Technology forecasting of electric vehicles using data envelopment analysis

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Some food for thought…

- *The General Motors EV1 was the first mass-produced electric car by a major car manufacturer since 1961. The EV1 was produced between 1996 and 1999 and made available through lease-only contracts to residents of Los Angeles, California, and Phoenix and Tucson, Arizona.*
- *The EV1 had a 3-phase AC induction electric motor with an output power of 102 kW at 7000 rpm and a torque of 149 Nm at 0-7000 rpm.*
- *The 1st Generation EV1s released in 1996 used acid-lead batteries with a capacity of 16.5 kWh and provided a range of 96 km/charge.*
- *The 2nd Generation EV1s released in 1999 used Panasonic acid-lead batteries with capacity of 18.7 kWh and provided a range of 161 km/charge.*
- *Soon after, the EV1s were fitted with Ni-MH batteries, with a capacity of 26.4 kWh which provided a range of 257 km/charge.*
- *The decision to produce the EV1 was taken in order to comply with the Zero Emission Vehicle (ZEV) Mandate released in 1990 by the California Air Resources Board (CARB), which stated that if car manufacturers wanted to continue selling cars in California, a certain percentage of their fleet should be made up by zero emission vehicles: 2% by 1998, 5% by 2001 and 10% by 2003.*
- *The ZEV Mandate was litigated in court by an alliance of the major automakers resulting in much more lenient requirements.*
- *Shortly after, in 2002, GM withdrew all the EV1 vehicles from the road, without giving the possessors of the leases the chance to purchase the cars. With the exception of a few EV1s which were deactivated and donated to universities or museums, the rest of the EV1 vehicles were completely crushed by GM.*
- *The reactions of different parties were very diverse: GM claims very high production costs and insufficient demand to continue the production of EV1 vehicles. Environmentalist groups accuse GM of self-sabotaging the electric car project in order to maintain sales of spare parts, and the oil companies for conspiring to keep the electric cars off the road.*

Source: http://en.wikipedia.org/wiki/General_Motors_EV1

Summary

This research performed technology forecasting (TF) of electric vehicles (EV) using data envelopment analysis (DEA) with the purpose to determine to what extent TFDEA can be applied to predict the technological progress of electric vehicles.

This study was commissioned by SKF, who is interested in having a useful forecasting tool to analyze EV technological advancements and identify whether one of the existing EV configurations has potential to become the dominant design in the future. SKF dedicates a major part of its resources to supplying the car industry; therefore changes in the automotive industry may impose technological changes on their current development projects and state of affairs. New market opportunities or threats brought about by the introduction of electric vehicles need to be signaled in due time to be able to adjust corporate and research activities to better serve the car industry and maintain a strong market position.

Electric vehicles are available in several configurations: battery electric (BEVs), hybrid electric (HEVs), plug-in hybrid (PHEV), and extended-range electric vehicles (EREV). This indicates that electric vehicles represent a heterogeneous class of products with different technical and performance specifications. Therefore, two aspects need to be accommodated by the forecasting technique used to produce electric vehicle forecasts:

- EV technology is not homogeneous, therefore the forecasting method should allow for the simultaneous analysis of different EV configurations in order to measure and predict technological change over the whole class of EV technology.
- EVs are characterized by several performance attributes which may be differently valued by different user categories, therefore the forecasting method should allow for multi-criteria evaluation of the technology performance and technological progress.

This research used TFDEA to forecast the technological progress of electric vehicles. The reason is that TFDEA appeared to have significant advantages over conventional trend extrapolation methods. Unlike conventional techniques, TFDEA can simultaneously evaluate multiple technologies using multiple variables. Furthermore, TFDEA is an extreme point method which means that it can calculate the individual performance of an observation instead of calculating the average performance over the data set. For this reason TFDEA is able to identify the state-of-of the art frontier (i.e. the best performing technologies at a given time). In addition, TFDEA can determine rates of technological change without assuming non-correlated attributes and can account for dynamic trade-offs between performance parameters.

The description of TFDEA fits the requirements identified for the forecasting method needed for EV technology. Remaining concerns about the usefulness of the method were related to the amount of data needed for the model to produce reliable results and the inherent assumptions of TFDEA listed below:

1. Technology performance is a linear function of the technology inputs.

2. The inputs of technology remain constant over time.
3. The rate of technological change remains constant over time.

The focus of this study was to identify the impact of these assumptions on the accuracy and validity of the EV forecasts.

A technical system analysis of electric vehicles was performed to provide understanding of the basic operation mechanisms of EV systems and of the relations between different EV design variables. Such information was necessary in order to properly identify and select those design parameters that are responsible for the EV performance and which can pose limitations to further technological advancements. For both families of vehicles, the output power of the propulsion unit, the charge storage capacity of the battery and the vehicle weight were found to be the main determinants for EV performance. In this study, the performance of BEVs was expressed in terms of acceleration possibilities and driving range, while for HEVs fuel economy, CO2 emissions and acceleration were selected as key performance indicators.

The technical and performance attributes of EVs were used as inputs and outputs respectively in three TFDEA models. Two of the models ware applied on BEVs or HEVs only and were used to evaluate the individual technological progress of BEVs and HEVs as homogeneous products, while the third model was used to determine the rate of technological change over the full class of EVs. Each model was used to produce a forecast for yearly EV performance levels until 2020. These forecasts were verified for accuracy against a set of existing products. Then, it was analyzed how the data availability and the assumptions of the TFDEA model impact the reliability and validity of the forecast.

The results of the analysis are shown below:

- For the first 11-12 time periods all vehicles in the data set were ranked as SOA, therefore no rate of change could be calculated, which reduced significantly the possibility to analyze whether there is a visible pattern of constant progress. This was caused by the large number of attributes included in the model, combined with a low number of products released over a relatively short time window.
- TFDEA assumes linear relations between technology inputs and technology performance. For electric vehicles, this assumption is realistic to a limited extent. The results showed that in the case of battery electric vehicles there seems to be a linear relation between battery capacity and electric range.
- It was shown that TFDEA models consistently underestimated the performance parameters subjected to regulation. This indicates that the method is very sensitive to exogenous drivers of technological change. The EV case study shows that the approach to evaluate the performance of a technology as a linear function of its inputs may be an oversimplification.
- The results of the three models show that the TFDEA cannot anticipate the introduction of potentially disruptive technologies, such as the PHV and the EREV. This is due to the fact that the forecasts produced with TFDEA indentify what may be feasible in the

future based only on what exists today. TFDEA assumes that inputs remain constant over time and has no mechanism to identify future re-configurations of inputs which could lead to better performance.

The present study has concluded that TFDEA is not a suitable method for analyzing technological progress of electric vehicle technologies. This is due to the high sensitivity to exogenous drivers and its limited capability to anticipate the introduction of potentially disruptive design configurations. These limitations are mostly a result of the assumptions that inputs and the rate of change remain constant over time.

As a general note on TFDEA, it was observed that TFDEA would not be a useful forecasting tool for emerging technologies with significant economic and socio-political implications. The model could be used for mature technologies which have shown constant progress over time, given that no exogenous forces are expected to influence the technological change. Furthermore, TFDEA could be used for forecasting emerging technologies whose performance can be expressed with very few attributes (at most three times less than the number of products available), and whose performance is not targeted by governmental regulation.

With respect to EV forecasting, this study identified that a simple analysis of technological progress is not sufficient to determine the evolution of EV technology. Due to the economic, environmental and political consequences, it is expected that the adoption of electric vehicles will not depend solely on performance, but also on different technological and context factors, such as battery technologies, available infrastructures, standardization opportunities, consumer acceptance, national interests and governmental support. To better understand the development possibilities of EV technology, this study recommends the use of technology forecasting and market shift indicators analysis to identify possible innovations in EV-supporting technologies, such as battery charging stations and smart grit technologies. Furthermore, combined analysis of consumer research and market structure analysis can help identify the market forces expected to affect further advancements of electric vehicles. In addition, monitoring government and industry plans can provide information on potential standardization opportunities and strategies meant to accelerate the adoption of BEVs.

Contents

Glossary

Term	Definition
• **All-electric range (AER)**	Distance traveled in electric mode (engine off) on standard driving cycles. [41] Unit: kilometers (km).
• **Battery capacity**	The amount of electric charge a battery can store. Unit: kilowatt hour [kWh].
• **Combined hybrid system**	Incorporates features of both parallel and series hybrid systems. [38]
• **Data envelopment analysis (DEA)**	A mathematical programming model that uses a set of non-parametric, linear programming techniques to estimate the relative efficiency of one decision making unit (DMU) in converting inputs to outputs, compared to other similar DMUs, by identifying a 'best practice' frontier. [***Error! Reference source not found.***]
• **Decision making unit (DMU)**	The production elements analyzed in a data envelopment analysis.[18]
• **Drive train structure**	Determines how the hybrid vehicle combines the power from on board rechargeable energy storage systems and fueled power source for vehicle propulsion. [39]
• **Driving range**	The maximum distance that can be driven in electric mode on a single battery charge. Unit: kilometer per charge (km/charge).
• **Electric operating mode**	Propulsion and accessories powered by the electric drive and onboard electric energy storage (i.e., engine off). [41]
• **Electric vehicle (EV)**	A battery-powered electric vehicle does not contain an internal combustion engine (ICE), a drive train and a fuel tank. Instead, EVs use an electric motor for propulsion with batteries for electricity storage. The batteries provide the motive and auxiliary power onboard the vehicle and can be recharged from the electricity grid or through break energy recuperation and also from non-grid facilities, such as solar panels at recharging centers. [38]
• **Electricity consumption**	Electrical energy consumed in electric or hybrid mode. [41] Unit: kilowatt hour per 100 kilometers (kWh/100km).

- **Fuel economy** — Distance traveled per unit of fuel consumed on standard drive cycles. [41]
  Unit: kilometers per liter (km/L).

- **Hybrid electric vehicles (HEV)** — A hybrid electric vehicle (HEV) combines a conventional propulsion system with a rechargeable energy storage system (RESS) to achieve better fuel economy than a conventional vehicle. [39]

- **Hybrid operating mode** — Propulsion and accessories powered by the electric drive and/or engine, encompassing all power sharing/blending strategies. [41]

- **Input** — Any resource used by a unit to produce its output. [18]

- **Output** — A measure of how effectively a unit has achieved its goals. [18]

- **Parallel hybrid system** — A system which has both an internal combustion engine (ICE) and an electric motor. The fuel tank supplies gasoline to the engine, while a set of batteries supply power to an electric motor. Both the electric motor and the gas engine can provide propulsion power. [39]

- **Plug-in hybrid electric vehicles (PHEV)** — A plug-in hybrid electric vehicle retains the entire internal combustion engine system, but adds battery capacity to extend the operation of the electric motor. Therefore these vehicles combine the efficiency advantages of hybridization with the opportunity to travel part-time on electricity provided by the grid, instead of only relying on the vehicle's internal recharging system. [38]

- **Recharge time** — The total time (in hours) to fully charge the electric battery of a vehicle.

- **Relative efficiency (efficiency score)** — The relative efficiency, denoted by θ or ϕ, is the efficiency score allocated to a unit as a result of the data envelopment analysis.

- **Series hybrid system** — A system where the combustion engine drives an electric generator instead of directly driving the wheels. The electric generator charges the battery and powers the electric motor which drives the vehicle. The gasoline engine never powers the car directly. [39]

- **State of the art (SOA)** — 'The state of best implemented technology as reflected by physical and performance characteristics actually achieved during the time period in question'. [27]

1. Introduction

A world without transport sounds like a real nightmare to the average person of the twenty-first century. How would one get to work? How would one visit their friends and parents? These are valid questions for the modern individual, and 'walking' is not an acceptable answer. Developments in the transport sector and the rise of the automobile industry have been changing society and spatial demographics for about two centuries, changing the way we live, the way we think and the way we do business [1]. And now they are on the verge of changing the way we fuel our cars.

Pressing environmental concerns and increased dependency on oil imports have revived interest in developing electric vehicles in the 1960s and 1970s. In 1976, following the oil crisis, the US Congress enacted the federal 'Electric and Hybrid Vehicle Research, Development and Demonstration Act of 1976', which was intended to stimulate research and demonstrate the feasibility of commercial electric vehicles. Among the performance criteria specified by this act, were a driving range of 50 km for electric vehicles and 200 km for hybrid vehicles, less than 75% consumption of non-electric energy and acceleration from 0 to 50 km in less than 15 seconds [2].

Increased manufacturing possibilities due to technological breakthroughs over the past two decades, combined with stringent environmental regulations, such as the 'Zero Emissions Vehicles (ZEV) Act' released by the California Air Resources Board in 1990, brought electric cars back on the market in the mid 1990s [3, 4]. In 2011, the Obama administration proposed to double the fuel economy standard by 2025, to a new level of 15.1 km/l. The new standard was conceived in order to offer an incentive for car manufactures to continue investments in development projects for more economical cars [5]. At present, there are a significant number of electric vehicles on the market and this number is expected to increase over the coming years. Most of the big car manufacturers will have released over the past 15 years battery electric and/ or hybrid electric vehicles which are commercially available under different purchasing and leasing conditions. However, the overall percentage of electric vehicles on the road is still very small [6] due, mostly, to price related factors, performance and consumers' reluctance to embrace the new technology [1]. The attitudes towards electric vehicles are quite diverse. Advocates of this emerging technology emphasize the social benefits resulting from the improved environmental performance of electric vehicles, while critics focus on the limited performance which causes distrust and nuisance to the vehicle owner.

The widespread adoption of electric vehicles in the future does not only depend on the performance of the vehicles, but also on the dynamics of the market. Like any emerging technology, electric vehicles are perceived either as a threat or as a new source of opportunities by different players in the car industry arena. The EV1 case was presented in the beginning of this report to illustrate the complex context surrounding EV technologies. The complexity stems from the conflicting interests of the players. Companies in the business of spare parts for conventional cars might be affected by the introduction of a new type of vehicle which may cause the demand for their products to drop. Companies in the oil and gas industry, such as Shell and BP, could feel directly threatened by the large scale introduction of new vehicles which do not drive on gasoline, but on electricity.

For governments, the widespread of electric vehicles could be an instrument to decrease the dependency on oil imports from OPEC members. In addition, pollution reduction is another important driver behind the EV introduction, since transportation is the main source of pollution, accounting for one third of all energy usage [7]. Also, a large scale diffusion of electric vehicles is likely to bring significant changes to the energy sector, for example, through potential impacts on the electricity grid [8] and the imminent introduction of a charging infrastructure. Such changes need to be signaled and accommodated in due time in order to ensure a proper coordination between different sectors of activity.

In addition, private investors also have an interest to support the widespread of EV technology, since it can bring new business opportunities. For example, the fast-food chain *McDonalds* has installed charging spots for EVs in some of their parking lots as part of their corporate social responsibility program [9]. Despite the initial investment for the installation of the charging stations and the additional electricity cost incurred, McDonalds sees an opportunity for additional profit in this strategy. Quick charging the battery of an electric vehicle takes roughly 30 minutes for the battery to be charged 80% and allow for a limited driving range. Since EV drivers, waiting for their cars to charge, will likely enter the restaurant and purchase the McDonalds products, the company estimates to recover its entire cost within two to three years [1].

The high level of complexity and uncertainty in determining technology roadmaps and planning corporate activities requires reliable tools to anticipate and analyze the consequences of future technological developments of electric vehicle technologies on the current state of the matter. Technological changes and the consequences of the widespread of electric vehicles can be identified using *technology forecasting* (TF). The generic term “technology forecasting” refers to the activity of identifying possible relevant technologies for an organization and covers all tools used in this activity [10]. TF is used to provide data about future technological developments or to gain insight about potential impacts these developments might have. The output of the technology forecasting activity *“is a quantified prediction of the timing and of the character or degree of change of technical parameters and attributes associated with the designs, production, and use of devices, materials, and processes, according to a specified system of reasoning”* [11, pp. 21].

From this point of view, TF can be carried out to identify and evaluate potential business opportunities brought about by the introduction of electric vehicles. For example, technology forecasting can be used by companies to evaluate market implications of this emerging technology and identify threats for the current status quo. Alternatively, TF may be able to point towards the need for developments of complementary products, such as batteries, which can help improve the performance of electric vehicles, or could identify a technology design that is likely to become the new trend for the auto industry in the future. Furthermore, TF results can also be used as input in governmental assessments of EV technology. Governments are interested in such information because it helps determine necessary programs for consumer and environmental protection, as well as identify technologies which might need governmental support to develop, or might affect other sectors of activity [11].

Now that the need for technology forecasting of electric vehicles is clear, it is important to identify a forecasting method which is suitable for this technology. In the present research, the purpose of performing EV forecasting is to analyze the technological progress of the EV technology over time. *Technological progress* or *technological change* can be interpreted as the total changes in the attributes of a product (e.g. quality, price, performance) over a given period of time [12]. Mishra et al. [13] state that "the quality of forecasts would greatly depend on proper selection and application of appropriate techniques" [13, pp. 1]. As will be explained below, two readily obvious problems need to be accommodated by the forecasting technique used to produce the forecast of electric vehicles:

- EV technology is not homogeneous, therefore the forecasting method used should allow for the simultaneous analysis of different EV configurations in order to measure and predict technological change over the whole class of EV technology.
- EVs are characterized by several performance attributes which may be differently valued by different user categories. Therefore the forecasting method should allow for multi-criteria evaluation of the technology performance and technological progress.

One of the main challenges for choosing the appropriate technique and producing meaningful forecasts is the inherently heterogeneous nature of many products. The heterogeneity stems from the multitude of ways products are being produced and used. This indicates that in order to measure and predict technological change for heterogeneous products, the method chosen should be able to accommodate the diversity of product characteristics [14]. The existence of several EV configurations shows that EVs are not homogeneous products. Electric vehicles can be classified as battery electric vehicles (BEVs) and hybrid electric vehicles (HEVs). The difference between the two 'families' of EVs is given by their drivetrain architecture. BEVs use an electric motor (EM) and a battery to propel the vehicle, while HEVs use both a conventional internal combustion engine (ICE) together with an EM and a battery. HEVs can be further classified as strong and mild hybrids, based on their degree of hybridization. The degree of hybridization is given by the extent to which the electric motor is used to propel the vehicle. A complete overview of available EV configurations and their particularities is provided in Appendix A.

All products are characterized by *performance parameters* and *technical parameters*. Performance parameters are those characteristics of the product which provide utility to the end user, while technical parameters are the characteristics which enable the product to deliver its performance to the user [15]. Not all the performance attributes are shared by the BEV and HEV families. For example, one of the main performance parameters for BEVs is the driving range. BEVs have a limited driving range due to their reliance on battery to power the EM, which is not the case for HEVs. For HEVs, one of the key performance parameters is the CO2 tailpipe emissions. This parameter is not shared by the BEV family, because BEVs are considered to release zero emissions while driving, since they run on electricity – the zero tailpipe emissions, however, exclude the CO2 produced as a result of the electricity generation process. This indicates the need to use a method which allows for simultaneous analysis of the different EV families, despite their differences in technical and performance parameters, in order to determine the technological progress over the full class of EV technology.

Furthermore, the differences in technical parameters (i.e. differences in the drivetrain structure) for each type of EV will lead to different performance parameters. In addition, users are also heterogeneous in their preferences for certain performance parameters, which means that different product attributes will be valued differently by different users [16]. Some vehicles offer better fuel efficiency, which makes them more economical; others offer more horsepower at the expense of a higher fuel consumption, which is more appreciated by fast car enthusiasts; others offer a silent drive and zero tailpipe emissions, which is important for environmentally-aware drivers. Each characteristic appeals to certain user categories, making it difficult to focus the EV technology forecast on a single parameter. This indicates that the forecasting method used should allow for a multi-criteria approach to provide a realistic evaluation of technological progress for EV technologies.

Inman [17] performs an extensive review of available tools for technology forecasting. Techniques which rely on historical data to determine past technological patterns and anticipate future states of technology, such as trend extrapolation, are recognized to be very useful. Yet these methods appear to be too rigid to fit the purpose of the EV forecast for this research.

First of all, such methods address an average of available technologies instead of focusing on the best performers. This means that the effect of outliers is averaged out over the data set, when it is actually the information about outliers which is most interesting for companies [17]. Since most companies aim to develop products which perform better than those of competitors, an analysis of average performance may not necessarily give them a complete picture of what they are competing against.

Secondly, extrapolative methods require predetermined weights for technology attributes and are too rigid to accommodate dynamic trade-offs between performance parameters.[17] As previously discussed, different EV attributes are not rated equally by all users, which makes it very hard to accurately assign weights to each attribute. Also, certain performance levels may often be too expensive to achieve. Companies will therefore need to make trade-offs between different performance parameters or between cost and performance in order to address a certain market segment.

Furthermore, extrapolative methods require that the performance variables used in the analysis be non-correlated, which is not always realistic. At the same time, these methods can analyze only a single aggregated output variable which limits the possibility to better evaluate future technology capabilities [17]. As was discussed earlier, a single-criterion analysis would not suffice in the case of electrical vehicles since EV performance cannot be described through a single parameter; and even if it could be, focusing on a single parameter would not account for the multiple development possibilities which can lead to technological progress.

Inman (2004) suggests that *data envelopment analysis* (DEA) is an alternative method which eliminates the described limitations of extrapolating techniques [17]. DEA is a mathematical method which allows for the evaluation of different organizations or products in terms of how efficient they are in producing a certain level of output by using a particular level of input. One specific advantage of the DEA method is that it can perform this evaluation using multiple input and output variables, without requiring a predetermined mathematical relationship between the variables. The ratio of the total weighed output to the total weighed input produces a single measure for productivity, which is called *relative efficiency* or *efficiency score*. In DEA, the organizations or products under analysis are called "decision making units" (DMUs). Each DMU is free to choose any combination of inputs and outputs in order to maximize its relative efficiency, which makes DEA capable of embedding dynamic trade-offs in its construction. Furthermore, DEA is an extreme point method, which means that it can analyze the products individually instead of providing data set averages. This allows for the possibility to evaluate the performance of outliers and identify the best performers. The best performers delineate the efficiency frontier, which sets the benchmark for the underperforming DMUs. The main limitation of DEA for technology forecasting is that it can only evaluate products at a given point in time, but it cannot provide information about changes in performance over several periods.[17- 20]

To cope with the limitations of extrapolating techniques and of the classical DEA method, scholars from Portland State University [17] developed a new forecasting method: *technology forecasting using data envelopment analysis* (TFDEA). TFDEA builds upon the assumption that the performance of a product or device (i.e. the output) is a linear function of the performance of its internal components (i.e. input). In this way past data can be used to calculate the rate of change which will then be used to forecast new technology frontiers. Unlike conventional techniques, TFDEA can simultaneously evaluate multiple technologies using multiple variables and identify the state-of-of the art frontier. The *state-of-the-art* (SOA) concept is defined by Dodson [21] as "the highest degree of technical accomplishment that could be achieved at a given time" [21, pp. 393]. TFDEA uses the efficiency frontier found with DEA to determine the SOA technology frontier, which contains the recognized superior technologies at different points in time. Next, the annual rate of change (RoC) in benchmarks is determined. The rate of change is then used to forecast future performance trendsetters [22]. The weaknesses of the method are the sensitivity to disruptive technologies and its reliance on the assumption of a constant *rate of technological change* (ROC) [10, 17, 22].

Using DEA makes TFDEA a more flexible method which can determine rates of technological change without assuming non-correlated attributes and static trade-offs. This corresponds to the requirements identified for the forecasting method needed for EV technology. Due to the advantages of TFDEA over other conventional methods, this research will use TFDEA as a method to determine and analyze technological progress of electric vehicles based on the past and current characteristics of EV technology. A broad overview of the TFDEA method will be provided in section 2.4 of this report. Remaining concerns are related to the inherent assumptions of the method of constant ROC and linear relations between inputs and outputs of technology. It has to be determined if these assumptions are valid in the case of electric vehicles, or if they can lead to errors in the forecast. These concerns will be addressed in this study.

1.1 Problem statement

This project was commissioned by SKF with the request to investigate the predictive capabilities of technology forecasting using data envelopment analysis (TFDEA) with respect to electric vehicle technologies. The evolution of the EV technologies is of great interest for SKF, since it can have a direct impact on the research and development focus of the company, and consequently on their sales and budget allocation.

SKF is a global company operating on five technological platforms: Bearings and units, Seals, Mechatronics, Services, and Lubrication Systems. According to SKF's Annual Report [23] for 2011, almost one third (29%) of SKF's sales in 2011 came from the automobile industry. These sales were distributed over customer segments as follows:

- Cars and light trucks: 12%
- Vehicle service market: 10%
- Trucks: 4%
- Two-wheelers and electric: 3%

These numbers show that a large proportion of the company sales come from sectors concerned with the manufacturing and maintenance of conventional vehicles, and only a very small percentage (3%) is generated by the electric vehicle sector. This is mostly due to the architecture of electric vehicles. While hybrid electric vehicles maintain most of the architecture of a conventional vehicle, battery electric vehicles contain very few moving parts, compared to conventional vehicles. Therefore the demand for SKF products may be limited in the EV market.

A very fast growth in the number of electric vehicles on the road and a decrease in the number of conventional vehicles could have technological consequences for SKF and similar companies which supply the conventional automobile industry. For this reason, it is important for the company to anticipate well in advance the technological progress of EV technologies and their diffusion on the market in order to develop early strategies that ensure the stability and prosperity of the company. Such strategies could, for example, target a change of R&D focus and budget allocation from existing projects for the cars and light trucks sector, towards applications that could better serve the electric sector, or towards other sectors with a lower level of uncertainty with respect to future developments.

The complex technical, social, economic and political background surrounding EV technologies makes it very difficult to anticipate the course the vehicle market will take in the future. It would therefore be useful to have a robust and easy to use forecasting tool which could help predict reliably technological developments of electric vehicles.

