient to incentivize EV use from regional and urban government strategies.

The presented results are based on a constant the average electricity MIX per country. However, better results might be obtained considering the variability of the EV impact in relation to the charging time of the day (Messagie et al., 2014), as the share of electric energy sources changes during the day. Thus, the emissions related to electric energy generation are typically lower at night, especially in countries where a high share of wind power production is present. The introduction of such a time factor could enhance the use of EVs, taking into account that most of them are usually charged over night.

The analysis on financial incentives and other socio-economic factors on electric vehicle adoption carried out by (Sierzchula et al., 2014) pointed out some of the main factors for pushing forward EV penetration, being the income-per-capita a major factor, and classified the countries by economical incentives on EV. Surprisingly, many countries in which the existing power plant fleet is well prepared for the arrival of the EV are the ones providing fewer financial incentives to electro mobility; this is the case for Spain, Sweden, Austria or Portugal.

On the contrary, Norway is the country where the energy MIX and the EV incentives are better aligned. Similarly, France is also encouraging the EV penetration, it is the sixth country with higher incentives in Europe, and additionally, local car manufacturers are strongly investing in electro-mobility. On the other hand, the U.K. is the fifth country providing higher EV incentives while it is the country having higher GHG emissions for electricity generation. Germany, which is the third country in EV sales in Europe mostly because it is the most populated country (EV market share is yet low, 0.34%), has the second worse electricity MIX. However, both sectors are well aligned, as there are almost no incentives to EV purchases and the institutional efforts are concentrated on decarbonizing the electricity grid. The latter two countries, besides Netherlands, Italy and Denmark represent clear cases in which the promotion of renewable energy generation resources is highly advisable for the enhancement of the environmental benefits obtained from EV use.

Conclusions:

The present study calculates the EV GWP for the higher selling European countries under various driving conditions. Thereafter, the GWP was compared with the GWP of an ICEV to determine in which countries there are immediate GWP reductions when switching from ICEV to EV.

Results shown in this paper suppose a new approach when addressing the suitability of several European countries to the widespread use of EVs as an environmentally efficient alternative to conventional vehicles.

It can be concluded that for most countries covered in the analysis, current electricity generation MIX is well suited to accommodate EV market penetration, and the usage of EVs will generally imply reductions in the net GHG emissions from the transportation sector. Moreover, most European countries are transforming and decarbonizing their electricity generation fleet. However, U.K., Germany and Netherlands (being in the TOP 5 most EV selling countries) still feature highly pollutant electricity power plant fleets. In those cases, an improvement of the infrastructure and increases on the renewable share should precede EV penetration in order to ensure reductions in the net GHG emissions produced by both electricity and transportation sector. It should be noted that according to the results presented, with their current electric energy production fleet, the introduction of EVs in these countries does not ensure GWP reduction.

This study covered only the GWP of EVs in the European Countries selling most EVs. Knowing that the environmental impact of EVs goes beyond the GWP; it should be noted that even in the cases where the EVs penetration does not imply GHG emissions reduction, other benefits still may arise from the electrification of transportation, such as lower dependency on fossil fuels, environmental consciousness-raising or reductions on the air pollution in urban areas, which entails important consequences over human health.

To further delve into the EV environmental impact, a deeper analysis of other phases of the LCA (*e.g.* maintenance or disposal) could be advisable in order to achieve more reliable results, although significant deviations from the results obtained in this study are not foreseen.

In summary, the coupling between renewable share and EV penetration is clear, and hence, it is crucial to consider the energy generation sector before promoting EV penetration.

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