Technology forecasting using data envelopment analysis (TFDEA) appears to be a robust tool which can be used to measure the rate of technology change over time. Yet there are some open questions with respect to how useful the TFDEA method can be in analyzing technological progress of EVs. These questions stem mostly from the inherent assumptions of the method, such as constant rate of change and linear relations between technology inputs and outputs. From the available TFDEA literature and without further analysis of the EV technology system it is not clear if these assumptions are realistic in the case of electric vehicles. Additionally, TFDEA is a data intensive method, meaning that it requires a large amount of historical data. Therefore it has to be identified whether there is sufficient EV data available to produce meaningful EV performance forecasts using TFDEA.

1.2 Research gaps

The TFDEA method has been developed as a technology forecasting tool in 2001 by scholars at Portland State University in the United States and is claimed to cope with many of the shortcomings of popular forecasting tools such as regression analysis.[22] Since it was first introduced, there have been a few applications of the TFDEA algorithm with successful results.

- In 2001, Anderson et al. [24] were able to identify with the use of TFDEA that the open source software could potentially act as a disruptive technology for the traditional database systems.
- In 2002, Anderson et al. [25] obtained better forecasts for the introduction of integrated circuits with TFDEA than previously obtained with Moore's Law.
- In 2006, Inman et al. [22] performed a technology forecast on US jet fighter introductions from 1944 to 1982 using TFDEA A similar study had been done by Martino [26] in 1993, using regression analysis. The authors' conclusion was that TFDEA produced more accurate results for forecasting new product introductions, compared to regression analysis. One reason for that is the fact that TFDEA is built on data envelopment analysis (DEA), an econometric technique which does not share the problem regression has with multicollinearity. Therefore TFDEA makes it possible to analyze simultaneously more input and output variables compared to regression analysis [22].
- In 2008, Anderson et al. [27] made a step further in their research and used the method to successfully forecast the introduction of wireless communication systems. This was the first time when the method was used to include not only product innovation, but the service innovation perspective as well.
- In 2010, Lamb et al. [28] used the TFDEA algorithm to forecast introductions of commercial airplanes. The authors showed that TFDEA is a robust tool which can help overcome difficulties in the R&D decision making process such as external/ competitor

technology monitoring; necessary methods to help determine milestones reliably; necessary trend analysis/ forecasting.

Although the TFDEA method has already been applied to a few technologies, the literature on the topic is scarce and the application base of the method is rather limited. One thing to notice is that so far, the method has been applied on technology cases which had reached a certain level of maturity, but there is no indication in the TFDEA literature of whether the usefulness of the method and the reliability of the results produced with it depend on the maturity stage of the technology under study.

Furthermore, the available literature gives little indication of requirements for or amount of data to be used for the forecasts. The data used in the studies performed so far was gathered over large time windows (a few decades) and the technologies used as case studies, except for the wireless technology, were already rather mature at the point of the analysis. Therefore it is not clear from the previous research whether the method is suitable only for well-defined, conventional technologies, or if it can also be used for new, emerging technologies for which only limited data is available.

Moreover, the forecasts were performed using only technical inputs and outputs endogenous to the technology under study and very few validation tests have been performed to determine the capabilities of the method to foresee the impact of exogenous drivers, such as regulation or unexpected technical developments in sub-component technologies, substitute and complementary products, on technological progress.

1.3 Research objective

At present, there are several electric vehicle structures available on the market but it is not readily obvious from the existing vehicles or from announced plans of the manufacturers if there is a tendency for one of these structures to become dominant. For example, Toyota seems to be one of the market leaders who focus on plug-in vehicles mostly. Honda has been working on improving the integrated motor assist (IMA) drivetrain structure. Companies such as Renault announced intentions to only develop battery electric vehicles. And then there are companies such as GM, who have explored and released both hybrid and battery electric vehicles.

This research project aims to investigate whether technology forecasting using data envelopment analysis is a suitable method to determine which of the current electric vehicle technologies has potential to become dominant in the future. For the method to be suitable in this situation, the EV data availability should fulfill the requirements of the TFDEA method. In addition, the inherent assumptions of TFDEA should be compatible with the design principles of electric vehicle technologies. Since there is no indication in the TFDEA literature whether the method is more suitable for particular technologies than for others, the only way to determine the applicability of TFDEA in the case of electric vehicle technologies is to apply the method as was developed by Inman et al. (2004) and analyze the results.

Therefore, technology forecasting using data analysis will be carried out on electric vehicles with the scope to analyzed how the EV data availability and the assumptions of the TFDEA model impact the results of the EV forecast. In addition, it will be verified, based on the results of the forecast, whether the TFDEA assumptions can be held valid in the case of electric vehicles.

1.4 Research questions

Following from the research objective, the main question for this research project is:

Q1. To what extent can the TFDEA method be used to identify a potentially dominant EV design in the future?

Before attempting to answer this question, it has to first be determined whether the method is applicable for the EV technology case. Therefore the following question and its sub-questions need to be answered:

Q2. Can the method be implemented given the current state of EV technology?

- What are the consequences of data availability for the application of the method?
- Is the DEA assumption that technology outputs are a linear function of technology inputs supported by vehicle design theory?
- What are the implications of assuming a constant rate of change on the accuracy and validity of the forecasts?
- Can the method anticipate the consequences of external factors such as innovation in substitute and subcomponent technologies, or regulation of performance parameters, such as fuel economy and CO_2 emissions, on the technological change of EV technology?

1.5 Contribution of the research

This analysis adds to the limited TFDEA literature by further applying the method to the EV technology. The EV case study served to identify further limitations of TFDEA method caused by its inherent assumptions and reliance on a large amount of data.

These limitations are presented below:

- TFDEA is very data intensive, which constitutes a problem for emerging technologies for which only a few products have been introduced.
- The number of variables which can be included in the analysis is limited by the number of products in the data set, therefore the fewer the products available, the fewer the number of variables which can be used. This is a disadvantage for complex technologies characterized by many attributes.
- The DEA model does not require predetermined mathematical relations between inputs and outputs or pre-assigned weights for each variable. Yet, the quality of the forecast depends mostly on the selection of variables used. This means that the forecaster should have sufficient knowledge and understanding of the technology under study and its operation mechanisms to be able to select the right set of variables.
- Even in situations when the technology is more mature and sufficient data exists, product data confidentiality can impact the quality of the forecast. TFDEA requires information on the inputs of a technology, but much of the manufacturing related information which could be used to determine technological progress, such as manufacturing costs, for example, will not be disclosed by companies. Therefore forecasters may find themselves constrained to a limited choice of variables for which data can be acquired. This limits the possibility to investigate the full range of opportunities for technological advancement.
- TFDEA is very sensitive to exogenous drivers of technological change. The EV case study shows that the approach to evaluate the performance of a technology as a linear function of its inputs is an oversimplification which cannot be used for complex technologies with economic and socio-political implications.
- Using a constant ROC for forecasting is not realistic, because innovation does not occur at a regular pace. Such an assumption can be valid in situations when historical data is able to identify that the technological progress remained constant over the years and no external forces are expected to cause disruptions. If this is not the case, the forecast will be biased by the reference data set used to produce it. Using as reference data from a year with a relatively low rate of change can lead to underestimations of future performance, as could be seen from the results of the HEV model. Alternatively, choosing a reference year with a large rate of change, may predict non-sustainable improvements in product performance.
- The model could, provide a simple and easy to use forecasting tool for established technologies which have shown constant progress over time, given that no exogenous forces are expected to influence the technological change.

- TFDEA could be used for forecasting simple technologies whose performance can be expressed with very few attributes, and whose performance is not targeted by governmental regulation.

In addition, this research has a practical contribution by analyzing the applicability of TFDEA with respect to the SKF interest. The present study has indentified that TFDEA is not a suitable method for analyzing technological progress of electric vehicle technologies due to the high sensitivity to exogenous drivers and its limited capability to anticipate the introduction of potentially disruptive design configurations. It was identified that a simple analysis of technological progress based on the current state-of-the-art technology would not be able to provide a realistic indication of whether a certain EV configuration could become the dominant design in the auto industry. There seems to be a recognized need for introducing electric vehicles on a large scale, for reasons of national security, oil resource depletion, air quality concerns etc., which means that it can be expected that technological progress of EVs will be accelerated by external factors. Therefore additional research on developments and innovations in supporting technologies (e.g. battery technology, battery charging stations, smart grid technologies), is required in order to get a clearer picture if and when there will be a transition towards a certain EV configuration.

A by-product of this project is an extensive data list of available electric vehicles and their technical specifications, which can be used by SKF for internal purposes.

1.6 Structure of the report

Section 2 provides a literature review on technology forecasting and the TFDEA method. This section will explain how technology forecasting can improve the management of technology and what tools there are available to perform technology forecasting. The limitations of conventional forecasting tools are summarized and a detailed description of TFDEA is provided.

Section 3 will carry out an EV technology system analysis to provide understanding of the basic principles of the electric vehicle technology. This is necessary for identifying the main EV attributes. This section will use the general concept that technologies are modular architectures created from combinations of existing technologies [29], to describe the electric vehicle as a modular system and understand its mechanisms. The section will conclude with the selection of DEA variables. To avoid confusion, it should be noted that the focus in this section is to determine those factors that can influence the technical performance of an electric vehicle. Factors determining the successful market penetration, such as consumer preferences and policy instruments, will not be addressed here.

Section 4 describes the data used for this analysis. The two types of EVs are structurally different and are characterized by different performance parameters. For these two types of products, a data set was collected, containing respectively all the BEVs and HEVs released and commercialized on a large scale between 1997 and June 2012. The data set comprises of 106 electric vehicles, out of which 64 are HEVs and 42 are BEVs. The information collected for each product is described in section 4.1. The complete data set is provided in Appendix C.

Section 5 describes the steps taken to apply the TFDEA method, as was developed by Anderson et al. [24] and summarized in section 2, to the EV case study. Once the inputs and outputs for the DEA model were selected and the data collected, the TFDEA method could be applied to identify the state-of-the art frontier and evaluate the technological progress of electric vehicle technologies.

Section 6 presents the results and discussion of the TFDEA carried out on EV technologies. The results are forecasts of future frontiers produced with the three models described in section 5. The forecasts were verified for accuracy against a set of existing products. Then, it was analyzed how the data availability and the assumptions of the TFDEA model impact the results of the forecast. In addition, it was verified, based on the results of the forecast, whether the TFDEA assumptions can be held valid in the case of electric vehicles. The discussion of the results and potential threats to validity conclude this section.

Conclusions and recommendations are presented in section 7.

2. Literature review

The high level of complexity and uncertainty in determining technology roadmaps poses challenges for managers of technology. Technology forecasting is an activity which can help the decision making and planning processes by providing estimates of future performance parameters of a technology. Several tools are currently available to perform technology forecasting. This section will begin by describing technology forecasting and clarifying its purpose. Next, the limitations of conventional forecasting tools are summarized. Then the focus will narrow down to introduce TFDEA as a new, superior method for technology forecasting and describe its algorithm.

2.1 Technology forecasting for better management of technology

In 1969 Martino [30] was writing for the first issue of the "Technology Forecasting" journal that the "advance of technology is outstripping society's ability to control it" [30, pp.73]. The rapid changes in the technology arena have transformed the structure of market competition by causing an increase in investment opportunities to occur. Over the past century, technology has become one of the main instruments which add value to a business, hence proper management and planning is required to create a competitive advantage for companies. Needless to say, integrating emerging technologies into existing investment plans is not a trivial task [31].

Development teams are responsible for planning activities and milestones for deliveries of future products and services. Planning a new high-technology business requires a great deal of technical and commercial decisions to be taken prior to the launch of the new product [32]. Strategic decisions made by technology managers with respect to new product introductions are often hindered or influenced by technical, economic, political and environmental drivers. Lane et al. [28] made an inventory of target-setting difficulties for R&D departments based on literature review. The following factors were enumerated as main obstacles in the R&D decision making process: external/ competitor technology monitoring; necessary methods to help determine milestones reliably; necessary trend analysis/ forecasting; vision driven/ need to depart from neutrality; difficulties in choosing the pursuit of incremental or breakthrough technology development; necessary methods to identify sub-technology components and their relationships; alternatives to reduce costly R&D operations. Therefore proper management of technology requires understanding of the technology capabilities, as well as of the conditions which need to be created to accommodate technological developments [4, 11-15].

Technology forecasting (TF) emerged in the 1960's in an effort to anticipate research and development activities important for the U.S. Air Force and has become over the years a common practice in trying to anticipate relevant technological breakthroughs, as well as to determine the necessary course of action to achieve a particular state of technology within a given period of time [11]. TF provides the means to identify characteristics such as needed performance and timing of new products which help ensure a competitive position for the firm.

Such data helps long-term planning by giving an indication of necessary resources such as facilities and human capital.

TF enables the understanding of different technological contexts, which means that it can help anticipate technological changes and their potential consequences. From this point of view, TF can be seen as an activity to identify and evaluate potential business opportunities or implications of technology for private or public actors. For example, technology forecasting may be able to point towards the need for a scientific breakthrough or could identify a technology that is likely to become of great technical importance. Alternatively, TF can be used to evaluate market implications of new products and processes and identify threats for the current state of business. TF results can also be used as input in governmental assessments of technology. Governments are interested in such information because it helps determine necessary programs for consumer and environmental protection, as well as identify technologies which might need governmental support to develop [11, 12, 21].

2.2 Technometrics for technological forecasting

Creating a meaningful forecast requires extensive knowledge of the technology itself, as well as a good understanding of the technological innovation process. It is important to understand how technologies emerge and develop and more importantly, which are the forces that shape this evolution process. For this reason, it is necessary to have reliable tools to measure and monitor technological progress. The recognized need to measure technology and its implications [12] led to the emergence of a new discipline, called *technometrics*.

Technometrics was initiated in the 1950's by scholars of the RAND Corporation [12] with the purpose to develop a framework to measure technological advantages between different nations. Technometrics uses interdisciplinary knowledge from mathematics, economics, statistics and engineering to develop quantitative methods for evaluating technological characteristics. Some technometric methods use the system approach to represent technology [12]. Coccia [12] cites Sahal (1981) to indicate that this is the most suitable approach to analyze technology. Evaluating technology as a system provides understanding of the technology "in terms of certain measurable, functional characteristics", [12, pp. 946] and provides the means to measure technological change, as opposed, for example, to the neo-classical approach, which treats technology as a production function.

Technology forecasting is one area of application of technometric methods, next to operations research or government planning for national research. The object of technometrics is to provide mathematical tools to evaluate measures of technological performance such as:

- *Productivity* (i.e. maximizing output with minimum resources) [12]
- *Quality* (i.e. the utility provided by the essential attributes of a product) [12]
- *Technological change* or *technological progress* (i.e. the change in the quality of a product which occurred over a given period of time) [15]

- *State-of-the-art technology* (i.e. the best available technology at a given point in time) [21]
- *State-of-the-art surface* (i.e. an n-dimensional space containing all the combinations of relevant attributes of a product, with the remark that while moving along the surface, different design parameters are traded-off for others, without decreasing the efficiency level of the product) [21]
- *Technological advancement* (i.e. a shift in the SOA surface which indicates that at least one attribute of the product has been improved, without decreasing any of the others) [12]

After the functional characteristics of the technology have been identified, most technometric models use statistical methods to determine *the rate of technological change* which is the speed with which technological progress occurs.

2.3 Traditional technology forecasting tools

Several technometric techniques have been developed to facilitate the forecasting activities. Some of them rely on complex mathematics, others on expert judgment. These techniques are built upon one or more of these three assumptions [11].

- Technology evolves in an orderly pattern which can be identified through analysis of historical data and extrapolated to the future.
- Technology appears as a response to needs, opportunities and availability of resources, therefore technological progress can be anticipated through proper identification of the drivers and stoppers of the technology under study.
- New technologies stem from existing technology therefore technology forecasting can be achieved through analysis of technological innovation.

There is significant debate in the literature over the superiority of one technique over another [10]. Each method is more suitable in particular situations, therefore the TF method employed should be chosen based on the context of the technology, the stage the technology is in and the data availability [11, 13]. Common TF methods can be grouped into three categories:

- Subjective assessment methods of TF: committees of executive opinion, formal surveys and market-based assessments etc.
- Exploratory methods of TF: Delphi method, scenario analysis, morphological analysis, curve fitting and envelopes, game theory, trend extrapolation etc.
- Normative approaches to TF: relevance trees, system dynamics etc.

Conventional TF methods are described extensively in the literature and will not be repeated here. For a detailed overview, the reader is referred to [11, 13,17, 18]. These methods can provide valuable insight into the evolution of technology trends, however they have significant limitations.

- Qualitative forecasts based on consultation of experts always carry the risk to be influenced by the individual bias of the participants. First of all, it is often difficult for the study organizer to identify the appropriate experts to consult. In the case of the Delphi method, the number of rounds and the quality of experts can affect the accuracy and reliability of the results. In addition, the technique is very time consuming and results may often be difficult to interpret since they are based on a compilation of expert opinions which can sometimes be contradictory.[11, 13]
- Econometric (parametric) methods tend to focus on the process measures and often ignore outcome measures. In addition, they require quantification of output and input measures and explicit formulation of input-output relationships. In practice this may not always be a suitable approach due to the complexity of input-output relationships which cannot easily be translated into mathematical formulas.[18]
- Regression models are quite robust, but they do not allow for multiple inputs and outputs and the analysis is restricted to a single dependent variable. Also, the result of regression analysis is an average line across all observations and such methods, based on averaging performance over many observations, do not give an indication of *the best* available technology.[17]
- Trend extrapolation requires appropriate understanding of the forces that have caused the past trend. Forces impacting the evolution of technology may change over time; therefore the forecaster is expected to have a good grasp of both past and future drivers of progress when analyzing the trends. At the same time, it is recognized that trend extrapolation loses its validity over time; hence it may not be suitable for long-term forecasting.[11]
- Conventional extrapolative methods generally provide one estimate for model success, but they do not provide any feedback for improvement. On the other hand, econometric approaches offer a better predictor for future performance at the collective unit level if the assumed inefficiencies cannot be eliminated.[18]
- Conventional extrapolative methods fail to account for the possibility of changing preferences and dynamic trade-off decisions. In addition, some of the used methodologies require that the technology attributes be independent, which is often difficult to achieve in practice due to insufficient understanding of a given technology.[17, 33]
- DEA is a non-parametric method which does not require mathematical specification of functional relations between input and output. It has the capability to analyze multiple inputs and outputs simultaneously and to produce an efficiency frontier that contains the best performers. The main limitation of DEA for technology forecasting is that it can only evaluate products at a given point in time, but it cannot provide information about changes in performance over several periods.[17- 20]

Unlike conventional techniques which make use of regression analysis, TFDEA applies a non-parametric method, which means that it does not assume that the data follows a certain probability distribution. This leads to one of the main differences [18] compared to conventional forecasting tools based on stochastic methods, namely the tolerance to the noise in the data set. Stochastic methods are less sensitive to noise generated by measurement errors, since they are able to average it over the data set, or filter it out during the data interpretation. The non-parametric approach, on the other hand, analyzes performance only based on a certain population, and evaluates the individual efficiency of each observation, relative to the other observations in the data set. Therefore measurement errors will not be accounted for, but they will be evaluated as part of the performance of an observation, making TFDEA result more likely to be affected by measurement noise.

2.4 Technology forecasting using data envelopment analysis

In order to cope with the shortcomings of traditional forecasting methods described in the previous section, Anderson et al. [24] developed technology forecasting using data envelopment analysis (TFDEA) as a new method for technology forecasting. As opposed to conventional techniques, TFDEA focuses on the best technology available. TFDEA is able to forecast and estimate the availability of future characteristics of a particular technology and can simultaneously evaluate multiple technologies. The weakest points of the method are the sensitivity to disruptive technologies (i.e. technologies which produce a change in the behavior of users, or attain levels of superior performance using innovative techniques [34]) and its reliance on the assumption of a constant rate of technological change.[10, 17, 22]

TFDEA makes use of the data envelopment analysis (DEA) technique, which gives it the capability to analyze multiple inputs and outputs simultaneously and produces an efficiency frontier that contains the best performers [19].

The remaining concerns arise from the sensitivity of the TFDEA method with respect to disruptive technologies and the assumption of a constant rate of change obtained from historical data. This is not always consistent with the nature of technological change and may lead to errors in long-term forecasting.[10, 17,22]

2.4.1 Data envelopment analysis (DEA)

Data envelopment analysis (DEA) is recognized in the literature as a powerful method, more suitable for performance measurement activities than traditional, econometric methods such as regression analysis and simple ratio analysis.[17- 20, 22, 25, 33]

Data envelopment analysis (DEA) is a mathematical method using linear programming techniques to convert inputs to outputs with the purpose of evaluating the performance of comparable organizations or products [18]. One specific advantage of the DEA method is that it can perform this evaluation using multiple input and output variables, without requiring a predetermined mathematical relationship between inputs and outputs. In DEA, the organizations which are evaluated are called "decision making units" (DMUs).[17- 20]

Linear programming is a mathematical programming technique which helps create and solve optimization problems with linear objective functions and linear constraints. "Mathematical programming (MP) is a field of management science that finds the *optimal* or *most efficient* way of using limited resources to achieve the objectives of an individual or a business. For this reason, mathematical programming is often referred to as optimization."[35, pp. 17]

The goal of the optimization problem is to determine the values of the decision variables which maximize or minimize the values of the objective function without violating any of the constraints. The objective function identifies a function of the decision variable which needs to be either maximized or minimized by the decision maker. The mathematical representation of an objective function in an optimization problem is MAX or MIN, based on the case. The constraint is a function of the decision variable that must be equal to, greater than or less than a specific value.[35]

The 'relative efficiency' concept

In DEA, each DMU is free to choose any combination of inputs and outputs in order to maximize its relative efficiency. The *relative efficiency* or the *efficiency score* is the ratio of the total weighed output to the total weighed input.[17- 20]

DEA uses linear programming to estimate relative efficiency. The relative efficiency, denoted by θ or ϕ, is the efficiency score allocated to a decision making unit as a result of the data envelopment analysis. This relative efficiency is a non-negative value calculated based on linear relations between the inputs and outputs of the DMUs under analysis. In order words, it determines how efficient a DMU is in producing a certain level of output, based on the amount of input it uses, compared to similar DMUs. The main assumption behind the DEA method is that if the most efficient DMU produces Y output with X input, the other DMUs are expected to produce the same.

The most efficient DMU will have an efficiency score of 1.0. If a particular DMU uses more input to produce the same output, or produces less output with the same input as the most efficient DMU then this DMU is considered inefficient and will get an efficiency score lower or higher than 1.0, based on the orientation of the DEA model. The efficiency score is not an absolute value, but it is calculated relative to the other units included in the analysis, which means that the efficiency of a DMU is influenced by the choice of DMUs included in the analysis. [17-19]

The basic principle of DEA is that the efficiency of a DMU is measured relatively to other similar DMUs by identifying 'a best practice' frontier with the restriction that all DMUs lie on or below the efficiency frontier.[33]

DEA – strengths and weaknesses

DEA is a non-parametric method which does not require mathematical specification of functional relations between input and output. It has the capability to analyze multiple inputs and outputs simultaneously and to produce an efficiency frontier that contains the best performers. This means that DEA measures the performance of a DMU against the performance of the most efficient DMU instead of the average performance. In addition DEA is able to provide diagnostic information which is useful in defining measures to correct for the underperformance of certain units. This gives the decision makers more flexibility in adjusting their strategies to increase the efficiency of certain units.[17- 19, 22, 33]

There seems to be general agreement in the literature that the DEA method has three major weaknesses: the impact of omitting variables, the impact of outliers and the impact of missing observations. Donthu et al. (2005) investigated the impact of these three factors on the results of DEA. Their main conclusion is that the variable choice plays a major role in the analysis, therefore inputs and outputs need to be carefully considered. Furthermore, outliers can also introduce large errors in the results. On the other hand, the method is not very sensitive to omitted observations.[18, 33]

Applications of DEA

The DEA method can be performed in order to [17, 18]:

- determine the efficiency frontier and rank efficient and inefficient units based on their relative efficiency scores;
- determine how far from the efficiency frontier the inefficient units are;
- determine targets for improvement for the inefficient units through virtual production of these units onto the efficiency frontier;
- identify technical and allocative inefficiencies;
- identify and quantify the sources for inefficiency;
- evaluate the progress of a DMU over time;

2.4.2 DEA as part of the TFDEA method

Using DEA makes TFDEA a more flexible method which can determine rates of technological change without assuming non-correlated attributes and static trade-offs. It has to be pointed out that in the context of TFDEA, DEA is not used for its conventional purpose of optimizing performance by increasing the output-to input ratio. TFDEA uses the efficiency frontier found with the DEA model in combination with the 'state-of-the-art' (SOA) technology concept, to delineate the technological frontier at a certain point in time.[27] In the context of TFDEA, DEA has the sole purpose of *ranking products as state-of-the-art when they obtain an efficiency score of 1.0, or as non-state-of-the-art, when their efficiency score is different from 1.0.* Thus the standard DEA vocabulary will be translated into TFDEA vocabulary as follows:

- The *decision making units* (DMUs) in DEA represent the *products* in TFDEA.
- The *efficiency score* determined by the DEA model becomes the *technology index* in TFDEA and shows the position of a product relative to the SOA frontier.
- An efficiency score of 1.0 indicates in DEA an *efficient DMU*, which in TFDEA will be referred to as *best-performer* or *SOA product*.
- A score higher than 1.0 for an output-oriented DEA model refers to an *inefficient DMU*, which in TFDEA will refer to an *under-performer* or *non-SOA* product.

2.4.3 The TFDEA process step-by-step

This section describes how the TFDEA process, as designed by Anderson [24] and Inman [17]. All relevant details which will be used in this report to apply TFDEA on the EV technology are summarized in this section. For a complete description of TFDEA, the reader is referred to [17, 22, 27, 28].

The TFDEA algorithm builds upon the DEA algorithm and consists of the sequence of steps indicated below [17]:

1. Determine the scope of the forecast
2. Define a product
3. Define SOA characteristics
4. Determine the DEA model
    a. Orientation
    b. Returns to scale
5. Collect data

6. Analyze technological Progress
   a. Mapping technological progress
   b. Time considerations
   c. Forecasting future technologies
7. Examine results

TFDEA step 1: Determine the scope of the forecast

The purpose of the technology forecast under discussion is to determine the current state of the EV technology and to determine how the EV performance will evolve in the future. When applying TFDEA, it is recommended that the scope of the forecast be chosen as broad as possible, as to facilitate a better understanding of the technological context of the technology under analysis. The advantage of using a DEA-based model is that several attributes can be evaluated which means that different market segments can be analyzed at the same time. Choosing a broader scope of the forecast (i.e. analyzing multiple market segments), could lead to a more meaningful analysis and might offer the possibility to detect potentially disruptive technologies.[17]

TFDEA step 2: Define the product

Once the scope of the forecast has been determined, the products to be analyzed have to be defined. This products are the decision making units (DMUs) used in the DEA model. These DMUs need to be similar in terms of functionality and need to be screened under similar market conditions for the comparison to be relevant.[17, 18]

One additional attribute that has to be available is the release date for each product. [17] This is not required to determine the state of the art technology, but it is necessary in the later phase of the TFDEA when the technological change has to be calculated.

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TFDEA step 3: Define SOA characteristics

Once the product has been defined, the relevant attributes of the technology have to be selected. "An attribute is the qualitative description of a characteristic of the technology or its performance." [11, pp. 72]. In order to identify the important attributes, the structure, production and usage of the technology need to be analyzed.

Inman [17] references Alexander (1973) to classify technology characteristics as either functional or structural and to describe technology as 'the ability of structural characteristics to deliver functional characteristics' [17 pp. 84-85]. The structural characteristics can be seen as the physical structures of the technology, while the functional characteristics can be interpreted as the purpose the technology serves. Further, the concept of technological change is related with 'the change in efficiency with which the structural characteristics provide the functional characteristics' [17, pp. 85].

To identify the EV technology characteristics a system analysis s is performed in section 3. In the case of electric vehicles, the structural characteristics are the characteristics of the different components of the vehicle drivetrain which work together to help operate the vehicle, while the functional characteristic is to provide transportation within the performance requirements, as will be explained in section 3.

The DEA model converts inputs to outputs in order to determine the relative efficiency of a particular product. This differentiation between functional and structural characteristics is very helpful because it facilitates the selection of input and output variables. The SOA characteristics at a certain moment will then be identified by analyzing the DEA efficiency scores of the existing products at that particular point in time.

TFDEA step 4: Determine the DEA Model

The choice for a particular model should be driven by the 'overall objectives of the technologies being analyzed' [17, pp. 85] There are several DEA models to calculate the efficiency scores for the DMUs. A comprehensive list of existing DEA models with their equations and constraints can be found in [20] and will not be repeated here.

In order to determine the efficient (i.e. 'best practice') frontier using DEA, one can choose between DEA input-oriented and output-oriented models, based on the objective of the technology under study. An input-oriented model is used when the target for the product under analysis is to minimize its input for a given output. An output-oriented model is used when the scope is output maximization for a given input.

For the EV technology and output oriented model will be used. The mathematical construction of this model will be summarized in the next section.

DEA output-oriented (OO) model

Very simple models with small numbers of DMUs and input/output variables can be calculated by hand. However, for most problems the data set is more complex and requires the use of linear programming software. Several DEA software packages are commercially available to solve data envelopment analysis problems. These software packages are built based on the algorithm explained below.

The efficiency score for the output oriented model is denoted by ϕ. DMU_k is one of the *n* DMUs from the data set. Each DMU has *m* inputs and *s* outputs. Parameters x_{ik} and y_{rk} are the *i*-th input and *r*-th output of DMU_k. Variables λ_j are positive scalars, representing the weight of DMU_j used to set the target for DMU_k under evaluation. DMU_k is compared against the best possible combination of the other DMUs to determine its efficiency score.

The objective function of the output-oriented model is to maximize the efficiency score by maximizing the output produced while keeping the input at the same level. The mechanism to calculate the objective function is presented in equations (1) - (3).

For *DMUk*

$$\max \phi_k \qquad (1)$$

Subject to:

1. The summation of the weighed combination of inputs of the other DMUs is lower than or equal to the level of input used by DMU_k under evaluation.

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ik} \quad \forall i \in \{1,\ldots,m\} \qquad (2)$$

Where: *k* is the index of the DMU under analysis, j = 1,…, n; i = 1,…, m; r = 1,…, s and $\lambda_j \geq 0$

2. The summation of the weighed combination of outputs of the other DMUs is higher than or equal to the level of output produced by DMU_k under evaluation.

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq \phi_k y_{rk} \quad \forall r \in \{1,\ldots s\} \qquad (3)$$

Where: *k* is the index of the DMU under analysis, j = 1,…, n; i = 1,…, m; r = 1,…, s and $\lambda_j \geq 0$,

$$\phi_k \geq 0$$

If θ_k equals 1.0, then DMU_k is considered efficient. If it is higher than 1.0, it is implied that DMU_k produces too little output for the level of input it uses, compared to the other DMUs [17]. The efficiency scores of each DMU are used to determine the empirical best-practice frontier or the efficiency envelope. The envelope is used to set a benchmark for inefficient units or inferior products.[20] The efficiency scores can be used as indicators of the SOA technology during a certain period of time.

Returns to scale

The ‘returns to scale’ concept refers to situations when changes in the size of the input and/or output determine changes in efficiency. For technologies where returns to scale influence the state-of-the-art of the technology, the appropriate constraint for the returns to scale model variant should be added to the selected DEA model. There are four variants of returns to scale [17, 20]:

- constant returns to scale (CRS) – when the output/input ratio remains constant regardless of the size of the input;
- increasing returns to scale (IRS) – when the output/input ratio increases the larger the amount of output and input becomes;
- decreasing returns to scale (DRS) – when the output/input ratio starts to decrease with an increase in "input beyond points of infliction" [17, pp.61];
- variable returns to scale (VRS) – in situations when there is both a minimum cost of entry and diminishing returns.

When returns to scale are considered, the suitable constraint from the ones listed in Table 1 need to be added to the pre-selected envelope model.

Table 1 Returns to scale: additional constraints [17, pp. 61]

Returns to Scale	Additional constraint
Constant	$\lambda \geq 0$
Increasing	$\sum \lambda \geq 1$
Decreasing	$\sum \lambda \leq 1$
Variable	$\sum \lambda = 1$

DEA Example

In order to illustrate the DEA model, a simple example is provided, using a small sample of the electric vehicles data to be investigated further in this report.

a) Determine the scope of the DEA:

The analysis is performed to determine the state-of-the-art frontier for battery electric vehicles for 4-5 passengers currently available on the market.

b) Define DMU:

For this analysis, a DMU is a 4 or 5 seat electric vehicle which has been and/or still is being mass produced. Assume, for the sake of simplicity, that the only attributes of interest for evaluating the efficiency of BEVs are the electric range and the battery capacity of each vehicle.

c) *Determine the inputs and outputs of the DEA model:*

The range of an electric vehicle is mainly determined by battery capacity; therefore the input will be considered to be the battery capacity and the output will be the electrical range.

d) *Select DEA model*:

An efficient car should be able to drive the longest range using the least battery capacity. For this reason, an output-oriented model will be used.

e) *Collect the data:*

The data to be used in this example was collected from various on-line sources and is part of the data set to be used further in the analysis section of this report.

Table 2 DEA example - Electric vehicles data set

EV	OEM	Product	Release date	Input Battery capacity [kWh]	Output Range [km]
1	Honda	EV-Plus	Jan-97	26	210
2	Nissan	Leaf	Dec-10	24	160
3	PSA/ Peugeot	Peugeot iOn	Dec-10	16	160
4	Mitsubishi	I-Miev (M Grade)	Jul-11	10.5	120
5	BMW	BMW Active E Concept (1 Series Coupe series)	Sep-11	32	160
6	Volvo Cars	Electric C30	Oct-11	24	149
7	Renault	Fluence Z.E.	Jan-12	22	185
8	Honda	Fit EV	Jun-12	20	200

f) *Perform the output-oriented DEA:*

An output-oriented DEA model will be used to determine the efficient and inefficient vehicles. Since this is a very simple exercise with a small number of DMUs, the DEA model was performed with a simple Excel Spreadsheet. More complex models with several inputs and outputs require designated software.

First, the output/input ratio will be determined for each product (Table 3):

Table 3 Output/input ratio of the DMUs

EV	Input (x_j)	Output (y_j)	output/input
1	26	210	8.08
2	24	160	6.67
3	16	160	10.00
4	10.5	120	**11.43**
5	32	160	5.00
6	24	149	6.21
7	22	185	8.41
8	20	200	10.00

Since the target is to achieve as much range as possible with as little battery capacity, the 'best performing' vehicle is the one with the largest output/input ratio, namely EV4, with a ratio of 120/10.5.

For EV1 to be efficient, with a battery capacity of 26 kWh, it should be able to achieve a range of:

$$y_1^{'} = 26 \times \frac{120}{10.5} = 297.14 \text{ [km]}$$

The next step is to determine the efficiency score of EV1 by applying equation (1):

$$\phi_1 = \frac{y_1^{'}}{y_1} = \frac{297.14}{210} = 1.41$$

This means that for EV1 to be considered efficient, it should reach 1.4 times more range than it currently does using a 26 kWh battery capacity.

The same process is repeated for the rest of the vehicles and the results are recorded in

Table *4*.

Table 4 DEA example - EVs efficiency scores

#	Input x_j	Output y_j	Output/Input	efficiency output $y_j^{'}$	efficiency score ϕ_j
1	26	210	8.08	297.14	1.41
2	24	160	6.67	274.29	1.71
3	16	160	10.00	182.86	1.14
4	10.5	120	**11.43**	120.00	1.00
5	32	160	5.00	365.71	2.29
6	24	149	6.21	251.43	1.69
7	22	185	8.41	251.43	1.36
8	20	200	10.00	228.57	1.14

From the efficiency scores it looks like the only efficient EV is EV4, since it is the only one which scores 1.0. The SOA frontier will therefore be determined by EV4 and the projections of the other EVs onto the efficiency frontier. In other words, the SOA frontier will be a line comprising of the output of EV4 and the 'efficiency outputs' of the other vehicles, as can be seen in Figure 1:

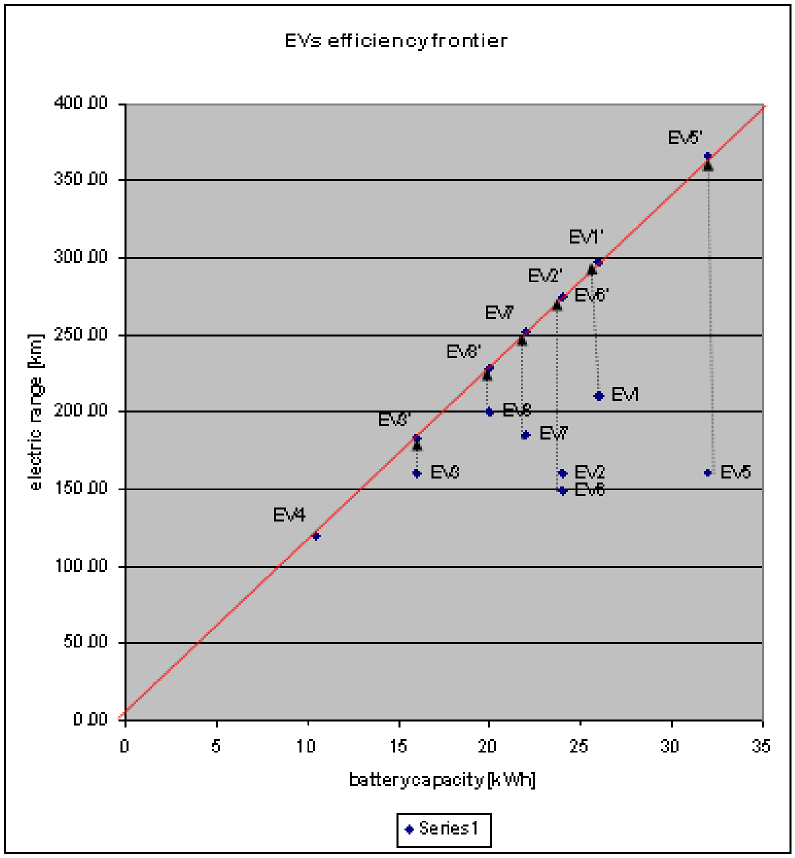

Figure 1 Efficiency frontier for EVs

g) Analyze DEA results:

When checking the results and the shape of the frontier it looks like it is possible to increase the electrical range and decrease the battery capacity used infinitely. In reality this is not the case due to technology limitations. It may not be physically possible to decrease the battery capacity below 10.5 kWh (the input of EV4) and still achieve a reasonable electric range. Also it can happen that even if the existing technology allows for better output to input ratios, it may become too expensive, and hence an unattractive solution, to improve efficiency past the performance level of EV4. In order to obtain more realistic results, the variable returns to scale constraint should be applied and the analysis performed again.

TFDEA Step 5: Data collection

One of the advantages of the TFDEA method is that it can manage multiple input and output variables with different units and without placing a requirement on the independence of the variables. Still, a few guidelines should be respected for the data collection. The following requirements were laid out by Inman [17]:

- The data set to be used for the analysis consists of all instances of the technology (i.e. all products) under study previously released.
- For each product, all the technology attributes identified at step 3 of the TFDEA algorithm have to be available, including the release date of the product.
- TFDEA data has to be discrete and has to have well defined values.
- Sufficient "past history" [17, pp. 160] data should be available, meaning that only technologies which have existed for several periods should be chosen for the analysis.
- A sufficiently large data sample has to be available. A rule of thumb for the size of the data set is that the total number of observations used in the DEA analysis should be around three times larger than the number of input and output variables used.
- The technology attributes used in the DEA model are shared by all products.
- The products used in the analysis should fulfill similar functions and be observed under similar market conditions.

TFDEA step 6: Technological progress analysis

The DEA model is run iteratively, starting from the first product released, and with each run adding a new product in the model, until all the products in the data set have been evaluated. This means that the efficiency score of the product introduced the last is calculated relatively to all previously introduced products. The earlier products used to determine the relative efficiency of the newest product constitute the 'Reference Set'. The newest product in each model run is referred to as *DMU (or the product) under analysis*.[24]

Once all products have been evaluated, the SOA surface is mapped to the DEA efficiency frontier by turning the efficiency score into a technology index. The technology index indicates the position of a product relative to the position of the SOA. The DEA score $\phi_k^{t_k}$ becomes the technological index for the position of product k relative to the SOA surface at t_k, the release date of the product.[17]

Mapping technological progress

To determine the technological change, the following equations are used, where $\gamma_k^{(t_k+1)}$ represents the technological change of product *k* with respect to the SOA frontier at time t_k.

$$\gamma_k^{(t_x+1)} = \frac{\phi_k^{(t_k+1)}}{(\phi_k^{t_k})} \qquad (4)$$

- If $\gamma_k^{(t_k+1)}$ > 1.0, it means that technological progress occurred (i.e. more output was produced with the same level of input).
- If $\gamma_k^{(t_k+1)}$ < 1.0, it means that there was technological regress.

To allow for a continuous interval, (4) is expanded to an exponential form:

$$\phi_k^t = (\gamma_k^t)^{(\Delta t)} \phi_k^{t_k} \quad \text{or} \quad \gamma_k^t = (\phi_k^t)^{1/\Delta t} \qquad (5)$$

Where: $\Delta t = t - t_k$ and t represents time.

The technological change is calculated for each product in the data set to determine its progress or regress compared to the state-of-the-art at a particular point in time. In order to shift the SOA frontier (i.e. forecast new technologies), only the products considered SOA at the time of release will be used, meaning that at t_k their $\phi_k^{t_k}$ was 1.0.

The overall rate of change (ROC) is the mean of the technological change indices of the products considered efficient at the date of release. The ROC is calculated with equation (6):

$$\gamma^t = \frac{\sum_{j=1}^{l} (\phi_j^t)^{1/\Delta t}}{n_{efficient}} \forall l \in \phi^{t_l} = 1 \qquad (6)$$

Where: $n_{efficient}$ is the total number of SOA (efficient) products, and *l* is the subset of SOA products .

Time considerations

When the SOA frontier contains only products from the same time period, time is considered to be the same for all products currently on the frontier and the time interval between the current SOA and the time of release will simply be the difference between 'time now' and time of release. In situations when the SOA surface is defined by products from different time periods, the effective time interval can be calculated with the formula:

$$t_k^{'} = \frac{\sum_{j=1}^{n}(t_j - t_k)\lambda_{kj}}{\sum_{j=1}^{n}\lambda_{kj}} \quad (7)$$

This represents the effective time interval between release dates t_j and t_k of SOA product *j* and of now non-SOA product *k*. Variable λ_{kj} represents the weight of the reference observation *j* on the efficiency score of product *k*. If the model uses variable returns to scale (RTS), the denominator in equation (7) becomes 1.

Forecasting future technologies

Once the technological progress γ has been calculated, future SOA frontiers can be determined with equation (8). To achieve this, SOA outputs will be multiplied by the corresponding technological progress raised at a power equal to the number of past time periods. This means that the method assumes a constant rate of change over time.

$$y_{rk}^{t} = y_{rk}^{t_k} \times (\gamma)^{t-t_k} \; \forall r \in \{1,...,s\} \quad (8)$$

The constant rate of change assumption is recognized by the TFDEA literature to be one of the weaknesses of the TFDEA method.[17, 22, 25] Literature on technology forecasting and technology innovation indicates that technological performance grows in an exponential pattern, but the exponent depends on the phase of technology. For this reason, technological progress in the early phase of the innovation may appear as a straight line, but will grow exponentially as the innovation matures. [11, 29] Therefore, calculating the rate of change with TFDEA at an early phase of technology and assuming it will remain constant may lead to flawed predictions, because the model might anticipate a much slower progress than what is possible in reality.

3. System analysis: EV technology

The purpose of applying TFDEA on the EV technology case is to analyze the technological progress of electric vehicles to determine whether a certain EV configuration has potential to become dominant in the future. The products used in this analysis are passenger hybrid and battery electric vehicles mass-produced and commercialized between 1997 and June 2012. Now that the products have been defined, the TFDEA method requires that the technology attributes are identified in order to select the input and output variables to be used in the DEA model. For a meaningful forecast of EV performance, the selected variables need to be representative of the factors which can pose barriers to technological progress.

Arthur [29] argues that technologies are modular architectures created from combinations of existing technologies. He claims that technologies evolve through combinations of existing technologies, causing new technologies to appear. He describes technology in general as “an arrangement of building blocks” [29, pp. 21] - assemblies and subassemblies which are themselves technologies - organized around a central concept which allows it to work and supply a functionality. Technology consists of a main assembly – the backbone of the device, which is supported by other assemblies which ensure its operation. In order to understand a technology one has to understand its principle and how this principle translates into a working architecture.[29]

Following the train of thought set forward by Coccia [12] and Arthur [29], the electric vehicle will be introduced in this section as a modular system and its mechanisms will be described. This section will try to provide an understanding of the basic principles of the electric vehicle technology, which is necessary for identifying the main EV attributes. The section will conclude with the selection of DEA variables.

To avoid confusion, it should be noted that the focus in this section is to determine those factors that can influence the technical performance of an electric vehicle. Factors determining the successful market penetration, such as consumer preferences and policy instruments, will not be addressed here.

3.1 Electric vehicles as modular systems

The general purpose of a vehicle is to provide on-road passenger transportation. The general vehicle design fundamentals are rooted in classical mechanics and rely on relations between force and acceleration. Newton’s second law of motion states that the acceleration of a body is parallel and directly proportional to the net force exerted on it, and inversely proportional to its mass, where the ‘net force’ is the resultant of the forces applied to the object. In the case of a vehicle, the driving force is delivered by the propulsion unit (i.e. engine, motor or both), while gravity, air and tire friction act as resisting forces. A non-zero resultant of these forces will put the vehicle in motion, as dictated by Newton’s second law. The total mass of the vehicle is the sum of the masses of all of its mechanical and electrical subcomponents. In addition, the speed and acceleration of the vehicle depend on the power and torque delivered by the motor, on the vehicle's aerodynamics and on the road conditions.

Electric vehicles are complex technical systems consisting of thousands of components. A description of individual car components would not be relevant for the discussion at hand. Such detailed descriptions are widely available in the literature and will not be repeated here. The reader is referred to any textbook on car architecture and design for further information. What is relevant though for this analysis is how these components interact with each other and how they determine the operation and performance of a vehicle.

In order to tackle the complexity of the interactions between different components the vehicle will be treated as a modular system. The vehicle as a modular system consists of several independent modules (or sub-systems), each of them being entirely responsible for a particular functionality of the vehicle. For example, the motor, together with auxiliary components constitute the propulsion module which provides traction force to propel the vehicle; the battery provides power for the vehicle to operate; the electronic control units (ECUs) ensure the control and coordination between different modules such that the vehicle responds instantaneously to the driver's needs; the chassis provides the mechanical support for the rest of the modules to be mounted on, where the motor, the battery, the ECUs, the chassis are all independent modules.

The fact that modules are 'independent' implies that they do not determine each other's performance. In other words, given a vehicle which contains a particular motor and a battery, if the battery module is removed from the vehicle and replaced with another battery module with the same physical characteristics and performance specifications, the performance of the motor, or any other module will not change, and consequently, the overall system performance of the vehicle will stay the same. It has to be stressed out that while the modules do not impact the performance of one another in a particular combination, they do pose constraints on the alternative technologies that can be used, as will be explained shortly.

Viewing vehicles as modular systems follows Arthur's [29] approach to technology and is a choice made in this report in order to facilitate the understanding of the vehicle operation and to be able to provide an aggregated analysis of the technology system without omitting important characteristics of the technology. Also, this approach is in line with the vehicle design process.

3.2 EV design process

The vehicle design process is a top down approach [2], meaning that performance requirements of the modules stem from a set of general performance specifications defined on the system level. In this manner, the desired vehicle performance characteristics (e.g. top speed, acceleration etc.) will determine the energy and power requirements of the motor or engine; the desired driving range for the vehicle will determine the required battery or fuel tank capacity; the desired fuel efficiency of the vehicle will determine the required drivetrain architecture and so on, such that the integrated system (i.e. the vehicle) will deliver the expected performance.

Once the module requirements have been defined, an investigation is made to determine the suitability of different alternative technologies which can be used to build the vehicle. Since not everything that has been designed on paper can be built in practice, several trade-offs will occur to balance cost and quality of the chosen technologies, and consequently, the desired vehicle performance parameters will have to be revised and often readjusted, to match the manufacturing possibilities.

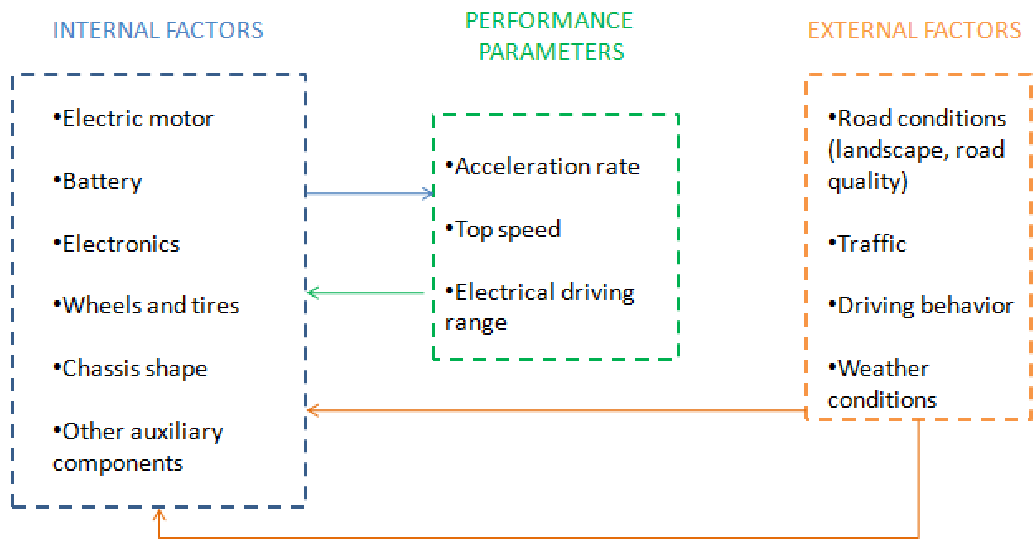

Figure 2 BEV System

Figure 2 and Figure 3 summarize the factors impacting the performance of a BEV and of an HEV respectively, as well as the iterative nature of the vehicle design process. The middle square contains the *performance parameters* specific to each EV family; these parameters provide value to the user of the vehicle. The main difference between a BEV and an HEV is the absence of the ICE, making the fuel consumption and the tailpipe emissions parameter irrelevant for the performance of the BEV. Performance parameters will be further discussed in section 3.2.1.

The left-hand rectangles in Figure 2 and Figure 3 summarize the *internal factors* or *technical parameters* of each family of EV systems; these are attributes of the internal components of the EV system which are responsible for delivering the system's performance. The internal factors represent *variables under the control of the designer*. The arrows between performance parameters and internal factors indicate that during the vehicle design process the desired vehicle performance will drive the requirements for the internal components, but, at the same time, the availability and/or cost of component technologies may lead to compromises on performance (i.e. lowering the desired performance target due to cost and time considerations). A clear and simple example here would be the choice of battery. Consider that one of the desired performance parameters for the vehicle under design is to be able to drive 300 km in electric mode only. Based on this requirement, the designer will evaluate the existing battery technologies and choose the best alternative. If there is no battery technology available that can fulfill the requirements, there are two options: to design a new battery or to compromise on vehicle performance. Designing new technologies is often costly and requires a long time, posing the risk that the vehicle would not be available on the market at the intended date. Thus the next best option is to compromise on performance and choose an available battery that could, for instance, only provide 200 km of electric range.

However, the internal components are not solely responsible for how a car performs; external factors also play a role. The right-hand rectangle summarizes the external factors of the technology which are universal for all vehicle types. External factors often have to do with road conditions, weather, traffic conditions, and the driver's personal style; therefore they are *variables out of the control of the designer*. The arrows in Figure 2 and Figure 3 indicate that external factors can have an influence both on the performance of the vehicle, as well as on the choice of internal components. Some of these factors could lead to better or lower performance of the vehicle. For instance, it is more demanding for a vehicle to drive on a road full of holes and cracks than on a smooth highway; also, during traffic jams an HEV will often be driven by the electric motor, therefore offering a lower fuel consumption and lower emissions levels than if the car were operated under normal traffic conditions over the same distance. External factors cannot easily be quantified and cannot be accurately predicted; however, the arrow between external and internal factors indicates that these external variables are estimated to some extent and accounted for in the definition of the module requirements. This is generally done through simulations of different driving conditions and scenario analysis.[2] For example, winter tires are designed such that they allow the vehicle to drive over roads covered in ice or snow. Or, the BEV batteries need to have sufficient capacity to support the use of air conditioning for different periods of time, while still allowing for a reasonable driving range.

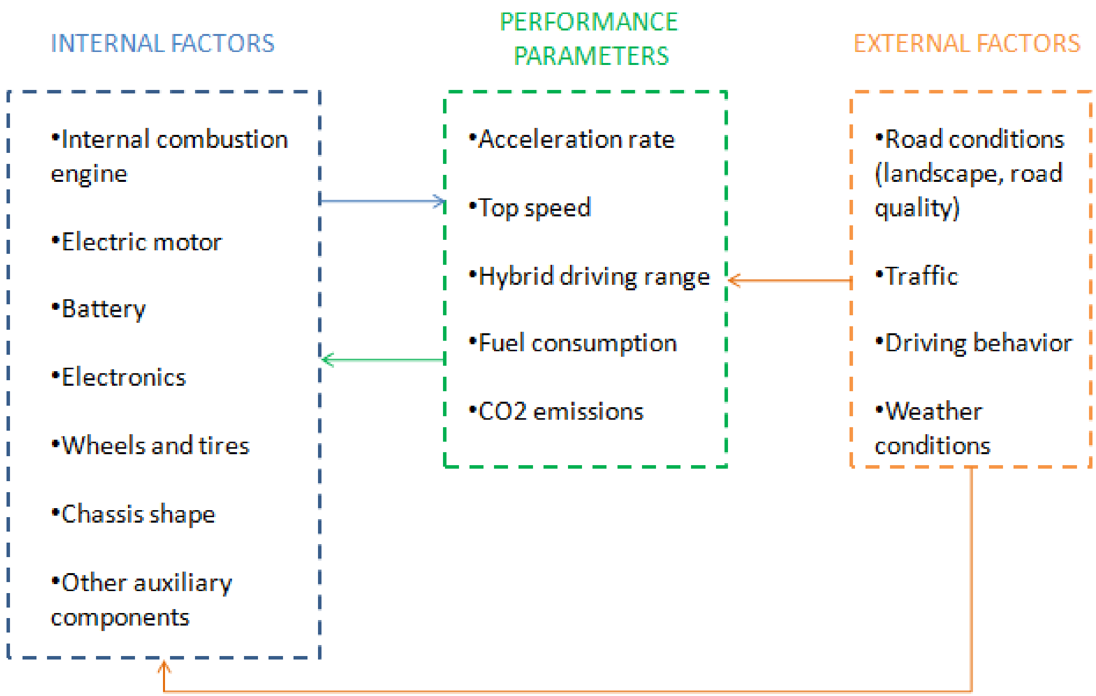

Figure 3 HEV system

3.2.1 Performance parameters

Over the past two decades, electric vehicles have been re-introduced as a way to cope with the shortcomings of the internal combustion vehicles (ICVs). The disadvantages of conventional vehicles are their high fuel consumption coupled with high levels of emissions, high maintenance costs and noise pollution. During driving, electric vehicles are very quiet and offer a much better fuel economy. With respect to emissions, they are more environmentally friendly releasing tailpipe emissions from zero (BEVs) up to 40% less than equivalent ICVs.[1, 2, 38]

While battery electric vehicles would represent the ideal solution to eliminate emissions and oil dependency, the main drawbacks of these vehicles are the high initial costs and short driving ranges due to battery limitations. In addition, the battery pack is large and heavy, increasing the total weight of the vehicle and taking away from the space which would otherwise be available to the passengers. Moreover, recharging the battery takes much longer than refilling the tank with gasoline, causing extra discomfort to the owner of the EV.[2, 36, 37, 39]

Hybrid electric vehicles were introduced as a solution to overcome the range limitations of battery electric vehicles and the high fuel consumption and greenhouse gas emissions of conventional vehicles. But just like BEVs, HEVs have a higher initial cost than an equivalent ICV.

In addition, the increased complexity of the drivetrain increases the number of components, leading to a higher risk of operational failures.[37, 38, 40]

The successful driving performance of a vehicle in general is mostly defined by the acceleration and speed possibilities it can offer. The additional performance indicators specific to the EV technology as emphasized in the literature [1, 2, 7, 36- 40] are summarized below:

- improved efficiency of the electric motor (EM) compared to the internal combustion engine (ICE);
- increased net weight of the vehicle due to either battery weight, in the case of BEVs, or the combined propulsion system, in the case of HEVs compared to ICE vehicles
- increased fuel economy for HEVs compared to ICE vehicles;
- reduced CO2 emissions for HEVs compared to equivalent ICE vehicles, and zero emissions for BEVs;
- reduced driving range due to limited battery energy storage capacity.

Acceleration rate

The acceleration rate value shows the vehicle's ability to accelerate at the driver's impulses. This parameter is indicated with the '0-100km/h in *x* seconds' notation. The faster the car can get from 0 to 100 km/h, the better the car performance because it shows a high reaction speed of the car to the driver's needs. This is not important only for the fast drivers, but it is a desirable feature in situations when an accident has to be avoided or when high speeds have to be achieved over very short driving distances.

Driving range

To distinguish between the driving ranges of BEVs and HEVs, the 'electric range' and the 'hybrid range' are used for the two types of vehicles respectively.

For BEVs, the electric range is the total distance that can be driven on a full battery charge. The range is almost exclusively a function of battery storage capacity.[1, 37] Although BEVs can provide up to three times the engine and drivetrain efficiency of an ICE vehicle [1, 38], they are reliant on the technical characteristics of the available battery technology, which pose significant limitations on the driving range performance. According to the International Energy Agency [38], in the United States, about 60% of the vehicles are driven less than 50 km daily, and about 85% of the vehicles less than 100 km daily. In Europe 85% of the daily trips are below 25 km. Yet, one of the biggest concerns for the electric car buyers is that the car will not be able to provide sufficient range for their driving needs.

This does not apply to HEVs. HEVs use much smaller batteries, but perform most of the driving on fuel, which allows them to reach ranges similar to ICV. For HEVs, the hybrid range is the total distance driven on a full tank combined with a full battery. The combination between the two power sources allows for a much longer driving range, compared to a BEV.[41]

Fuel economy

Fuel economy is measured in km/L and represents the ratio between the distance traveled (km) and the corresponding fuel consumption (L). This performance indicator is applicable for HEVs, which provide increased fuel economy compared to an equivalent ICE vehicle. The fuel economy of the vehicle is determined by the vehicle architecture, as well as by traffic conditions and the individual driving habits of the driver. The lower fuel consumption can be explained by the presence of the electric motor in the drivetrain. A more powerful engine will consume more fuel, but the HEV gets part of its necessary power from an electric motor, which runs on battery. Additionally, based on their drivetrain architecture, some HEVs can drive in full electric mode under certain speeds, which decreases the amount of fuel used.[36- 38]

CO2 emissions

The gCO2/km has been introduced over the past years as a regulated emission factor. The CO2 emissions, as well as other toxic gases such as unburned hydrocarbons or nitrogen oxides, occur due to incomplete combustion of the fuel. This is caused on the one hand by impurities in the fuel, and on the other hand by the inefficiencies of the combustion system. The automotive industry has already reached a very advanced level of combustion efficiency by using catalytic converters. However, it is considered that the CO2 emissions level can only be decreased further by decreasing the weight of the vehicle, or using reduced power engines. [1, 36]

The tailpipe CO2 is an important performance parameter for HEVs. HEVs are claimed to achieve much lower emission rates compared to equivalent ICE vehicles because they get additional power from an electric motor, and hence consume less fuel. In contrast, BEVs are considered *zero-emissions* vehicles, but this concept only refers to the fact the BEVs do now release any greenhouse gases while driving.

When looking at the whole value chain, coal-burning plants emit more CO2 during the energy production compared to the upstream oil extraction. However, the electric motor is three times more efficient in energy consumption [1] compared to a regular internal combustion engine. Worst case scenario analysis show that even if a very large fleet of BEVs would be powered with electricity produced in coal-burning-plants only, the amount of CO2 produced would still be below the amount produced by fuel-burning cars [1, 2].

Consumer preferences

Other than the aforementioned technical and environmental performance parameters, there are several other characteristics important to the buyer of an EV: functional characteristics (the number of passengers the vehicle can carry, cargo space etc.); aesthetic characteristics (chassis style, color, inside tapestry etc.); the availability of charging stations, and of course, the total cost of vehicle ownership (i.e. initial vehicle cost, fuel cost, repair costs etc.).

Estimating the cost of ownership for electric vehicles is not a trivial task since there are many uncertainties to be taken into account. Cost estimates provided in the literature differ to some extent, mostly due to the assumptions made and the cost components included in the analysis in each study. Delucchi and Lipman [42] identify as the main lifetime cost components for electric vehicles the initial costs, fuel costs, maintenance and repair costs and insurance costs. Based on an extensive review of previous studies, their conclusion is that electric vehicles generally have higher initial costs and possibly insurance costs, but lower external and maintenance costs than conventional vehicles. However, whether the overall cost of electric vehicles is higher or lower compared to a conventional vehicle is not clear and depends, among others, on factors such as costs for raw materials (e.g. as lithium for batteries), fuel costs, the cost of energy, which in turn depends on its production costs, as well as on charging time, since energy is priced differently during day time and night time.

Another feature which plays a role in the purchasing decision is the availability of recharging infrastructures [1, 2, 38]. If for HEVs the requirement on infrastructure is less stringent, for BEVs it could play a major role in the purchasing decision, and consequently for the adoption of battery electric vehicles. All electric vehicles can be charged over night from regular power outlets, but it takes between 6 to 10 hours to fully charge an empty BEV battery. On-road fast charging stations would ease that concern, however, such infrastructure is not yet available, making the fuel tank seem to be a more reliable energy source.

These features are associated with consumer preferences and are generally applicable for any type of vehicle. Not only are these features very difficult to quantify, but they are also not considered to be deterministic for the technical performance of the EV technology in particular. For this reason they will not be included further in the analysis.

3.3 Deterministic relations between internal factors and the system's technical performance

In section 3.2 it was discussed that the vehicle performance requirements will drive the choice for components and in turn, the chosen components will impact the actual performance of the vehicle. After describing the general characteristics of BEVs and HEVs, this section will try to identify the main mechanisms responsible for the operation and performance of EVs. Without digging too deep into the technical details of vehicle mechanics a few equations have to be introduced where necessary, in order to justify the causal relations between the module characteristics and the vehicle performance parameters. For further explanations on the mechanics of electric vehicles, other than the ones provided in the following paragraphs, the reader is referred to Husain [2].

Constraints on output power requirements

The propulsion module contains the electric motor (for BEVs) or the electric motor/internal combustion engine (for HEVs) and auxiliary units needed to set the vehicle in motion.

Newton's second law of motion is given by the formula:

$$\sum_i \overline{F}_i = m\overline{a} \tag{9}$$

where *∑F* is the resultant of all forces applied on the object, *m* is the mass of the object and $\overline{a}$ is the acceleration of the object. The acceleration is the first derivative of velocity ($\overline{a} = dv/dt$) where velocity is the first derivative of position ($\overline{v} = ds/st$).

The traction force (F_{TR}) is the force to be supplied by the propulsion unit (either EM or ICE/EM combination) in order to overcome the road load and allow the vehicle to move. This traction force can be represented with equation (10):

$$F_{TR} = k_m m \frac{d\nu_{xT}}{dt} + F_{RL} \tag{10}$$

where F_{RL} is the resistance posed by the road, *m* is the mass of the vehicle, $d\nu_{xT}/dt$ is the acceleration of the vehicle in the direction of movement (x_T), and " k_m is the rotational inertia coefficient to compensate for apparent increases in mass due to the onboard rotating mass" [2, pp.25].

The power required from the electric motor or from the EM/ICE combination can then be determined using the traction force from the propulsion unit and the maximum velocity of the vehicle:

$$Power = F_{TR} \cdot \nu_{xT} \tag{11}$$

Equations (10) and (11) show the interdependence between *mass, acceleration and power* of the EM or ICE/EM combination. Therefore, the higher the mass of the vehicle and the faster it has to accelerate, the higher the traction power will need to be. This means that based on the desired acceleration rate and top speed specifications, the electric vehicle will have to be provided with a propulsion unit (EM or EM/ICE combination) capable to provide the necessary output power to achieve those specifications. In addition, the weight of the vehicle will add another constraint on the required power output of the propulsion unit. This is summarized in Figure 4. The yellow squares indicate the performance parameters (i.e. the parameters which create value to the user) of the EV, while the blue squares are EV technical parameters (i.e. the EV attributes responsible to deliver the EV system performance). The gray squares indicate attributes of the lower level technologies which deliver the individual module performance. The arrows in the figure identify the dependencies and interdependencies between the different design variables.

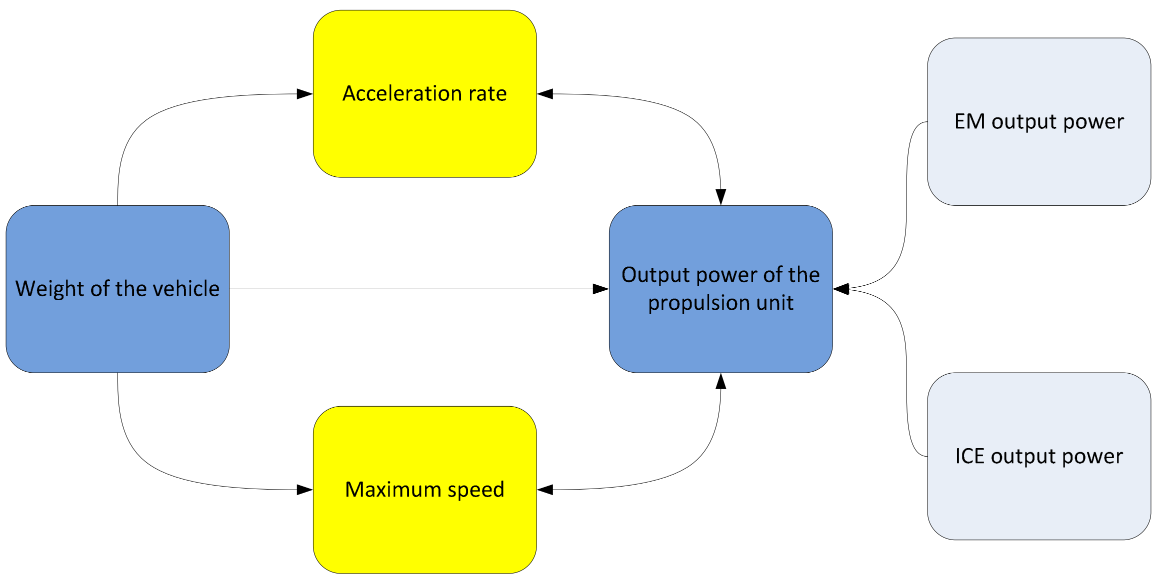

Figure 4 Output power constraints

Limitations on range: battery storage capacity vs. output power

Based on the literature overview it can be claimed that the battery is one of the major determinants of the BEV performance. The battery is responsible for providing power to operate the vehicle.

The driving range was defined as the maximum distance driven on a full vehicle charge. Different electric vehicle architectures impose different requirements on the battery performance. For example, batteries for BEVs require much higher energy storage capacity compared to HEVs in order to allow for an acceptable driving range. On the other hand, PHEVs require higher power densities.[37]

The electric range of a BEV is almost entirely determined by the stored energy capacity of the battery. The theoretical stored energy capacity of the battery E_T is given by the product between the nominal no-load terminal voltage V_{Bat} and the theoretical capacity (*Q*):

$$E_T = V_{Bat} Q_T \text{ [Wh]} \qquad (12)$$

Figure 5 shows schematically the connection between the EV battery pack and the propulsion unit.

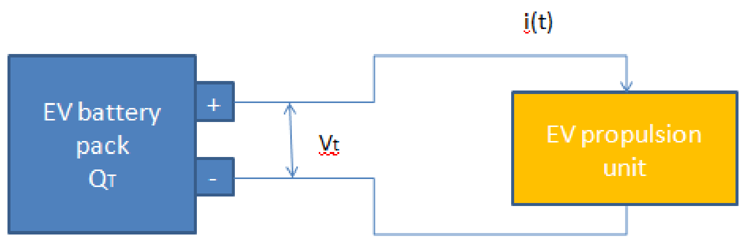

Figure 5 EV battery with load

In order to operate, the propulsion unit will deplete the battery at a particular rate, indicated by *i(t)*. Therefore, in this figure, *i(t)=dq/dt* represents the discharge current and V_t is the battery terminal voltage. The battery terminal voltage is the voltage available at the terminals of the battery when a load, in this case the propulsion unit, is connected to it. The terminal voltage will vary based on the charge level of the battery, from a full-charge value (when the battery is fully charged) to a cut-off value (when the battery is completely discharged).[2]

The practical stored energy available for the vehicle operation will be lower than the theoretical value due to practical inefficiencies of the battery and of the conversion processes. The practical capacity will thus be given by:

$$Q_P = \int_{t_0}^{t_{cutoff}} i(t)dt$$

causing the practical energy storage capacity to become:

$$E_P = \int_{t_0}^{t_{cutoff}} v(t)i(t)dt$$

where *i(t)* is the discharge rate, *v* is the terminal voltage, t_0 is the moment when the battery is fully charged, t_{cutoff} is the moment when the discharging has to stop (i.e. the terminal voltage reaches the cut-off value).[2]

This shows that the battery storage capacity is influenced by the discharge patterns imposed by the propulsion unit. Knowing that *P=UI* (i.e. power is the product between voltage and current), it can be inferred that a more powerful propulsion unit will deplete the battery faster than a weaker one. A faster depletion time means that a shorter range can be driven on a full battery charge. Therefore in order to meet the range requirement, the vehicle will either have to be provided with a lower power propulsion unit to decrease the depletion time of the battery, or it has to have a larger battery capacity to meet the needs of a powerful propulsion unit. These relationships are summarized in Figure 6:

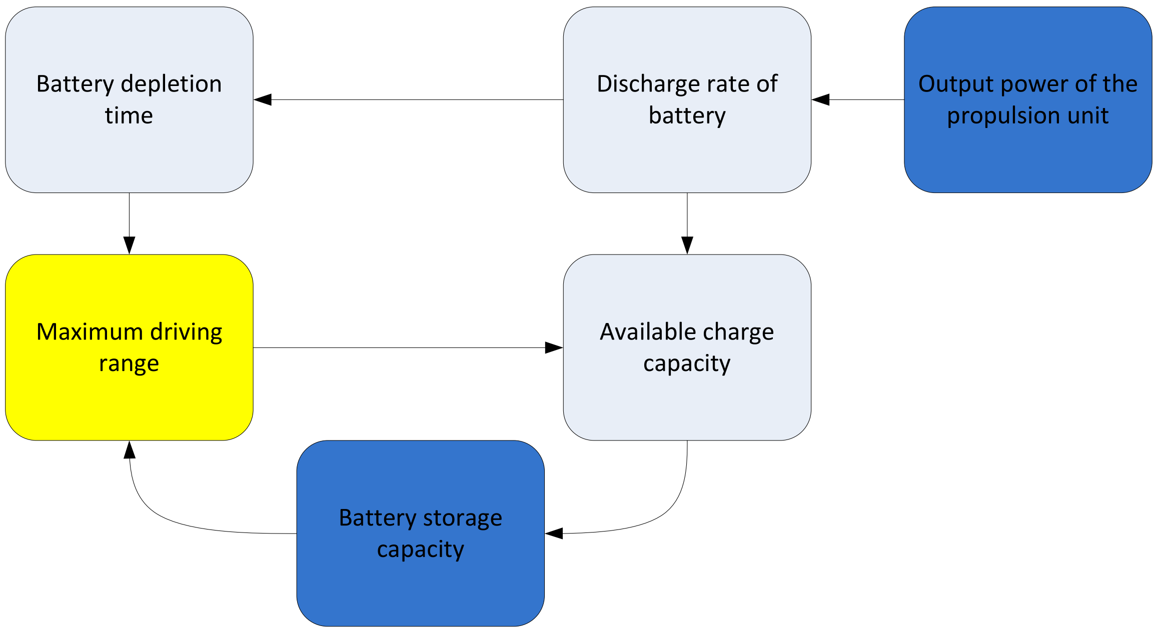

Figure 6 Relations between range, power and battery capacity. The yellow squares indicate the EV system performance parameters; the blue squares indicate the EV system's technical parameters; the gray squares indicate sub-module attributes which influence the EV module performance.

Although the desirable solution in this situation would be to increase the battery storage capacity, there are several limitations of the battery technology to be taken into account. The storage capacity of a battery is closely related to the energy density (Wh/kg). This parameter is material-specific, therefore batteries manufactured from different materials (Lithium-ion, Lithium-polymers, acid-lead, Nickel metal hydride etc.) will exhibit different performances. This means that based on the material used, a higher storage capacity for the battery requires to either use a reactive material with a better energy density or to use a higher mass of reactive material. Increasing the mass of the battery will lead to an overall increase in the weight of the vehicle. Consequently, a higher weight will require a more powerful propulsion unit in order to meet the desired acceleration and speed requirements.

Figure 7 summarizes the most important relations between the characteristics of a BEV's components and its performance parameters.

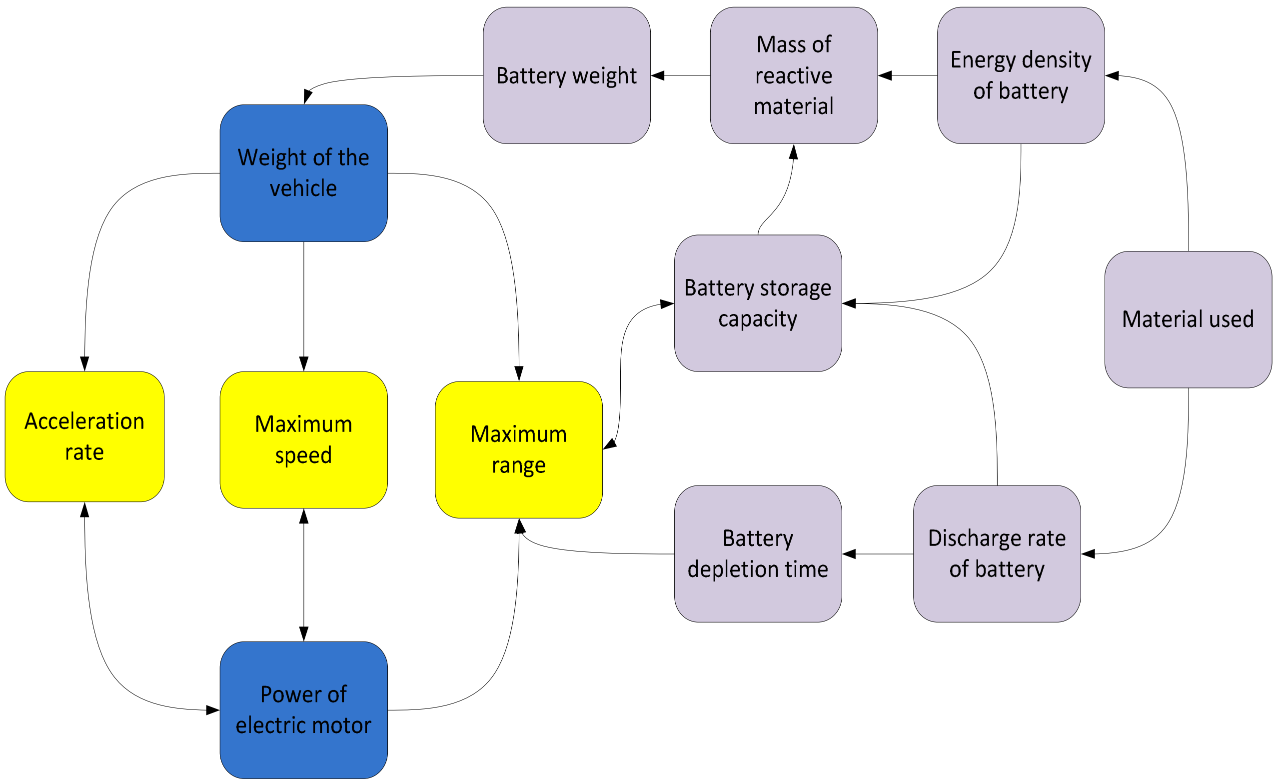

Figure 7 Causal relations for a BEV system. The yellow squares indicate the EV system performance parameters; the blue squares indicate the EV system's technical parameters; the gray squares indicate sub-module attributes which influence the EV module performance.

Emissions and fuel economy of HEVs

The HEV technology is not as dependent on the battery technology. HEVs run on fuel and achieve hybrid ranges (i.e. the combined range in electric and hybrid mode) comparable with ICE vehicles therefore the range does not necessarily constitute a limiting factor. Instead, two other performance parameters are important for HEVs, namely the CO2 emissions level and the fuel economy. Both of these parameters are indicators of the efficiency of the drivetrain of the HEV.

The level of emissions will be proportional to the amount of fuel the HEV uses. It was discussed that based on their drivetrain architecture, HEVs are able to drive in electric only modes below particular speeds. In addition, the fact that they are provided with regenerative breaking systems reduces the requirement on having a large battery to achieve sufficient electric ranges. This helps decrease their fuel consumption especially in urban areas where the speed limit is low, and consequently decreases the level of emissions.

The fuel consumption is determined on the one hand by the output power requirements and the efficiency of the ICE, on the other hand by the driving style of the driver. The more powerful the ICE, the more fuel it will consume. HEVs have the advantage of using electric motors which can complement the power provided by the ICE in order to achieve the total output power for the vehicle. This allows for the use of weaker ICEs and helps further reduce the fuel consumption.

However, it was discussed that a higher weight drives the need for more traction power from the propulsion unit. HEVs are heavier than ICE cars because they carry a more complex drive train, which includes the electric motor and battery in addition to the conventional internal combustion system. This implies that the weight of the vehicle will increase the fuel consumption based on the extent to which the ICE contributes to the overall output power required from the propulsion unit.

Figure 8 provides an overview of the causal relations between the characteristics of HEV components and the performance parameters of an HEV.

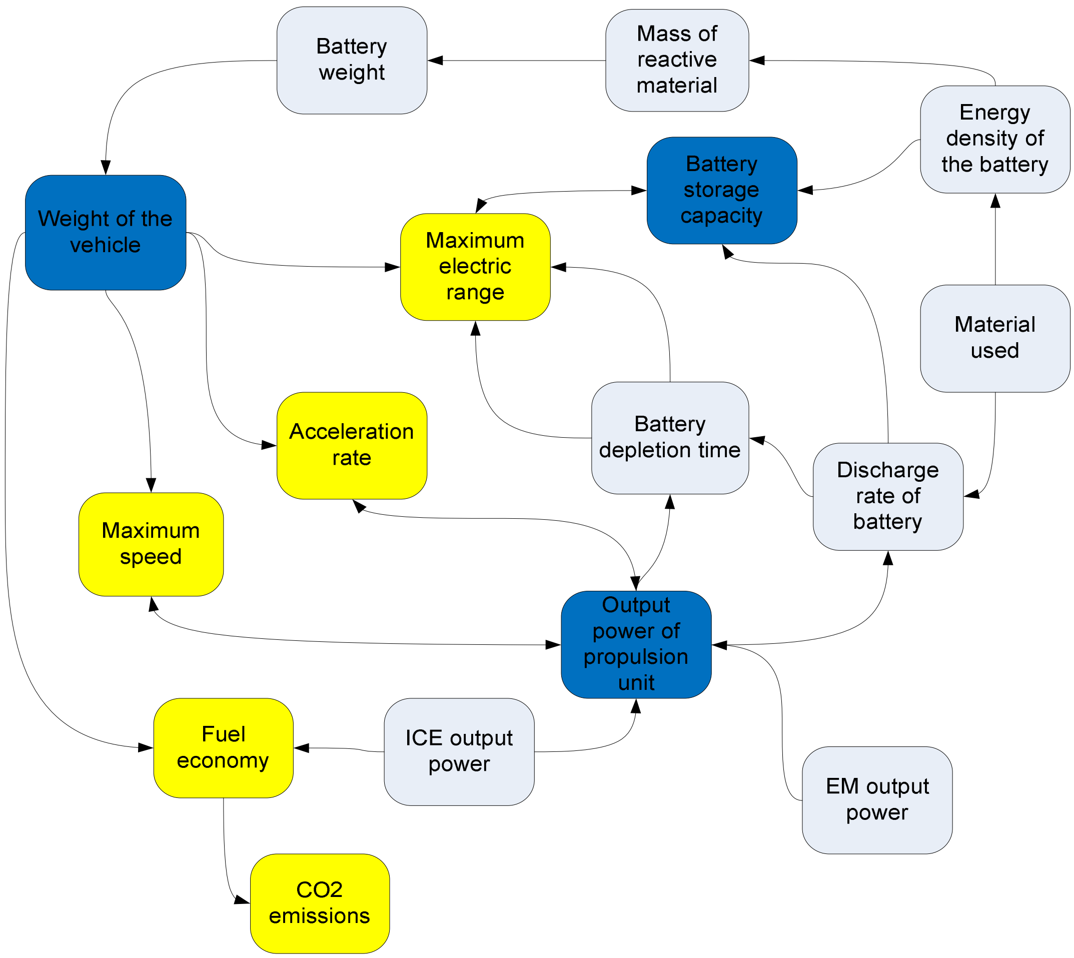

Figure 8 Causal relations for an HEV system. The yellow squares indicate the EV system performance parameters; the blue squares indicate the EV system's technical parameters; the gray squares indicate sub-module attributes which influence the EV module performance.

Summary

This section presented a system analysis in order to describe how different vehicle components interact with one another and how they impact the overall performance of the vehicle. Based on this analysis, the following conclusions can be drawn:

1. The performance of an electric vehicle is determined by the performance of the components chosen for its drivetrain. Therefore it can be claimed that the efficiency of an electric vehicle depends strictly on the efficiency of the drivetrain, or, differently phrased,

on the way the drivetrain is able to make use of the individual inputs provided by each of its components.

Based on the interactions between different parts of the electric vehicle drivetrain and the impact these have on the vehicle performance, the main characteristics of the electric vehicle technology can be deduced.

- In the case of BEVs, the main performance indicators are the *electric range*, the *acceleration rate* and the *top speed*, while the major limitations to performance can be caused by the: *battery storage capacity, output power of the electric motor* and *vehicle weight.*
- The performance of HEVs is indicated by the *acceleration rate* and *top speed*, as well as by the *fuel economy* and *CO2 emissions*. The main performance limitations are caused by the *output power of the propulsion unit*, *the weight of the vehicle,* and, to a lesser extent than BEVs, *battery capacity.*

Based on this system analysis, the input and output variables for the DEA model can be selected. It is important that the variables reflect possible limitations to technological progress of EVs. For this reason, the following attributes were chosen:

- ➢ Outputs: acceleration rate, electric range (BEVs only). CO2 emissions (HEVs only), fuel economy (HEVs only).
- ➢ Inputs: vehicle weight, output power of the propulsion unit, battery capacity.

DEA outputs

- ✓ The acceleration rate is representative for design difficulty. As was discussed, the weight of the vehicle and the output power of the EM/ICE have a strong impact on the acceleration possibilities.
- ✓ The electric range reflects the dependency on sub-component technologies such as batteries
- ✓ Fuel economy and the CO2 emissions are regulation driven parameters, therefore they are assumed to reflect the impact of regulation on performance developments of EVs.

Although the top speed was identified as a main performance indicator in the system analysis, it will not be part of the DEA model because some electric vehicles, especially BEVs, have a programmed top speed much lower than the actual speed that can be achieved by the vehicle. This is done as a means to save on battery power and extend the range of the vehicle. Since the actual top speed is not known, using the value indicated by the auto makers would not be relevant for the performance of electric cars.

Another variable which might be able to provide valuable information about the manufacturing and scale possibilities for electric vehicles would be production cost. However, production costs for each vehicle would be hard to obtain, therefore it will not be used.

DEA Inputs

- ✓ The weight of the vehicle is the first input for the DEA model. As was discussed in the system analysis, the weight of the vehicle has a direct impact on all performance characteristics used as outputs and constitutes one of the physical limitations to further developments of the technology.
- ✓ The second input variable is the output power of the propulsion unit. The system analysis showed that the choice of the propulsion unit has to take into account all the physical properties of the vehicle, as well as the desired vehicle performance. Therefore this variable is used as an input which reflects limitations due to the interdependency between different car subcomponents. For BEVs, this is the output power of the electric motor. In the case of HEVs, this power output is the combined power provided by the ICE and EM in order to propel the vehicle. Both the EM and ICE have individual power specifications, however, different HEV architectures use the EM and the ICE for different purposes. In some cases, both the EM and the ICE are used to drive the vehicle. In other cases, the EM is only used to assist the ICE, meaning that the EM for a power assist car simply does not need to be as powerful as the EM of a parallel hybrid SUV. Including individual EM and ICE power values in the model would not be relevant. What is relevant for the performance of an HEV is how the EM and the ICE work together to deliver traction power to the vehicle, not the individual capabilities of the two components. As was discussed in the system analysis, the propulsion unit is directly responsible for the fuel consumption and consequently for the CO2 emissions of the vehicle. Therefore this parameter is used in the model to give an indication of how electric vehicles are able to meet restrictions imposed by regulations.
- ✓ The battery capacity was identified to be responsible especially for the limited performance of BEVs. Therefore the battery capacity will be used as an input variable which reflect the limitations posed by the availability and performance of supporting technologies.

4. Data

As previously discussed, electric vehicles can be either fully electric (BEVs) or hybrid electric (HEVs). The two types of EVs are structurally different and are characterized by different performance parameters. For these two families of products, a data set was collected, containing respectively all the BEVs and HEVs released and commercialized on a large scale between 1997 and June 2012. The data set comprises of 106 electric vehicles, out of which 64 are HEVs and 32 are BEVs. The information collected for each product is described in section 4.1. The complete data set is provided in Appendix C.

Several electric vehicles, either BEVs or HEVs, have been introduced on a small scale as public transport vehicles (buses, taxis). Although these vehicles have the same characteristics as commercial cars, they are generally designed and introduced on the road as part of governmental projects to alleviate the pollution in urban areas. Since these vehicles are not intended to be mass-produced and sold to regular consumers, they are excluded from the analysis. Additionally, those electric vehicles built as concept models or prototypes without any mass-production plans are not included either.

4.1 Data collection

In the light of the analysis in section 3, for each electric vehicle released between 1997 and May 2012, the parameters listed in Table 5 were collected. The data was collected from online sources and multiple references were compared in order to ensure the accuracy of the data.

Table 5 Data collected for BEVs and HEVs

BEVs	HEVs
Release date	Release date
Acceleration rate	Acceleration rate
Electric range	Fuel economy
Battery storage capacity	CO2 emissions
Power output of the electric motor	Power output of the propulsion unit
Vehicle weight	Vehicle weight
	Battery storage capacity

Release date

The release date is the month and the year when sales started for each vehicle, as announced by the manufacturer.

Acceleration rate

For both BEVs and HEVs, the acceleration rate shows the time (in seconds) it takes for a vehicle to go from 0 to 100 km per hour. Not all vehicles are provided with a "0-100 km/h" range, some vehicles have lower speed range indications (e.g. 0-80 km/h in 8 seconds). In all cases, to determine the acceleration rate, the following calculation was made:

acceleration rate (km/hour per second) = speed range (km/h)/time (second)

Electric range (km)

This is the theoretical value provided by the manufacturer as the maximum distance which can be driven on a full charge of a battery. The actual driving range will be influenced by driving habits and road conditions; however, such a value would be very difficult to estimate with accuracy. Therefore the theoretical electric driving range will be used in the analysis. A longer driving range is a required feature for BEVs in order to capture the interest of consumers.

Battery storage capacity

The value collected for battery storage capacity, both for HEVs and BEVs, is the nominal energy storage capacity of the electric battery, measured in kWh. In the case of vehicles where this value was not specified, the nominal voltage (V) and the theoretical charge capacity (Ah) values were collected and the battery storage capacity was then calculated with:

Storage capacity (kWh) = Current (Ah) x Voltage (V)/1000

The "/1000" is added in the formula to convert the units to kWh from the standard unit of Wh.

Power output of the electric motor (kW)

This value was collected only for battery electric vehicles and represents the maximum power the electric motor can deliver, as provided in the vehicle specification sheet.

Power output of the propulsion unit (kW)

This parameter applies only to hybrid electric vehicles and represents the combined output power delivered by the electric motor and combustion engine together. It was discussed that

HEVs use both an electric motor (EM) and an internal combustion engine (ICE) to provide traction force to move the vehicle. Both the EM and the ICE will have individual output power specifications. However, the combined output power will not be the nominal sum of the two power values. Depending on the architecture of the car, the EM and ICE will contribute a particular amount to the overall system power. Since the individual contribution of the EM and ICE are difficult to determine, the system output power value was used as indicated by the manufacturers.

Fuel economy (km/L)

For HEVs, fuel economy represents the number of kilometers that can be driven on one liter of fuel and is measured in km/L. The fuel economy is specified with three values, one value each for city drive cycles, highway drive cycles and combined cycles. For as many products as possible, the EPA combined cycle specification was collected. For some products, the EPA value was not available. In those cases, the available estimation for the combined fuel consumption was recorded. When a combined value was not specified, the average of the city and highway fuel economy values was taken. An HEV will be considered more efficient the more kilometers it is able to drive on a liter of fuel.

CO2 emissions (g/km)

This value is applicable only for HEVs and represents the average amount of CO2 released per kilometer driven. The BEVs are considered to release zero emissions.

Weight (kg)

The weight in kilograms of each vehicle was recorded as specified by the manufacturer.

5. Methodology – Applying the TFDEA

Once the inputs and outputs for the DEA model were selected and the data collected, the TFDEA method could be applied to identify the technological progress of electric vehicle technologies. This section describes the steps taken to apply the TFDEA method.

Three TFDEA models

Three different forecasts were analyzed separately:

1. TFDEA of hybrid electric vehicles only
2. TFDEA of battery Electric vehicles only
3. TFDEA of electric vehicles combined (HEVs and BEVs)

While the two homogeneous models aimed to calculate the individual rate of change for HEVs and BEVs, the combined model was an attempt to determine whether it is possible to analyze the two technologies in parallel and calculate the overall rate of change over the whole EV class, by combining the HEVs and BEVs in the same model. In this situation, HEVs were assigned a 0.0 value for the electric range, while BEVs were assigned 0.0 values for fuel economy and CO2 emissions. It could be argued whether this approach is completely correct or sufficiently representative of the real world context. Some HEVs are able to drive in electric mode for limited distances at very low speeds, while others are only able to drive on gasoline, depending on each vehicle's architecture. On the other hand, BEVs are considered to have a zero emissions level only while driving, yet, this is not the case if emissions generated during the electricity generation process are taken into account. At the same time, for many of the vehicles included in the analysis these details are not readily available and they would have to be estimated in order to comply with the data requirement of the DEA that the all attributes for all products should be present. Including these details in the model would probably turn the model into a better picture of reality but it would also increase the complexity of the model. DEA is an extreme point method which is very sensitive to noise which means that a large number of inaccurately estimated values could introduce disturbances in the results. For this reason, the simplistic approach was pursued.

DEA model implementation

For each case, an output-oriented DEA model with variable returns to scale was created. The assumption that a vehicle is more efficient when it can achieve better performance than other vehicles with similar architectures indicates that an output-oriented DEA model should be used.

At the same time, there is a minimum cost to entry and diminishing returns for a decrease in input. This means that past a particular level it might be too expensive to improve the performance of the vehicle. For example, in order to achieve 500 km of electric range the cost of the battery would become too high for the vehicle to remain competitive in the market. Thus the variable returns to scale constraint had to be included in the output-oriented model.

The structure of each model is summarized in Table 6, Table 7 and Table 8 respectively. Several DEA software packages are commercially available as indicated in [17]. For this report, the output-oriented DEA model with the additional constraint for returns to scale (Figure 9) was implemented using Excel Solver, following the mathematical constructions described in section 2.4.1 and guidelines presented in [20]. In addition, an Excel Macro was written in order to automate the DEA model runs and record the lambdas for each vehicle. This Macro is shown in Appendix B.

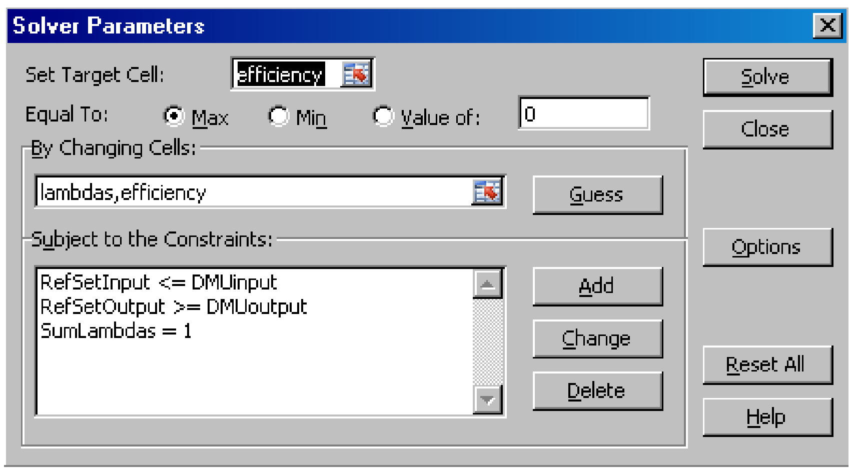

Figure 9 DEA constraints in Excel Solver

Table 6 HEV model data

Number of HEVs	Period	Technology attributes					
64	1997-June 2012	Inputs			Outputs		
		Weight	Combined output power	Battery capacity	Acceleration rate	CO2 emissions	Fuel economy

Table 7 BEV model data

Number of BEVs	Period	Technology attributes				
		Inputs			Outputs	
42	1997-June 2012	Weight	EM output power	Battery capacity	Acceleration rate	Range

Table 8 Combined model data

Total number HEVs & BEVs	Period	Technology attributes						
		Inputs			Outputs			
106	1997-June 2012	Weight	Output power	Battery capacity	Acceleration rate	CO2 emissions	Fuel economy	Range

Mathematical conversions

The constraints of the output-oriented DEA model indicate that a product is more efficient when it uses less input to produce a better performance. Due to the predetermined structure of the output oriented model, some mathematical transformations have to be made in order to respect the logic of reason.

The vehicle weight is an input parameter therefore the standard DEA model will assume that a vehicle will be more efficient when it uses less weight. In reality, a vehicle performs better when it manages to achieve a better performance despite carrying the same or more weight compared to its peers. This was represented this in the DEA model by using the "1/weight" transformation.

Similarly, an HEV is more efficient when it produces less CO2 compared to its peers. To comply with the output-oriented DEA model, the "1/CO2 emissions" transformation was used.

Calculating the ROC

Using the VRS output-oriented model, the efficiency scores were calculated for each time period for all vehicles released between 1997 and June 2012. This was done iteratively, staring with the vehicles introduced in 1997, and with each new model run, the vehicles introduced in the next time period were added in the DEA model. As mentioned in section 2.4.2, these efficiency scores were only used as a technology index [17] to rank the vehicles as SOA or non-SOA.

Once the technology index was calculated, the annual rate of change (ROC) for the technological frontier was determined. This analysis assumed time intervals of one year. The products ranked as SOA at time *t* constitute the technological frontier at time *t*. At time *t+1*, new products released on the market in the (*t, t+1*) interval will lead to a new technological frontier. The two frontiers can thus be used to calculate the rate of change, which shows the technological progress which occurred between time *t* and *t+1* and indicates the amount by which the technological frontier shifts from one year to the next.

For example, in order to calculate the 2009 ROC value for HEVs, the hybrid vehicles released up to 2008 were used. Since the rate of change would be used to determine future technological frontiers, only the products considered SOA in 2008 were included in the ROC calculation, as shown in Table 9 . Therefore, from the products available in 2008, only those with an efficiency score of 1.0 were chosen.

Table 9 HEVs on the 2008 technological frontier

#	Product	Year	Weight	System power output	Battery capacity	Acceleration rate	CO2	Fuel efficiency	Φ_'08
1	Prius 1st gen.	1997	1240	50	1.7	7.46	135	17.54	1
2	Tino	2000	1500	83	0.6	8.20	182	23	1
3	Prius 2nd gen.	2000	1640	57	1.7	7.97	120	19.23	1
4	Civic 1st gen.	2001	1290	69	0.85	7.04	137	20	1
5	Alphard	2003	2100	96	4.4	8.33	173	17.2	1
8	Civic 2nd gen.	2005	1260	82	0.86	7.63	129	17	1
9	Highlander	2005	2160	200	1.3	12.76	165	12.5	1
10	Mercury Mariner	2006	1664	115	1.8	8.98	110	14	1
12	Lexus GS450h	2006	1890	253	1.5	18.65	186	14.2	1
13	Estima	2006	2020	140	1.59	9.26	127	20	1
14	Altima	2006	1573	147	30	13.29	160	14	1
15	Chevrolet Tahoe	2007	3220	247	1.8	10.91	366	9.5	1
17	Lexus LS600h	2007	2340	327	1.3	17.54	219	12.2	1
18	Tribute	2007	1668	115	8.5	11.28	173	13.5	1
19	GMC Yukon	2007	2388	247	1.8	12.28	108	9.26	1

Next, the effective time interval between the vehicle release and 2009 was calculated, as well as the 2009 efficiency scores for each vehicle as shown in Table 10.

Table 10 Calculating the 2009 ROC

#	Product	Year	Φ_2008	Δt'	Φ_2009	γk_2009 = (ϕ_2009)^(1/Δt')
1	Prius 1st gen.	1997	1	12	1	1
2	Tino	2000	1	9	1	1
3	Prius 2nd gen.	2000	1	9	1	1
4	Civic Hybrid 1st gen.	2001	1	8	1	1
5	Alphard	2003	1	6	1	1
8	Civic Hybrid 2nd gen.	2005	1	0.87	1.12	1.12
9	Highlander	2005	1	4	1	1
10	Mercury Mariner	2006	1	3	1	1
12	Lexus GS450h	2006	1	3	1	1
13	Estima	2006	1	3	1	1.00
14	Altima	2006	1	0.94	1.11	1.11
15	Chevrolet Tahoe	2007	1	2	1	1
17	Lexus LS600h	2007	1	2	1	1
18	Tribute	2007	1	-1.20	1.08	1.08
19	GMC Yukon	2007	1	2	1	1

Since the technological frontier contains vehicles released in different time periods, for the vehicles which used to be SOA in 2008 but are no longer SOA in 2009, the effective time interval was calculated with the formula:

$$\Delta t_k' = \sum_{j}^{n} (t_j - t_k)\lambda_{k,j}$$

In this equation, t_j and t_k are the dates of release of 2009-SOA vehicle *j* and previously SOA, but in 2009 no longer a SOA vehicle *k*. Variable $\lambda_{k,j}$ represents the weight of product *j* on the efficiency score of vehicle *k* and was generated by the DEA model used to calculate the efficiency scores. It can be seen in Table 10 that Civic 2nd generation, Altima and Tribute are no longer SOA in 2009. Their Δt' intervals were calculated using the values shown below (Table 11).

Table 11 Calculation for the effective time interval when the SOA frontier

	Civic Hybrid 2nd gen	t_k	t_j	Δt'
λ_2	0.24	2005	2000	0.87
λ_4	0.13		2001	
λ_26	0.01		2009	
λ_31	0.62		2009	

	Altima Hybrid	t_k	t_j	Δt'
λ_5	0.16	2006	2003	0.94
λ_12	0.36		2006	
λ_31	0.48		2009	

	Tribute Hybrid	t_k	t_j	Δt'
λ_5	0.46	2007	2003	-1.20
λ_12	0.15		2006	
λ_31	0.39		2009	

The overall ROC for 2009 is then calculated as the average of the individual changes recorded by the 15 vehicles on the SOA frontier of 2008. The ROC for 2009 is thus 1.013, with a ±0.02 confidence interval.

Table 12 2009 ROC for HEVs

ROC_2009	std	95% confidence interval	
1.013	0.05	0.098	1.037

The values in Table 12 indicate that at a given vehicle weight, output power of the propulsion system and battery capacity, the three performance indicators (acceleration rate, fuel economy and CO2 emissions) are expected to increase at a rate of 1.3% each year. The 95% confidence interval on the mean is ±2.4%. The lower bound of the confidence interval will thus be 1.3-2.4 = -1.1% and will be called the conservative frontier. The negative value suggests technological regress cause by the introduction of several inferior products. The upper bound will be 1.3+2.4 = 3.7% and will be called the aggressive frontier.

The sequence of steps to calculate the rate of change is summarized in the flowchart below:

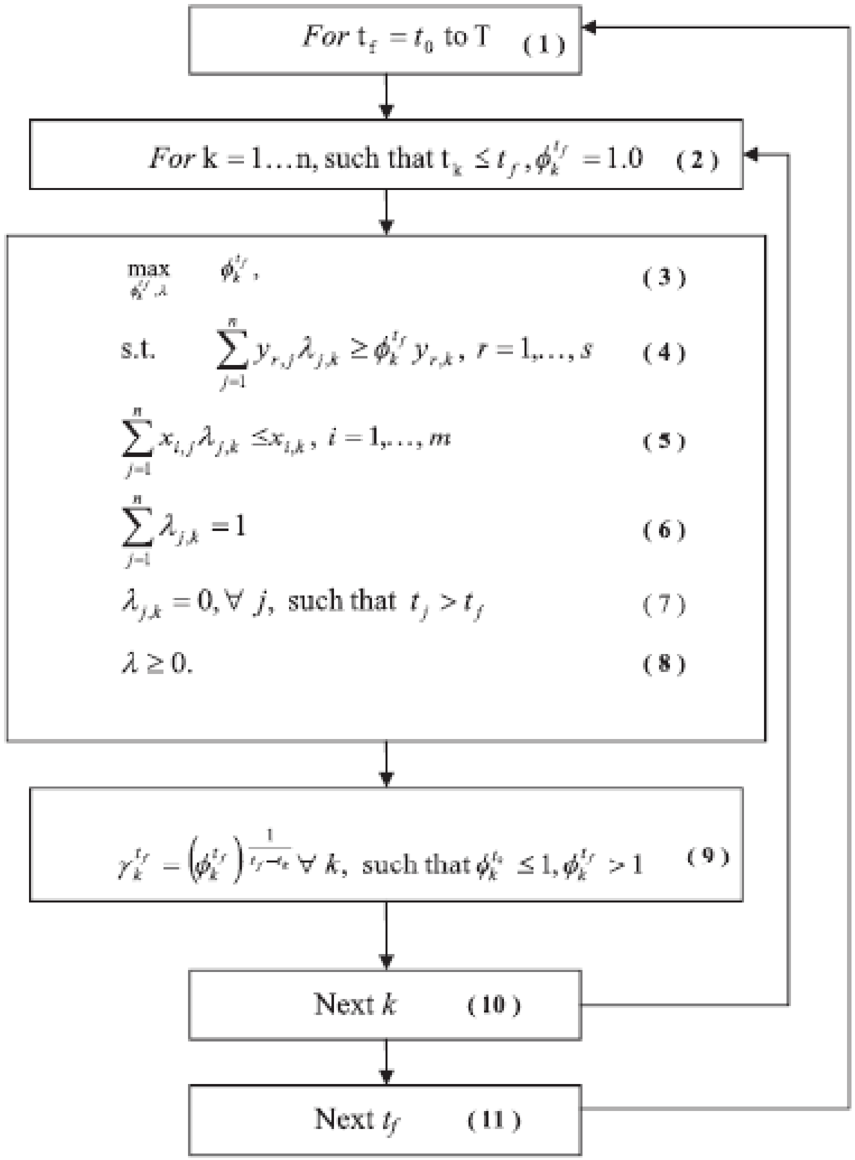

Figure 10 Flow of an output-oriented TFDEA algorithm [27]

Forecasting future frontiers

In order to forecast future frontiers the data was divided between the reference set (i.e. the earlier released vehicles used as historical data to determine the rate of change) and the verification set (the later released vehicles whose performance is verified against the predictions in order to determine the accuracy of the forecasts). This choice is not random, but it is based on the limitations of DEA to identify SOA and non-SOA products in a data set containing a number of products three times smaller than the number of inputs and outputs in the model. For this reason, EVs released up to 2008 are the reference set for the HEV and combined model. For the BEV model, year 2009 is taken as reference. Vehicles released between 2010 and June 2012 are used to verify the forecasts.

Once the rate of change is known, the 95% confidence interval values are used to forecast future technology frontiers for the specified performance parameters. The conservative and aggressive frontiers are determined by the lower and upper bound of the 95% confidence interval. The future frontiers are calculated by multiplying each performance parameter on the current frontier by the rate of change value raised at an exponent equal to the number of time intervals passed. This is expressed mathematically with the formulas in Table 13.

Table 13 Formulas to calculate future frontiers

Conservative frontier	Aggressive frontier
$acceleration_k^t = acceleration_k^{2008} \times \gamma_{conservative}^{t-2008}$	$acceleration_k^t = acceleration_k^{2008} \times \gamma_{aggressive}^{t-2008}$
$CO2_k^t = CO2_k^{2008} \times \gamma_{conservative}^{t-2008}$	$CO2_k^t = CO2_k^{2008} \times \gamma_{aggressive}^{t-2008}$
$FuelEconomy_k^t = FuelEconomy_k^{2008} \times \gamma_{conservative}^{t-2008}$	$FuelEconomy_k^t = FuelEconomy_k^{2008} \times \gamma_{aggressive}^{t-2008}$
$Range_k^t = Range_k^{2008} \times \gamma_{conservative}^{t-2008}$	$Range_k^t = Range_k^{2008} \times \gamma_{aggressive}^{t-2008}$

Applying these formulas to each of the 2008 SOA products, generates a set of future vehicle performance parameters which are expected to determine the SOA frontier at a future time.

The multidimensional nature of the HEV technology frontier makes it difficult to represent it graphically in a manner that is easy to visualize. Since the predicted values concern the future and some level of uncertainty should be taken into account, it is not interesting to look at forecast absolute values. Instead, the ranges predicted to be feasible for each parameter at a particular time in the future are considered. The range for each parameter is thus delimited by the minimum value on the conservative frontier and the maximum value on the aggressive frontier for each performance parameter.

Using the forecasts

These predicted frontiers can be used in two ways.

- One way is to determine how feasible the expected release date of a vehicle really is. If the desired performance lies above the expected aggressive frontier, the release date might be too ambitious for what is considered to be feasible technology at the desired time of release. Alternatively, if a product with superior performance is confirmed to be released at the announced date, it is likely that it can become the new state of the art and change the shape of the technological frontier.
- Alternatively, these frontiers can be used to determine whether an announced product has potential to be competitive at the intended date of release. If the announced performance of a product under development lies below the expected conservative frontier at the time of release chances are that the product will be inferior with respect to the SOA at that time, and may therefore not be competitive compared to other vehicles present on the market at the release time.

Forecast verification

In order to verify the forecasts, it was investigated whether the models were able to predict the remaining vehicles introduced from 2010 (2011 for the BEV model) until June 2012. It was considered that a vehicle was predicted if all of its performance specifications fall on or below the aggressive frontier. If at least one of its parameters falls above the aggressive frontier, the vehicle is considered to not have been predicted and is labeled as *superior*. Additionally, if all of the performance parameters of a vehicle fall between the conservative and the aggressive frontier, then the vehicle is considered to be predicted as *SOA*. If at least one of the parameters of a vehicle falls below the conservative frontier, then the vehicle is considered to be predicted as *inferior*. These conditions are summarized below:

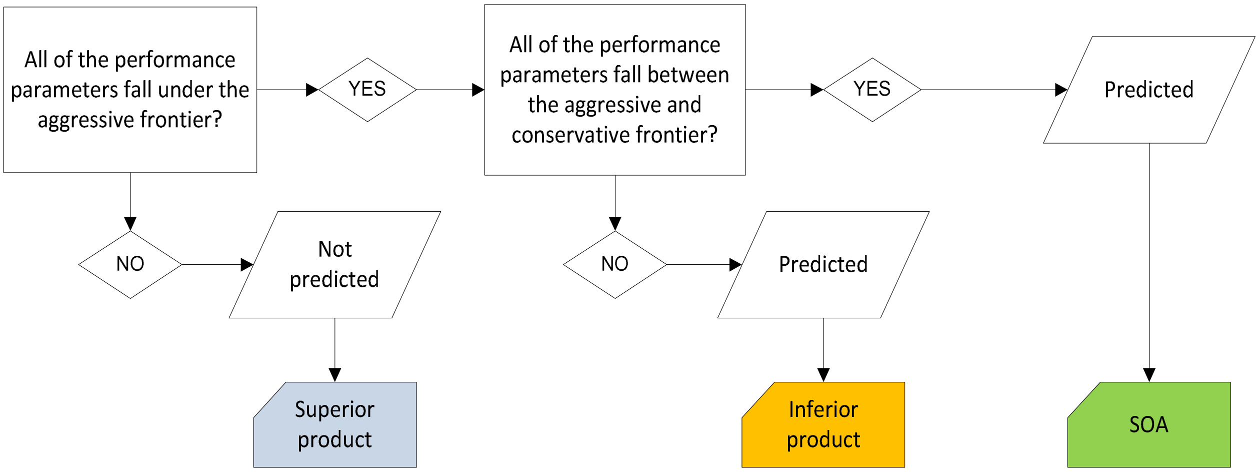

Figure 11 Flowchart to determine whether a vehicle was predicted by the model

6. Results and discussion

TFDEA was applied to the case of electric vehicle technologies as was presented in the previous section. The results are forecasts of future frontiers produced with the three models described in section 5. The forecasts were verified for accuracy against a set of existing products. Then, it was analyzed how the data availability and the assumptions of the TFDEA model impact the results of the forecast. In addition, it was verified, based on the results of the forecast, whether the TFDEA assumptions can be held valid in the case of electric vehicles.

6.1 Results

6.1.1 Applying the DEA model to determine the SOA of EV technology

The number of HEVs and BEVs released from 1997 onwards are shown in Figure 12. As described in section 5, the three DEA models were used to calculate the efficiency scores for each vehicle for each year in the 1997-2012 time window. These scores are provided in Appendix D-F for the HEV, BEV and combined models respectively. With these efficiency scores, the yearly rate of change was calculated for each model. Afterwards, using the ROC value from 2009, the new technology frontiers for 2010-2020 were predicted with the HEV and combined model. For the BEV model, the ROC value from 2010 was used and future frontiers were forecast for 2011-2020. Although the 2010-2012 period already belongs to the past, the "predictions" for these years were calculated in order to compare what was envisioned to be feasible vehicle performance during these years based on data available in 2009, with the actual performance of the vehicles released over this period. This comparison gives an indication of the accuracy of the forecasts produced with TFDEA and is therefore used as verification step for the TFDEA results.

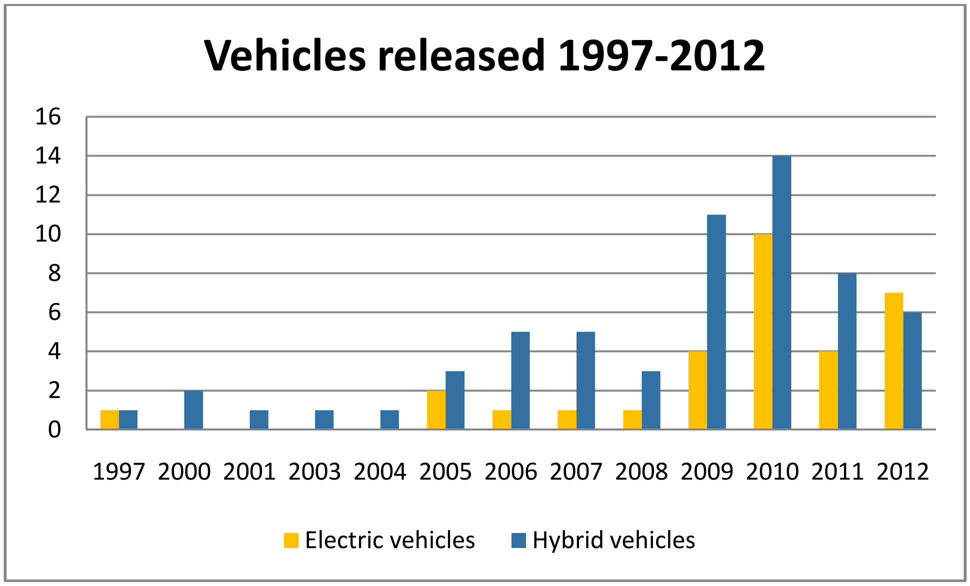

Figure 12 Vehicles released between 1997 and June 2012

6.1.2 Rate of change (ROC) curves

HEVs ROC

Looking at the ROC curve in Figure 13 and the HEVs released each year (Figure 12), it can be noticed that the ROC starts oscillating starting from 2006, which coincides with the moment when a larger number of HEVs were introduced on the market. It can be noticed that between 2012 and 2011 a larger technological change was recorded.

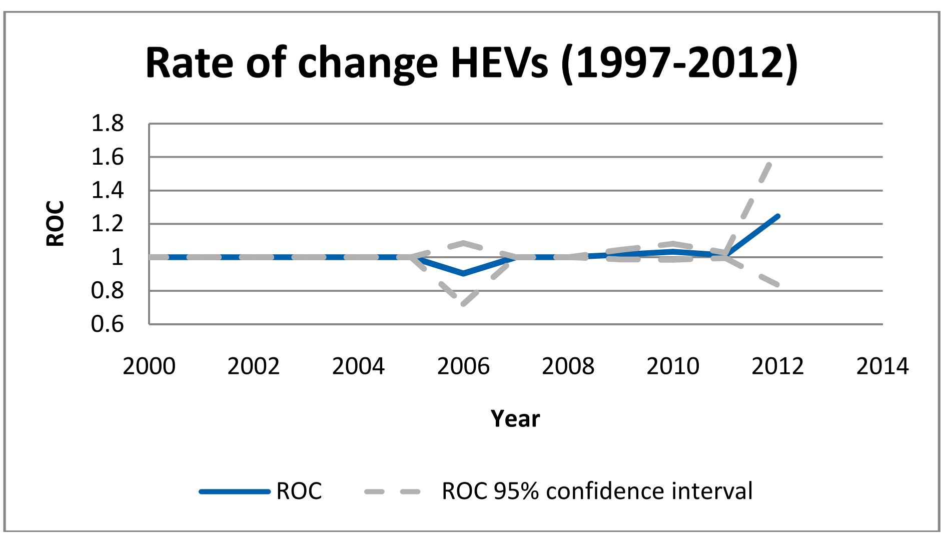

Figure 13 Rate of change HEVs 1997-2012

BEVs ROC

The BEV ROC curve is shown in Figure 14. With the BEV model, the most significant progress was recorded between 2008 and 2009. At this point, the number of BEVs available is large enough for the DEA model to be able to determine a rate of change. Up to 2008, there were only six BEVs on the market. This number is too small for the DEA model to be able to identify the SOA and non-SOA products, therefore the calculated rate of change is 0. This does not mean that no progress was recorded in reality, it only means that the model was not able to compute it. However, the calculated rate of change for 2009 onwards is still very low, indicating very slow technological progress.

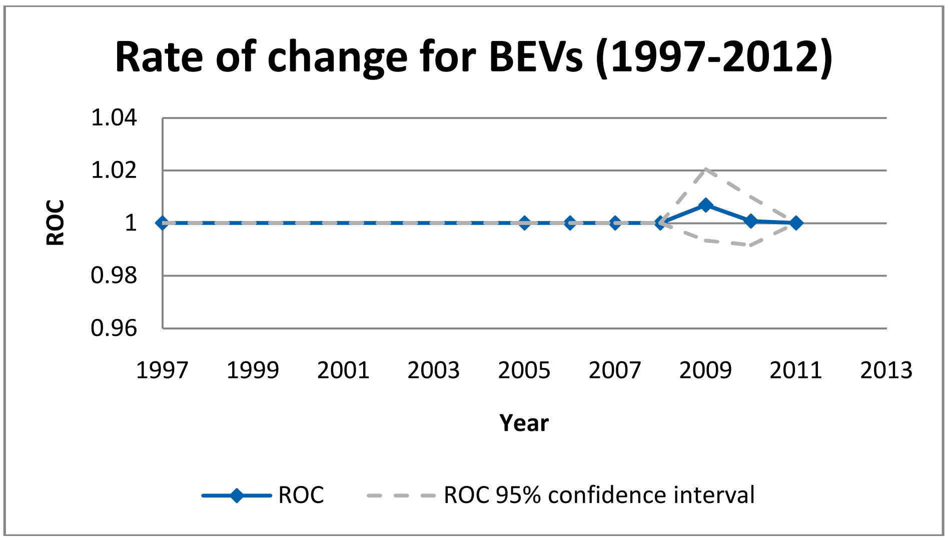

Figure 14 Rate of change curve for BEVs

Combined EV ROC

The ROC determined with the combined model is shown in Figure 15. This curve shows a much larger technological change compared to the homogeneous models. But in this case also, progress starts being recorded as of 2009 onwards, when the number of vehicles is sufficiently large for the DEA to be able to calculate the efficiency scores.

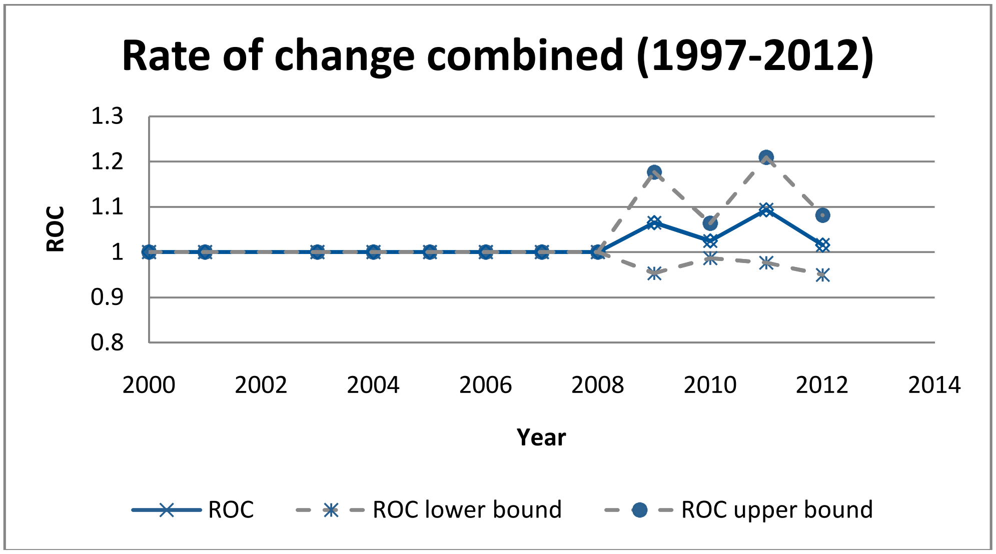

Figure 15 Rate of Change curve for EV technology

2012 SOA Frontier

The efficiency scores for the combined model were analyzed to determine the SOA frontier for 2012. The vehicles situated on the frontier are shown in Table 14. The weights imposed by these vehicles on the efficiency scores of the non-SOA vehicles are provided in Appendix H. These results help analyze the dominant technologies in 2012, which will be referred to as *dominant peers*. A state-of-the-art vehicle will be considered to be the dominant peer when it imposes the largest weight on the efficiency score of a non-SOA vehicle. Looking at the weights calculated with the DEA model, it can be seen that the benchmarks for BEVs in 2012 are *Tango,* from Commuter Cars, and *Chery QQ3 EV,* from Chery*.* These two BEVs are the dominant peers for the rest of the BEVs. For HEVs, the leading technologies seem to be *Toyota Prius PHV*, *Opel Ampera* and *Honda Insight.* The introduction of these three vehicles has changed significantly the shape of the technological frontier from 2012, imposing a new benchmark for HEV and PHV technologies.

Table 14 SOA frontier in 2012

#	Product	year	type	Acceleration rate	CO2	Fuel economy	Electric range	Φ_'12
2	Prius 1gen	1997	HEV	7.46	135	17.54		1
4	Prius 2 gen	2000	HEV	7.97	120	19.23		1
8	Tango	2005	EV	24.15			241	1
16	Lexus GS450h	2006	HEV	18.65	186	14.2		1
20	Chevrolet Tahoe	2007	HEV	10.91	366	9.5		1
22	Lexus LS600h/hL	2007	HEV	17.54	219	12.2		1
41	Forte LPI	2009	HEV	14.06	99	17.2		1
42	ActiveHybrid X6	2009	HEV	17.96	231	8		1
47	Zotye 5008 EV	2010	EV	7.14			200	1
61	ActiveHybrid 7 Series	2010	Mild-HEV	20.41	219	9.4		1
66	Fuga Hybrid	2010	HEV	18.65	162	14.3		1
68	Chery QQ3 EV	2011	EV	15.38			80	1
69	Twizy Z.E.	2011	EV	9.66			100	1
72	Inizio RTX	2011	EV	28.41			321	1
83	Aqua	2011	HEV	9.35	111	35.4		1
89	Karma S	2011	PHEV	16.67	83	22.1		1
90	Buick Regal	2011	Mild-HEV	12.05	129	11.05		1
101	Prius PHV	2012	PHEV	8.82	41	61		1
102	Ampera	2012	EREV	11.11	40	83		1
106	Insight	2012	HEV	9.42	96	27.2		1

6.1.3 Forecasting future frontiers

Future HEV technology frontiers

One of the data requirements for the DEA model is that the number of DMUs in the model as at least three times larger than the number of inputs and outputs combined.

Looking at the data sets, for the HEV model, there are 64 HEVs in total, introduced over a time window of 15 years and there are six technology attributes – three inputs and three outputs – in the model. During this time window, there are three periods (1998, 1999 and 2002) when no new vehicles were introduced. At the same time, 40 out of the 64 vehicles were released in the 2009-2012 period.

This means that only the DEA results from 2008 onwards could be considered reliable. For this reason, the 2009 ROC is used to determine the future technological frontiers for 2010 until 2020.

When analyzing the data in Table 9, it can be noticed that *Chevrolet Tahoe* has a much higher CO2 emissions level (366 g/km) compared to the rest of the vehicles.

Table 15 Chevrolet Tahoe removed from the reference data set

#	Product	Type	Year	Acceleration rate	CO2	Fuel efficiency	Φ_2008
15	**Chevrolet Tahoe**	**HEV**	**2007**	**10.91**	**366**	**9.5**	1

This data point is an obvious outlier and leads to strange predictions. Leaving this vehicle in the reference set leads to expected CO2 emissions levels of above 400 g/km by 2020. Although this is mathematically correct given the computation method, and could even be feasible based on a very inefficient physical structure of the vehicle, it is not a realistic prediction. The CO2 emission levels are expected to decrease as a result of technological progress. The Tahoe was therefore removed. This did not have an impact on the ROC value for 2009 as can be seen in Table 16**.**

Table 16 2009 ROC after removing the Tahoe

ROC_2009	std	95% confidence interval	
1.013	0.05	0.098	1.039

Using the formulas in Table 13 for HEVs, the conservative technological frontier in a particular year will be determined by the minimum values for acceleration rate, CO2 level and fuel economy, and the aggressive technological frontier will be determined by the maximum values predicted for the three parameters

In this manner, the future technological frontiers have been calculated for 2010 until 2020. The results are shown in Figure 16.

It has to be noted that the conservative frontier for the CO2 level contains the maximum values, while the upper bound holds the minimum values. This is due to the fact that a better vehicle performance is determined by a lower level of CO2 emissions.

To illustrate how the predictions can be used, the Toyota *Prius v* is taken as an example. *Prius v* was announced for release in 2011, with acceleration rate of 9.5 km/h/s, CO2 emission level of 132 g/km and fuel economy of 14 km/l. The predicted technology frontier for 2011 was expected to contain vehicles with acceleration rates between 6.87 and 20.19 km/h/s, fuel economies between 9.03 and 24.9 km/l and CO2 emissions between 237 and 105.31 g/km. The *Prius v* thus falls within the predicted conservative and aggressive frontiers of 2011 which means that the release date was realistic and the vehicle had potential to be SOA.

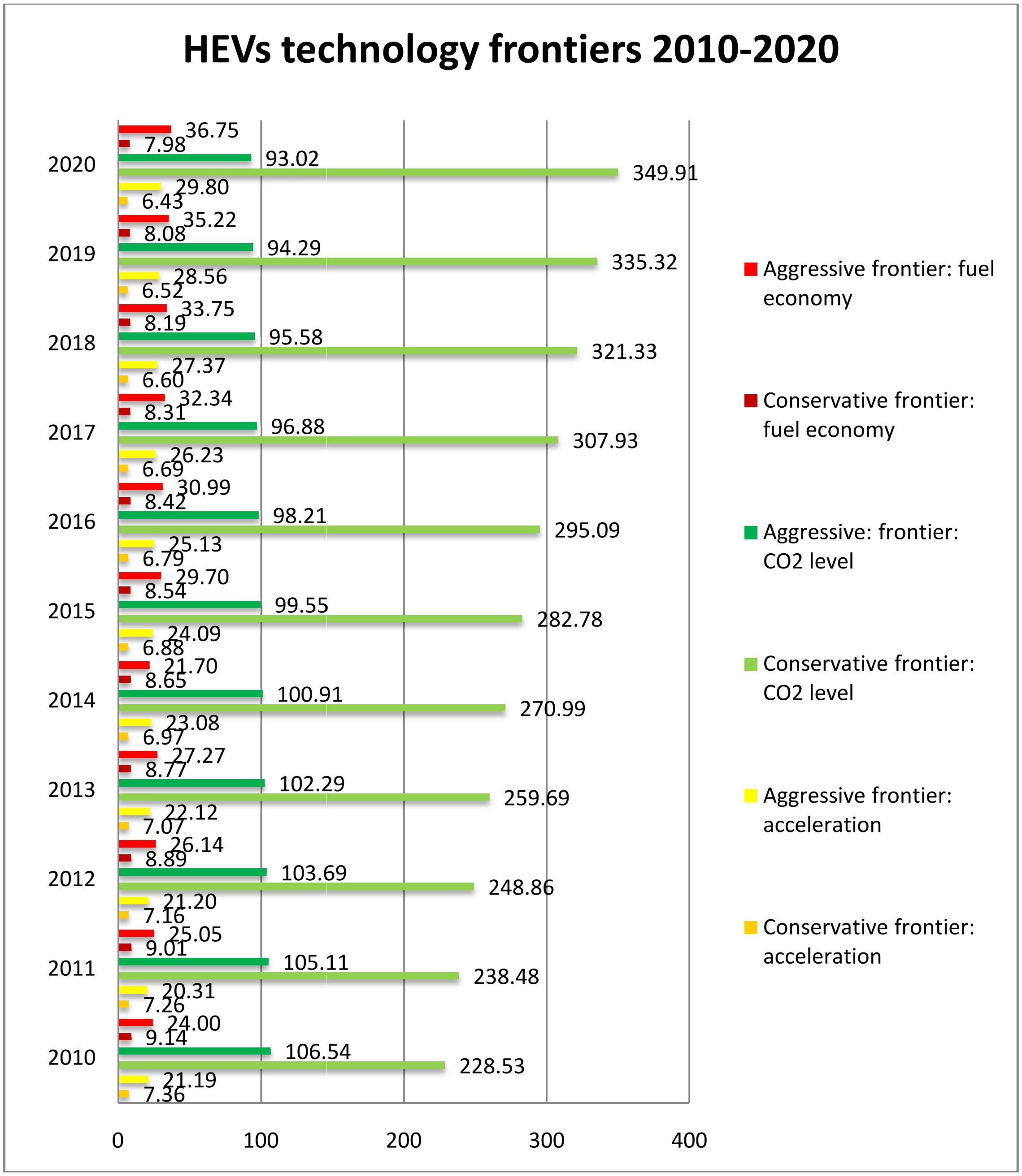

Figure 16 HEVs technology frontier

Future BEV technology frontiers

The BEV introductions have been even less regular than the HEVs. The BEV model uses a data set of 42 BEVs released between 1997 and 2012 and five technical attributes – three inputs and two outputs. During this time window, no new products were released between 1998 and 2005. Out of the 42 existing BEVs, 32 of them were released in the 2010-2012 period. Year 2011 saw 15 new BEVs, being the period with the most numerous releases.

For the BEV model, the 2009 data was used to calculate the 2010 ROC because only in 2009 were there sufficient vehicles released to be able to ensure the reliability of the DEA results. The ROC was then used to predict the technology frontiers from 2011 to 2020.

Table 17 shows the BEV data used for the 2010 ROC calculation. The EVs in the table are the vehicles which were SOA in 2009. Looking at the acceleration rate column, it can be seen that *Happy Messenger EV* is an outlier. Keeping this vehicle in the data set will predict feasible acceleration rates of 3.39 km/h/s by 2020. This means that a BEV which accelerates from 0-100 km/h in 29.44 seconds could be state of the art by 2020. This acceleration rate is already much lower than all EVs available on the market today and it is expected that future vehicles will have an even higher acceleration rate than the present ones. For this reason, *Happy Messenger* is removed from the data set, which does not change the value of the ROC.

Table 17 2009 BEV data used to determine future frontiers

#	Product	year	type	Acceleration rate	Electric range	ϕ_2009	Δt'	ϕ_2010	γ_2010 = (ϕ_2010)^(1/Δt')
1	EV-Plus	1997	EV	9.80	190	1	13	1	1
2	Happy Messenger EV	2005	EV	**3.60**	100	1	5	1	1
3	Tango	2005	EV	24.15	241	1	5	1	1
4	Venturi Fetish	2006	EV	22.47	350	1	4	1	1
5	Smart fortwo electric drive 1st gen.	2007	EV	9.23	110	1	2.34	1.12	1.05
6	Tesla Roadster	2008	EV	26.11	394	1	2	1	1
7	Subaru Plug-in Stella	2009	EV	7.73	80	1	1	1	1
8	Smart fortwo electric drive 2nd gen.	2009	EV	14.64	135	1	1	1	1

The 2010 ROC value was calculated to be 0.69% with a 95% interval of ± 1.35% (Table 18). This value was used to forecast the technology frontiers shown in Figure 17.

Table 18 2010 ROC for BEVs after removing Happy Messenger EV from the data set

ROC_2010	std	95% confidence interval	
1.0069	0.018	0.99	1.02

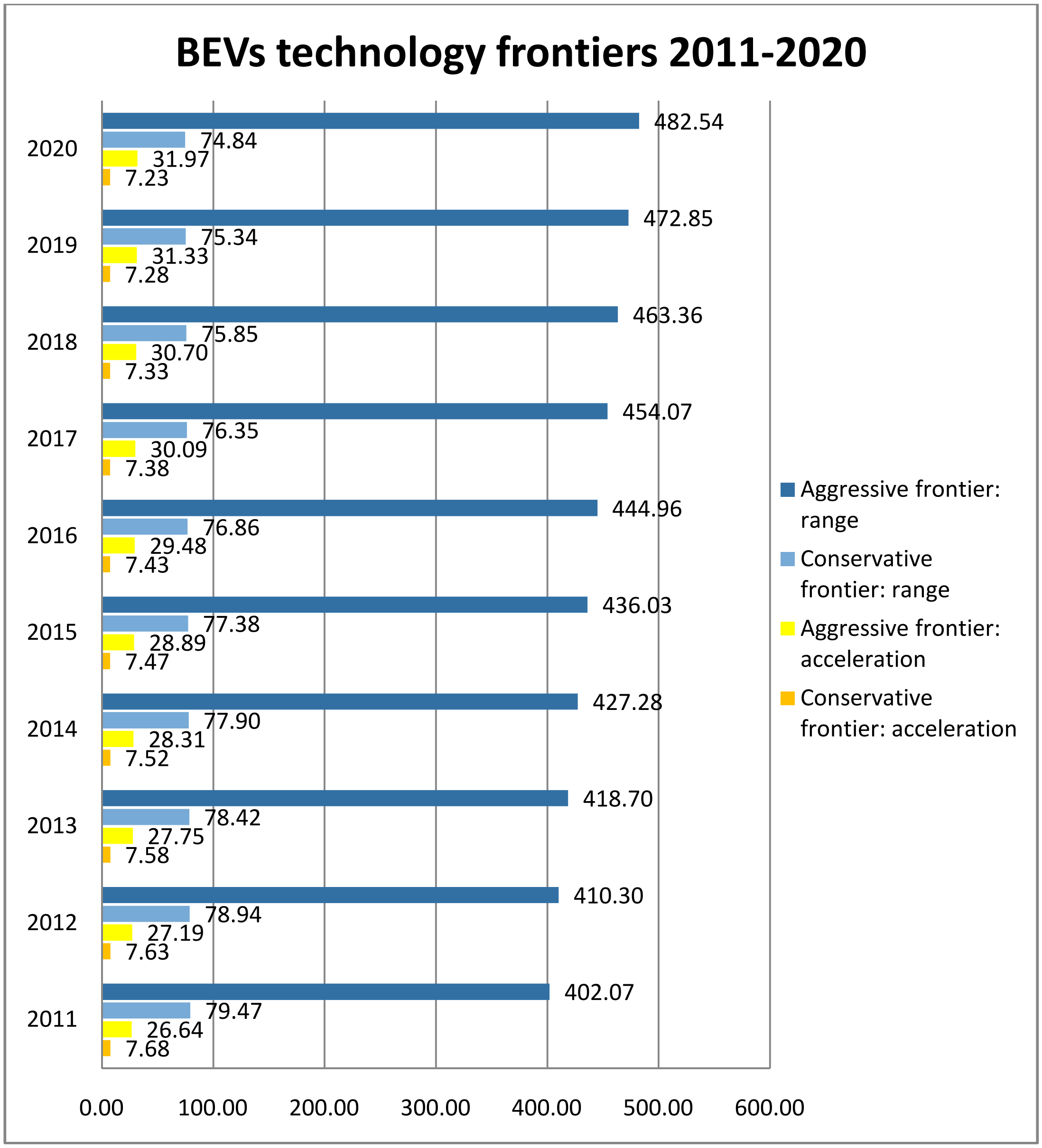

Figure 17 BEVs technology frontiers 2011-2020

Future EV frontiers

The combined model used a set of 106 vehicles and seven attributes – three inputs and four outputs. From the total number of vehicles, 63 were released in the 2010-2012 period, while in 1998, 1999 and 2002 no new vehicles were introduced. Year 2010 is the period with the most numerous releases, namely 24 new electric vehicles (HEVs and BEVs) launched.

In this situation, the 2008 data was used to calculate the ROC value for 2009 and forecast the technology frontiers between 2010 and 2020 for all four performance parameters: acceleration rate, CO2 emissions, fuel economy and driving range. The rate of change calculated for 2009 is 5.7% with a 95% confidence interval of ±10% as shown in Table 19. The rate of changed determined with this model is significantly higher than the rates of change calculated with the HEV and BEV models.

Table 19 2009 ROC for the combined data set

ROC_2009	std	95% confidence interval	
1.057	0.22	0.95	1.166

Using this ROC, the frontiers shown in Figure 18 were predicted.

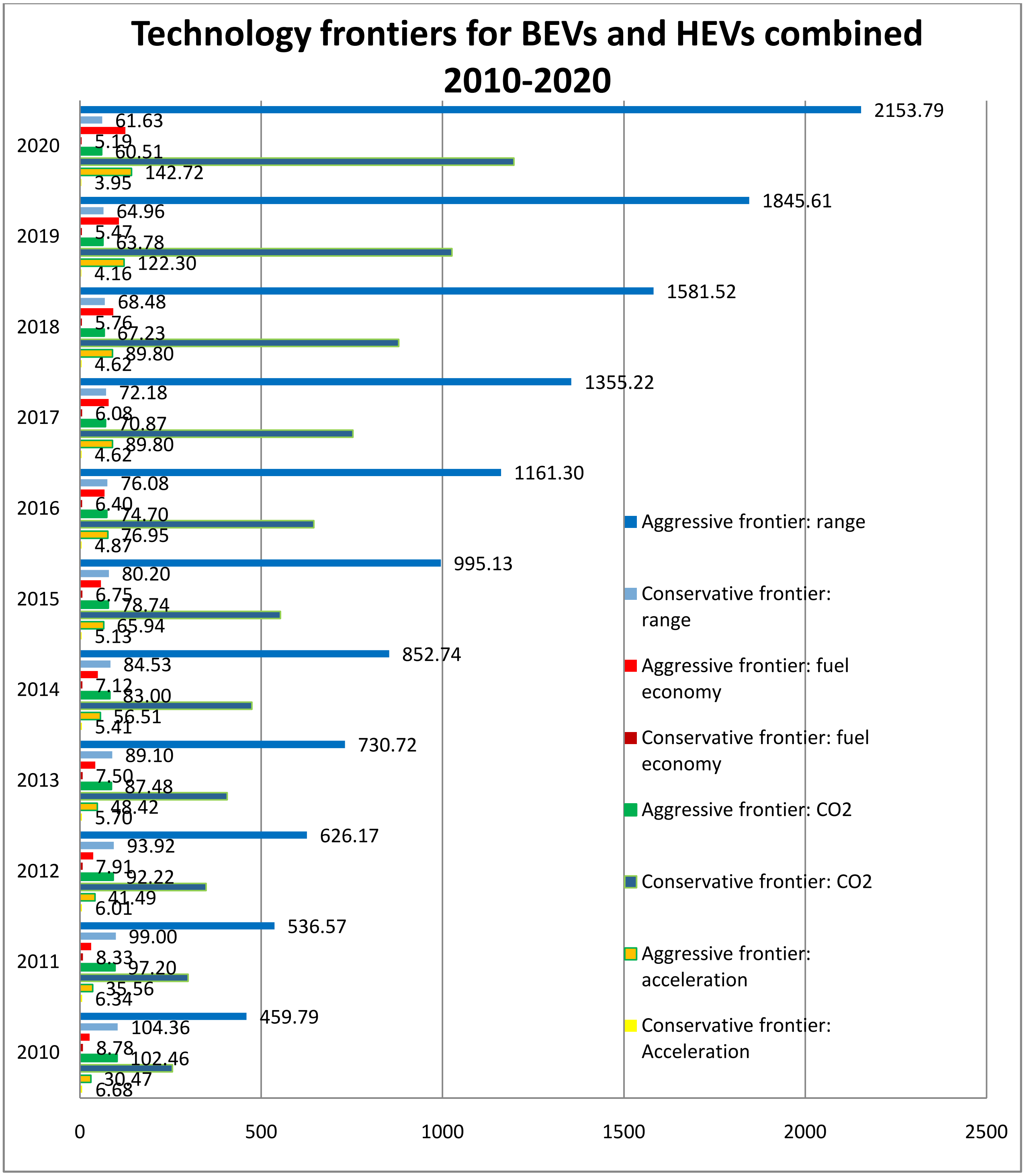

Figure 18 Predicted EV technology frontiers 2010-2020

6.1.4 EV forecasts verification

6.1.4.1 HEV forecast verification

Based on the 2008 data, it was verified if the HEVs released in 2010, 2011 and 2012 were correctly predicted. The individual results are shown in Appendix G, Table 33, Table 34, Table 35.

Verification of HEV model predictions for 2010 based on 2009 data

This model managed to predict 7 out of the 14 vehicles (50%) released in 2010, and all seven were predicted as SOA in 2010. Out of these 7 vehicles, two were correctly predicted to be SOA in 2010 - the *Active* and *Fuga* hybrids. The other five have measured efficiency scores larger than 1.0, therefore they should have been predicted below the conservative frontier by the model.

The remaining 7 HEVs released in 2010 were not predicted by the model. Five of the seven perform better than the predicted aggressive frontier in terms of CO2 emissions. *CR-Z* is the only vehicle with a superior fuel economy, while *Auris HSD* performs better both in terms of CO2 emissions and fuel economy.

Table 20 Verification of HEV model predictions for 2010 –model statistics

Vehicles	**Qty.**	**%**
Released in 2010	14	100%
Predicted below the aggressive frontier	7	50%
Predicted between the aggressive and conservative frontier	7	50%
Predicted below the conservative frontier	0	0
Not predicted	7	50%

Verification of HEV model predictions for 2011 based on 2009 data

The HEV model managed to predict 5 out of the 11 vehicles (45.45%) released in 2011. Out of these 5 vehicles, only two were correctly predicted to be SOA in 2011 - *Fit Shuttle Hybrid* and *Buick Regal*. According to the measured 2011 efficiency scores, *Optima K5*, *Prius v*, and *Civic 3rd* generation lay below the real technology frontier for 2011 when they should have been predicted below the conservative frontier by the model.

Out of the 11 released vehicles, 6 (54.55%) were not predicted. All of these 6 vehicles score better than the predicted aggressive frontier on at least one of the performance parameters. The superior performance appears in terms of CO2 emissions level and/or fuel economy.

Table 21 Verification of HEV model predictions for 2011 –model statistics

Vehicles	Qty.	%
Released in 2011	11	100%
Predicted below the aggressive frontier	5	45.45%
Predicted between the aggressive and conservative frontier	5	45.45%
Predicted below the conservative frontier	0	0
Not predicted	6	54.55%

Verification of HEV model predictions for 2012 based on 2009 data

In 2012, until June there were six HEVs released. Only three (50%) of the six were predicted by the HEV model and all three were predicted as SOA. The results are shown in Appendix G, Table 35 and the model statistics summarized in Table *22*. Comparing the predictions with the measured efficiency score, only *Lexus GS450*, with an efficiency score of 1.03 comes very close to the real 2012 technology frontier. *Prius c* and *Active Hybrid 5 series* have efficiency scores higher than 1.0, thus they should have been predicted below the conservative frontier by the model.

The remaining three vehicles - *Prius PHV, Ampera* and *Insight* – were not predicted. All three HEVs show superior performance in terms of CO2 emissions and fuel economy compared to what was considered to be feasible by 2012 based on the forecast from 2009.

Table 22 Verification of HEV model predictions for 2012 – model statistics

Vehicles	Qty.	%
Released in 2012	6	100%
Predicted below the aggressive frontier	3	50%
Predicted between the aggressive and conservative frontier	3	50%
Predicted below the conservative frontier	0	0
Not predicted	3	50%

The vehicles which were not predicted by the HEV model with their inputs are shown in Table 23. All of these vehicles show superior performance in terms of CO2 emissions and/ or fuel economy. Looking at the inputs of these cars, it can be noticed that they have slightly different input characteristics compared to the vehicles in the reference set which were used to create the forecast. What all these HEVs have in common is a smaller than average ICE and system output power, with the exception of *Karma S*. *Karma S* is a PHEV which drives in electric mode only and uses the ICE to power up a generator to charge the battery. The weaker ICE engines and the electric-only drive mode explain how it is possible for these vehicles to achieve such low fuel consumption levels and decreased CO2 emissions.

Table 23 HEVs not predicted by the HEV model

Product	Type	Year	Weight	Output power	EM power	ICE power	Battery capacity	Acceleration rate	CO2	Fuel economy
HEV set average			**1691.08**	**155.06**	**69.29**	**128.52**	**5.28**	**11.40**	**139.41**	**18.59**
Auris HSD	HEV	2010	1320	98	60	71	1.3	8.85	90	29
CR-Z	HEV	2010	1160	91	15	83	0.85	9.24	117	25.8
F3DM PHEV Low-carbon Version	PHEV	2010	1560	125	50	50	20	9.24	63	12.82
Jeep Patriot EV	PHEV	2010	1410	150	150	122	35	12.05	50	12.5
Besturn B50	PHEV	2010	1285	76	20	69	18	7.14	70	13.3
Fit/ Jazz Hybrid	HEV	2010	1130	75	10	65	20	8.26	104	22.73
Chevrolet Volt	PHEV	2010	1715	111	75	60	16	10.78	52.5	14.88
Aqua (the Japanese version of Prius c)	HEV	2011	1134	73.5	45	54	0.93	9.35	111	35.4
Lexus CT200h	HEV	2011	1420	99	60	73	1.3	9.71	89	26.3
Prius alpha 7 seats	HEV	2011	1480	100	60	73	1.3	10.00	100	31
3008 Hybrid4	HEV	2011	1660	121	28	122	1.1	11.36	99	26
Karma S (drives only in electric mode)	PHEV	2011	2400	300	300	193.88	20	16.67	83	22.1
Freed/ Freed Spike Hybrid	HEV	2011	1380	73	10	68	0.82	6.29	95	21.6
Prius PHV	PHEV	2012	1490	100	60	73	4.4	8.82	41	61
Ampera	EREV	2012	1715	110	111	0	16	11.11	40	83
Insight	HEV	2012	2747	73	10	65	0.6	9.42	96	27.2

6.1.4.2 BEVs forecast verification

Based on the forecast BEV technology frontiers, it was verified if the BEVs released in 2011 and 2012 were correctly predicted by the model. The individual results are presented in Appendix G (Table 36, Table 37) .

Verification of BEV model predictions for 2011 based on 2010 data

Out of the 15 BEVs released in 2011, 14 (93%) were predicted by the BEV model. Three of the 14 (20%) were predicted as inferior products, below the conservative frontier. Yet only one of these three – *Ray EV*- was correctly predicted as inferior; the other two, *BYD e6* and *Wave II SE*, lay on the real SOA frontier in 2011, thus should have been predicted between the conservative and aggressive frontiers by the model. From the 11 BEVs predicted to be SOA in 2011, only eight are indeed SOA based on their 2011 efficiency score. The other three – *Wave II s, Inizio R* and *Electric C30* – lay below the 2011 frontier and therefore should have been predicted as inferior products (below the conservative frontier) by the model.

Only one BEV released in 2011 was not predicted – *Inizio RTX*. This vehicle shows a superior performance in terms of acceleration, higher than the predicted aggressive frontier.

Table 24 Verification of BEV model predictions for 2011 – model statistics

Vehicles	Qty.	%
Released in 2011	15	100%
Predicted below the aggressive frontier	14	93.33%
Predicted between the aggressive and conservative frontier	11	73.33%
Predicted below the conservative frontier	3	20%
Not predicted	1	6.67%

Verification of BEV model predictions for 2012 based on 2010 data

With respect to the vehicles introduced in 2012, the model predicted all the 7 vehicles released to be below the aggressive frontier, and 6 of them were forecast as SOA in 2012. From these 6, only four of them are indeed SOA. *Zoe Z.E*. has an efficiency score of 1.06, which places it very close to the 2012 SOA frontier, but *Coda Sedan* has a score of 1.14 and should have been predicted below the conservative frontier. The model has wrongly predicted *Fluence Z.E.* as an inferior product, when in reality, this vehicle is SOA.

Table 25 Predictions for 2012 using the BEV model

Vehicles	Qty.	%
Released in 2012	7	100%
Predicted below the aggressive frontier	7	100%
Predicted between the aggressive and conservative frontier	6	85.71%
Predicted below the conservative frontier	1	14.29%
Not predicted	0	0

6.1.4.3 EV combined forecasts verification

Based on the EV technology frontiers forecast, it was verified if the HEVs and BEVs released in 2010, 2011 and 2012 were correctly predicted by the model. The individual results are provided in Appendix G (Table 38, Table 39, Table 40).

Verification of combined model predictions for 2010 based on 2009 data

Using the combined model, 19 (79%) of the 24 HEVs and BEVs released in 2010 were predicted below the aggressive frontier. Two of these vehicles – *REVAi* and *C-Zero* – were predicted as inferior products, but only *C-Zero* is indeed inferior with an efficiency score of 2.51; *REVAi* has a score of 1.0 and should have been predicted as SOA. From the 19 vehicles predicted as SOA, only five have an efficiency score of 1.0, the rest should have been predicted as inferior products.

Five vehicles were not predicted by the model. All these vehicles show superior performance in terms of CO2 emissions. *Auris HSD* performs better than the aggressive frontier also in terms of fuel economy.

Table 26 Predictions for 2010 using the combined model

Vehicles	Qty.	%
Released in 2010	24	100%
Predicted below the aggressive frontier	19	79.17%
Predicted between the aggressive and conservative frontier	17	70.83%
Predicted below the conservative frontier	2	8.33%
Not predicted	5	20.83%

Verification of combined model predictions for 2011 based on 2009 data

A total of 84.62% from the HEVs and BEVs released in 2011 were predicted based on the 2008 data and 15.38% were not predicted. From the 19 vehicles predicted as SOA, 13 are in reality inferior products. At the same time, two of the vehicles predicted as inferior – *Twizy Z.E.* and *Chery* - are in reality SOA. From the vehicles that were not predicted by the model, *Lexus CT200h* and *Karma* have superior CO2 emissions levels, while *Aqua* has a better fuel economy. *Freed* appears to be superior from the point of view of CO2 emissions, but inferior from the point of view of acceleration.

Table 27 Vehicles predictions for 2011 using the combined model

Vehicles	Qty.	%
Released in 2011	26	100%
Predicted below the aggressive frontier	22	84.62%
Predicted between the aggressive and conservative frontier	19	73.08%
Predicted below the conservative frontier	3	11.54%
Not predicted	4	15.38%

Verification of combined model predictions for 2012 based on 2009 data

From the vehicles introduced in 2012, only two were not predicted – *Prius PHV* and *Ampera*. Both of them perform better than the forecast CO2 level and fuel economy. The rest of the vehicles were forecast as SOA, although in reality only the Insight is indeed SOA in 2012; the rest should have been predicted below the conservative frontier.

Table 28 Vehicle predicted for 2012 using the combined model

Vehicles	Qty.	%
Released in 2011	13	100%
Predicted below the aggressive frontier	11	84.62%
Predicted between the aggressive and conservative frontier	11	84.62%
Predicted below the conservative frontier	0	0
Not predicted	2	15.38%

6.2 Discussion

DEA results

Looking at the efficiency scores calculated by all three models, it can be noticed that until 2008 all vehicles are ranked as state-of-the-art. This is a result of the computation mechanisms of the DEA model. The large number of attributes allows for a relatively large number of efficient vehicles, which increases the percentage of vehicles ranked as SOA. What happens is that, given a certain DMU, the model looks in the reference set for other DMUs with equal or higher output-to-input ratios. When there are very few DMUs in the data set, chances are that there are no comparable DMUs in the reference set, and consequently the DMU under analysis will automatically get an efficiency score of 1.0 and will be considered SOA, although this may not necessarily be the case. Therefore there are two problems which occur due to the limited number of products and a large number of model variables.

- Inferior (i.e. inefficient) products are not properly identified because there are no similar peers in the data set to prove their relative inefficiency.
- Superior (i.e. super efficient) products are not properly evaluated, because the best score a product can get is 1.0, and in order to identify a superior product, the model should be able to generate a positive score below 1.0.

As a consequence, there are less representative SOA frontiers to be analyzed. Therefore a large number of attributes included in the model, combined with a low number of products released over a relatively short time window will decrease the reliability of the forecasts.

Past and present SOA frontiers

Analyzing the vehicles on the past and present technology frontiers determined with the combined model, it can be noticed that the frontiers are mostly dominated by HEVs and PHVs. Only very few BEVs are present on the frontiers. This could indicate that hybrid vehicles tend to have a better performance on average compared to BEVs and are the dominating technology for the time being. This conclusion is in line with other analysis of EV technologies which claim that HEVs and PHVs might be the preferred technology until further improvements in the battery technology [37, 41] and is also shown by the fact that the number of HEVs on the market is double the number of BEVs. Still, this does not provide a strong enough argument to claim that the situation will remain the same in the future. Additional information on how different external forces, could accelerate the technological change in BEVs in order to determine whether the HEV can be expected to remain the dominant design for a long time.

ROC

The rates of change calculated with the three models are quite different (Figure 19). This is to be expected, since the rate of change is determined based on the efficiency scores, which are in turn dependent on the data in the model. The fact that for the first 11-12 time periods all vehicles were ranked as SOA by the DEA model, no technological progress can be calculated. This reduces significantly the possibility to identify if there is a visible historical pattern of progress. The variation of the ROC curves seems to be indeed very small, however, it is difficult to say if the assumption of a constant rate of change is valid under the conditions that for at least 11 out of the 15 time periods evaluated there is no information with respect to changes in technological progress.

The ROC curve for the HEV model shows a large increase in technological progress, almost 25% higher in 2012 compared to previous years. The year 2012 has seen the introduction of *Opel Ampera, Toyota Prius PHV* and *Honda Insight*. These vehicles show superior performance compared to any previously introduced HEVs or PHVs, becoming the leading benchmarks for HEV technology. The introduction of these superior vehicles changes the shape of the 2011 SOA frontier and leads to the highest level of technological change recorded by HEVs so far.

The inevitable question is whether from this point onwards the HEV technology should be expected to continue on this steep progress slope or if the rate of change will decrease again. Unfortunately, this cannot be deduced from the current analysis. The data available is not able to produce a historical pattern on which such a thesis could be built. What can be said though, is that given the large difference between the 2009 ROC and the 2012 ROC, it is expected that a forecast produced with the same model, but based on 2013 data will lead to a different estimation of future performance. Year 2013 is indicated and not 2012, because the vehicles have to be present in the model for at least one period of time, in order to determine whether they maintained their SOA position, or if their performance has been surpassed by newer releases.

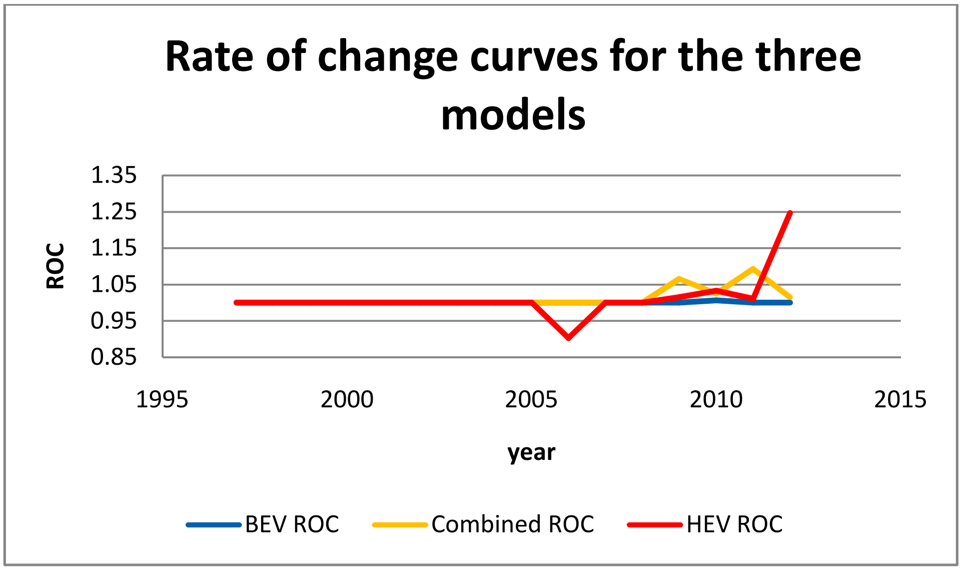

Figure 19 Comparison between the 3 ROC curves

Future frontiers

One thing to notice when looking at the predicted frontiers is that the range for each parameter grows ever wider the further it goes into the future. This is typical of forecasting based on extrapolating techniques and makes sense because the forecaster should be looking at ranges of possibilities, not at nominal predictions. Nominal predictions would be likely to fail because they would leave no room for future uncertainties.

For all three models, the lower bound of the 95% confidence interval of the ROC records technological regress. This is caused by the fact that many electric vehicles were released with inferior performance compared to older vehicles. This can be seen by looking at the efficiency scores of all three models. Cars such as *EV plus*, *Tino* and *Prius 1st* and *2nd generation*, which were released before 2001 remained SOA until at least 2011, while many cars released in 2010-2011 were not SOA at their time of release. This causes the TFDEA conservative frontier to predict a trend of technological regress, indicated by the downward shift, while the aggressive frontier keeps shifting upwards, recording technological progress.

The predicted ranges for each performance parameter (i.e. the interval between the minimum value on the conservative frontier and the maximum value on the aggressive frontier) grow ever wider the further they go into the future, up to the point when the conservative frontier reaches 0 and the aggressive frontier indicates unrealistic levels of performance.

Forecasts produced with extrapolating techniques are notorious for becoming invalid [11] the further they extend into the future. TFDEA seems to make no exception to the rule. It would be very useful if the TFDEA would offer a mechanism to maintain the forecast parameters within reasonable bounds. Of course, certain values could be manually removed from the frontiers based on the judgment of the forecaster, but this would, to some extent defeat the purpose of using an automated long-term forecasting tool which can generate future frontiers based on the existing state of the art.

Implementing a useful automated mechanism to restrict the variables from exceeding realistic values is very difficult to achieve. TFDEA allows for the simultaneous analysis of multiple variables of different natures and with different measurement units. As much as this is a valuable strength of TFDEA, it also means that not all variables can be restricted in the same way, therefore the mechanism should be customized per type of variable. In theory this could be done by thinking upfront of all possible types of variables users of TFDEA could introduce in their analysis and provide suitable constraints for each type. In practice however, this would be very labor-intensive and may not add value to the method. Imposing certain constraints on future performance may keep the variables within limits acceptable to the forecaster, but it could also prevent the forecaster to identify potential breakthroughs, which, by default, will have unusual characteristics.

HEV model forecasts

Concerning the frontiers predicted with the HEV model the following remarks can be made:

- One striking thing is the CO2 evolution. The model predicts for 2020 feasible emissions levels between 93.02 g/km (aggressive frontier) and 349.91 g/km (conservative frontier). The aggressive value is credible, although several vehicles available in 2012 already reach lower emissions levels. The conservative value on the other hand is significantly higher than most vehicles considered inferior in 2012. The expectations are that CO2 emissions decrease, therefore it is unlikely that products considered SOA in 2020 will be producing such quantities of CO2.
- The fuel economy values seem realistic; however, the forecast values for 2020 have already been exceeded in 2012.
- The forecast acceleration values also seem realistic and probable. The aggressive value for acceleration indicates that it will be feasible for an HEV to accelerate from 0 to 100 km/h in 3.36 seconds. The fastest HEV released to date is *ActiveHybrid 7 series* (2010) with a 0-100 acceleration time of 4.9 seconds, while the average 0-100 time of the vehicles released until June 2012 is 8.76 seconds. Therefore it sounds probable that with innovative techniques to decrease the weight of the car, or to use a stronger EM in the drivetrain over the coming years, future HEVs would be able to achieve this level of performance.

BEV model forecasts

The frontiers forecast until 2020 with the BEV model do not raise particular question marks since the values seem realistic. The aggressive frontier indicates feasible ranges of 480 km. This may seem rather high, considering the discussions focused on the current state of battery technology and the limitations it imposes on BEV performance. Yet, *Inizio RT* is able to drive 402 km on a battery charge since 2011. Taking this fact into account and considering the fast-speed battery developments for laptops, such a long driving range could be achieved within the coming years.

Combined model forecasts

Looking at the technology frontier for 2020 determined with the combined model a few things can be noticed.

- The conservative frontier indicates feasible CO2 emission levels of 1197 g/km. This value is completely unrealistic, given on the one hand, that the tendency is to decrease the CO2 level, and on the other hand, that the HEV with the highest CO2 level of emissions currently available is the *Chevrolet Tahoe*, emitting 366g/km; all the other HEVs perform much better than that .
- The aggressive CO2 frontier gives a rather reasonable prediction for the CO2 performance, however, in 2012, there are already vehicles capable of reaching values lower than this. Toyota's *Prius PHV* and *Opel Ampera* have been released on the market in the first half of 2012 and reach CO2 levels of 41 and 40 g/km respectively. It has to be noted though that *Prius* is a plug-in hybrid and *Ampera* is an extended range electric vehicle. The forecasts were made based on 2009 data, and at that point no EREV had been introduced yet, while the first PHV was released in 2008. This means that with the level of technology in 2009 such advanced performances could not be anticipated.
- The acceleration and range values predicted for 2020 are also rather extreme. The aggressive forecast indicates that by that time it will be feasible to accelerate from 0-100 km/h in less than a second. The fastest car in the world at the moment, *Bugatti Veyron Super Sport*, can reach 0-96.6 km/h in 2.4 seconds [43], yielding an acceleration rate of 40.25 km/h/s. It is hard to believe that this could be achieved within the coming eight years for a passenger vehicle without completely revolutionizing the way vehicles are built. Also, such a level of performance would not even be necessary for a regular car. In addition, these results suggest that it might be possible to drive about 2000 kilometers on a battery charge. This value is too high to be realistic. For such ranges to really be feasible, significant advancements in the battery technology would be required, as well as ingenious ways of improving the efficiency of a vehicle's drivetrain.

- As for the conservative frontier, the predicted acceleration (3.95 km/h/s) and range (61.63 km) values are lower than for most vehicles already available. On the other hand, these values could be an indication of the potential spread of a different type of EVs - small city battery vehicles, such as *REVAi* (Figure 20), which could offer performances comparable to electric scooters for example. Such vehicles would be used only for city drives and would not need to drive at high speeds or over long ranges.
- The aggressive frontier indicates a fuel efficiency of almost 126 km/l. This value could seem rather high, but then again, *Opel Ampera* can already reach 83 km/l in 2012, followed by *Prius PHV* with 61 km/l, after the best fuel economy in 2011 was achieved by *Toyota Aqua*, with 35.4 km/l. At present, most hybrid vehicles are able to drive in electric mode only up to a speed of 30-40 km/h. Looking at these three examples of vehicles, it could be possible to achieve fuel economies in the order of 100 km/l by 2020 focusing the designing efforts on cars capable to drive in electric mode over the whole speed range, and perhaps only use fuel to charge the battery while driving. Such a configuration is already implemented by Opel in their *Ampera* EREV. The 2012 SOA frontier and calculated efficiency scores show that *Ampera* is the new benchmark for the performance of other PHEVs and HEVs. Due to its superior performance compared to older HEV configurations, the EREV configuration used by *Opel Ampera* has potential to become a disruptive technology.

Figure 20 REVAi by Mahindra Revai Electric Vehicle

Using a constant ROC to forecast new technology frontiers implies that all the performance parameters are expected to grow or decrease at the same rate, since all parameter values are multiplied by the same quantity (i.e. the ROC raised at an exponent equal to the difference between the time of the forecast and the moment of the release). Two issues are noticed concerning this mechanism:

- First of all, this may not be the case in reality, especially since sometimes trade-offs between performance parameters need to be made. For example, in order to increase the acceleration rate, a more powerful engine may be required. A powerful engine consumes more fuel, therefore, based on the design priorities, the vehicle might be designed to achieve better fuel economy at the expense of acceleration.

- Secondly, when comparing the forecasts produced with the individual models and the combined model, it can be noticed that some of the forecast performance parameters achieve unrealistic values much faster with the latter. This happens especially with parameters that have large nominal values, such as range and CO2 emissions. The ROC value used to determine future frontiers with the combined model is much higher than the ROC used in either the HEV or the BEV model. This suggests that assuming as constant a large rate of change may invalidate the forecast faster than when the ROC is smaller, because it may calculate a rate of technological growth which cannot be sustained in reality. For this reason it is important to have sufficient historical evidence that the ROC does have the tendency to remain constant over time.

The constant rate of change is identified by the TFDEA literature as a weakness of the method which could lead to errors in long term forecasts. Based on the results presented in section it could be concluded that when the calculated rate of change is large, this assumption can also lead to errors in the medium-to-short-term forecasts.

Accuracy of predictions

The percentage of HEVs which were not predicted is higher than the percentage of BEVs. Especially the PHVs and the EREVs were never predicted by the models. All of the vehicles which were not foreseen by the model show a much better performance in terms of fuel economy and CO2 emissions. This indicates that in the case of HEVs technological change occurs even faster than predicted with the ROC calculated by the model. To an extent this makes sense, because while BEVs depend almost entirely on the battery limitations, the HEVs have more input variables which can be tuned in order to achieve the desired performance. Compared to BEVs, hybrid vehicles have a more complex architecture which allows for more design flexibility and possibilities for trade-offs. This gives more opportunities to improve the vehicle performance by modifying different parts of the drivetrain structure.

It was shown that all the vehicles that achieve a better performance than forecast manage to do that by using a different input configuration compared to the vehicles included in reference set of the forecast. This means that what appeared to be a relatively homogeneous HEV technology in 2009, at the time the forecast was created, has diversified into different configurations which can achieve higher levels of performance. When creating a forecast, the model assumes the proliferation of a certain input combination. Since none of these new structures were present in the reference set, they could not be anticipated.

One thing that is not taken into account in the reference set of the HEV model is the possibility to make more use of the advantages of driving in electric mode. Most of the HEVs in the reference set are strong hybrids with very small batteries and small electric motors, which allow the HEV to drive in electric mode only at very low speeds and accelerations. Therefore the reference set does not reflect the relevance of battery technology for the developments of HEVs because small batteries are sufficient for regular strong hybrids. The battery technology only becomes important for newer HEV configurations, such as PHVs and EREVs, which make more use of the electric drive mode.

By comparison, the combined model yields more accurate predictions than the HEV model. By including all electric vehicles in the model, the reference set is able to reflect the possibility to utilize larger batteries and to develop mechanisms which allow hybrid vehicles to drive in electric mode. But even in this case, most of the vehicles which were not predicted generally perform better from the point of view of CO2 emissions, and in some cases, fuel economy.

What might seem to be an odd coincidence is the fact that the performance parameters which tend to advance more abruptly than predicted by the model are exactly the ones which are the target of governmental regulation, namely fuel economy and CO2 emissions. This may not be accidental though. Although HEVs perform really well and manage to meet the imposed fuel economy and CO2 level on their own, the regulation targets the whole or at least a certain percentage of the total car fleet. This means that there is a strong incentive for the auto makers to improve the performance of the HEVs in order to drive down the average fuel economy and CO2 emissions of their fleet. This suggests that significant efforts should be expected from car manufacturers to improve these performance parameters in the future.

It should be taken into account that no matter how efficient HEVs will become, as long as they use fuel for any operation purpose, the fuel consumption and CO2 emissions will never disappear, therefore the only alternative in this respect is the BEV. In addition, the combined drivetrain carries additional weight when one of the main strategies for improving the environmental performance of HEVs is to decrease the weight. Therefore it is expected that eventually the combined drivetrain will become an obsolete configuration. Verbong and Geels [44] claim that the transition towards a niche technology can be achieved only when regulation and consumer behavior are ready to accept and accommodate the new technology. For electric vehicles this would mean that the BEVs would become the norm only when a beneficial regulatory framework would be in place and consumers would be willing to change their driving behavior from relying on fuel to relying on the car battery when driving.

Overall, the BEV model predictions seem to be quite accurate. The BEV model also calculates a much slower rate of change compared to the other two models. This is most likely due to the fact that the BEV technology is homogeneous compared to HEV technology. The battery capacity has the largest impact on the performance of a BEV. In terms of performance, no other limitations exist for BEVs except for the limited range caused by limited battery performance.

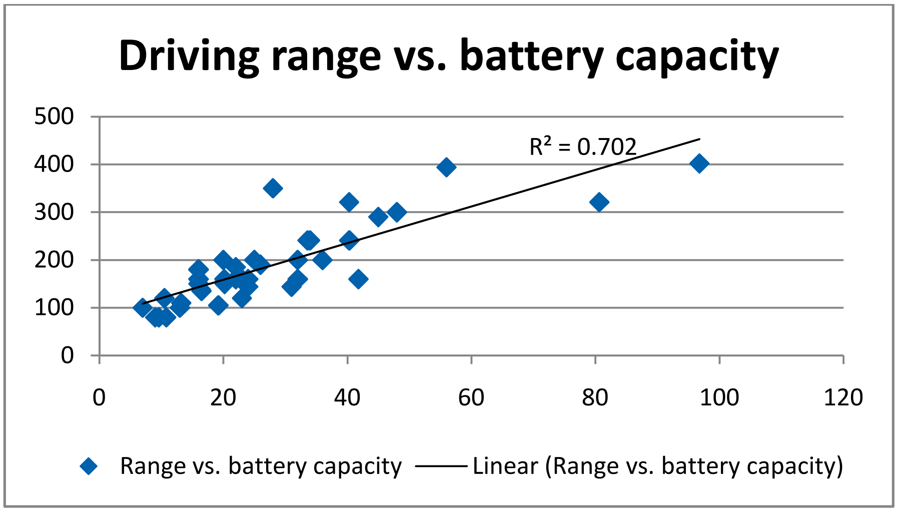

Figure 21 BEV driving range vs. battery capacity

Figure 21 shows that there is a linear relation between driving range and battery capacity which implies that technological progress in BEV technology will occur as a response to advancements in battery technology. This means that as long as 'better' batteries do not exist, or exist but are too expensive to achieve the desired performance at a reasonable cost, there are limited possibilities to improve the performance of BEVs. Therefore it could be assumed that BEV performance will only advance as fast as battery developments. This also means that an investigation of the technological progress of batteries may provide valuable information about what can be expected from BEVs in the future.

6.3 Threats to validity

The assumption of a constant rate of change had already been recognized by previous TFDEA research as a limitation which can lead to errors for long term forecasting. Yet the results of the HEV TFDEA model show that this can also be an issue for the short-to-medium term by causing the performance parameters to exceed reasonable bounds due to computational mechanisms. In addition, the assumption of a constant rate of change cannot be supported by the existing data, and therefore cannot be validated. Although very little variation can be seen in the annual ROCs recorded between 2008 and 2012 for the three models, the TFDEA algorithm is not able to generate sufficient information about the past to be able to evaluate technological progress from the first introductions of electric vehicles, thus there is insufficient proof to assume that the ROC will remain constant over time.

Parallel developments and regulations can also pose a challenge to the validity of the forecasts produced using TFDEA. Assuming a constant rate of change could be justified when the technology has reached a rather stable phase, when the design and manufacturing processes have been standardized. The mere existence of several electrical vehicle architectures (strong hybrid, plug-in hybrid, extended range hybrid, battery electric) shows that this is not yet the case. It was shown that superior performance was achieved through exploration of novel driving concepts and resulted in a further diversification of the drivetrain structure. The design process seems to be evolving, leading to innovative solutions to improve the performance. At the same time, significant research is being conducted in order to improve the current state of battery technologies, which is considered to have a major impact on the course of EV developments.

TFDEA assumes linear relations between technology inputs and technology performance. For electric vehicles, this may be an oversimplification of the relations between inputs and outputs, but the system analysis conducted in section 3 and literature on technology innovation and technology forecasting offers arguments that this could be a reasonable claim. What is not realistic for EVs is the assumption of constant inputs. The TFDEA method produces forecasts assuming that not much is changing in the input configuration, yet this is obviously not true for electric vehicles. The performance of a vehicle is delivered by the components of the drivetrain, therefore improving the performance requires different design choices for the component parts. In addition, some of the performance parameters of electric vehicles are influenced by regulation, causing a second order effect on the input configuration.

7. Conclusions & recommendations

Developments of EV technologies are likely to have significant social and economic implications for different public and private actors. EV technology forecasting is therefore needed to identify these impacts and signal necessary adjustments in corporate strategies and public policy. This report presented an investigation on whether it is possible to apply technology forecasting using data analysis (TFDEA) in order to determine which of the current electric vehicle technologies has potential to become the dominant design in the future.

The main concerns regarding the use of TFDEA in the beginning of this study were related to the model assumption of linear relations between inputs and outputs of technology and of constant rates of change, but also to uncertainties on whether the existing EV data would be sufficient to produce meaningful results. To identify if the method can be used to create reliable forecasts of the EV technological progress, a technical system analysis was performed first in order to determine the main technical attributes of EV technologies; then the TFDEA algorithm was applied.

The system analysis helped provide understanding of the basic operation mechanisms of EV systems and of the relations between different EV design variables. Such information was necessary in order to properly identify and select those design parameters that are responsible for the EV performance and which can impose limitations to further technological advancements. For both families of vehicles, the output power of the propulsion unit, the charge storage capacity of the battery and the vehicle weight were found to be the main determinants for EV performance. In this study, the performance of BEVs was expressed in terms of acceleration possibilities and driving range, while for HEVs fuel economy, CO2 emissions and acceleration were selected as key performance indicators.

The technical and performance attributes of EVs were used as inputs and outputs respectively in three TFDEA models. Two of the models were used to evaluate the individual technological progress of BEVs and HEVs as homogeneous products, while the third model was used to determine the rate of technological change over the full class of EVs. Each model was used to produce a forecast for yearly EV performance levels until 2020. These forecasts were verified for accuracy against a set of existing products. Then, it was analyzed how the data availability and the assumptions of the TFDEA model impact the reliability and validity of the forecast. The main conclusions of the investigation are shown in this section.

- Is the DEA assumption that technology outputs are a linear function of technology inputs supported by vehicle design theory?

TFDEA assumes linear relations between technology inputs and technology performance. For electric vehicles, this assumption is realistic to a limited extent. This is especially visible in the case of battery electric vehicles. As shown in Figure 21, there is a linear relation between battery capacity and electric range.

- What are the consequences of data availability for the application of the method?

It was noticed that a large number of attributes included in the model, combined with a low number of products released over a relatively short time window might decrease the reliability of the forecasts. This is caused by the computational mechanisms of the DEA model. The large number of attributes allows for a relatively large number of efficient vehicles, which increases the percentage of vehicles ranked as SOA. On the one hand, this causes inferior products to be ranked as 'best performers' because there are no similar peers in the data set to prove their relative inefficiency. On the other hand, superior (i.e. super efficient) products are not properly evaluated, because the best score a product can get is 1.0, and in order to identify a superior product, the model should be able to generate a positive score below 1.0. As a consequence, there are less representative SOA frontiers to be analyzed. Furthermore, for the first 11-12 time periods all vehicles in the data set were ranked as SOA, therefore no rate of change could be calculated. This reduces significantly the possibility to analyze whether there is a visible pattern of constant progress.

- What are the implications of assuming a constant rate of change on the accuracy and validity of the EV forecasts?

The assumption of a constant rate of change can lead to errors both in long term and short term forecasting. First of all, the assumption of a constant rate of change cannot be supported by the existing EV data, and therefore cannot be validated. Although very little variation can be seen in the annual ROCs recorded between 2008-2012 for the three models, the DEA algorithm is not able to generate sufficient information about the past in order to be able to evaluate technological progress from the first introductions of electric vehicles, thus there is insufficient proof to assume that technological progress will remain constant over time.

Secondly, using a constant ROC to forecast new technology frontiers implies that all performance parameters are expected to grow or decrease at the same rate, since all parameter values are multiplied by the same quantity (i.e. the calculated ROC raised at an exponent equal to the difference between the time of the forecast and the moment of the release). In reality, this is not always the case, because design trade-offs need to be made between different performance parameters.

With respect to accuracy, the BEV and combined models were more accurate in predictions than the HEV model. The percentage of HEVs which were not predicted is higher than the percentage of non-predicted BEVs. Configurations such as PHVs and EREVs were never anticipated. However, the inaccuracy of the HEV model is not caused by the constant ROC assumption, but by the assumption that technology inputs remain constant over time. This inherent assumption of the output-oriented DEA model is not realistic for the case of electric vehicles. As was shown in section 3, bottlenecks in improving the vehicle performance can often only be overcome by changing the internal configuration of the vehicle, in other words, by changing the technology inputs. All the vehicles that achieve a better performance than forecast use a different input configuration compared to the vehicles included in the reference set of the forecast. Thus, assuming constant inputs conflicts with vehicle design principles and vehicle manufacturing possibilities.

- ❖ Can the method anticipate the consequences of external factors such as innovation in substitute and sub-component technologies, or regulation of performance parameters, such as fuel economy and CO2 emissions, on the technological change of EV technology?

Based on the results analysis, it can be concluded that TFDEA is not capable of anticipating neither regulation influences, nor the impact of parallel breakthroughs on technological progress.

Different EV configurations can be considered substitute technologies – they all provide the same functionality (transportation), but one configuration could be preferred over another based on the EV attributes (e.g. limited range versus zero tailpipe emissions) that provide the most utility for the user. In order to determine if a certain EV design has potential to dominate the industry, it is important to be able to anticipate the emergence of possible disruptive substitutes and how these would affect the development of existing technologies. The results of the three models show that the TFDEA does not offer the possibility to foresee the introduction of potentially disruptive technologies, such as the PHV and the EREV. This is due to the fact that the forecasts produced with TFDEA identify what may be feasible in the future based only on what exists today. TFDEA assumes that inputs remain constant over time and has no mechanism to identify future re-configurations of inputs which could lead to better performance. With respect to developments in sub-component technologies, such as batteries, the previous argument still holds. Assuming constant inputs prevents the model from anticipating any sudden change which was not accounted for in the reference data set.

As could be seen from the results of the HEV model, TFDEA is not capable to anticipate the impact of regulation on vehicle performance. According to Bright [11], regulation of performance parameters might have as an effect the slow-down or the speed-up of the innovation process. It was observed that the TFDEA models consistently predicted lower CO2 emission and fuel economy levels than was achieved in reality. TFDEA assumes a constant rate of change, therefore, it is not able to foresee any disturbance in the progress of innovation caused by a force from outside of the technology system.

Q.2 Can the method be implemented given the current state of EV technology?

The relatively large number of variables used in the models limited the possibility to analyze technological change for the period 1997-2009. However, at the moment, there is sufficient data which meets the requirements of TFDEA, as well as arguments to consider that EV performance is a function of the vehicle sub-components, therefore the method can be implemented. The DEA technique offers the possibility to analyze multiple attributes for multiple EV technologies simultaneously which constitutes an advantage. The DEA model can also be used on its own for benchmarking purposes, to identify the state-of-the-art frontier for electric vehicles. Perhaps using fewer variables could have yielded better mathematical results, but it was decided that none of the selected variables could be removed, since that would limited the possibility to analyze the impact of certain factors on technological progress.

Q1. To what extent can the TFDEA method be used to identify a potentially dominant EV design in the future?

Before providing an answer to the main research question, some general observations concerning the TFDEA method, which resulted from the EV case study, are presented below:

- TFDEA provides a simple and easy to use tool for measuring technological progress, but it is very data intensive, which constitutes a problem for emerging technologies for which only a few products have been introduced.
- The method allows for multi-criteria analysis which is a definite advantage. The downside is that the number of variables which can be included in the analysis is limited by the number of products in the data set, therefore the fewer the products available, the fewer the number of variables which can be used. This is a disadvantage for complex technologies characterized by many attributes.
- The DEA model does not require predetermined mathematical relations between inputs and outputs or pre-assigned weights for each variable. Yet, the quality of the forecast depends mostly on the selection of variables used. This means that the forecaster should have sufficient knowledge and understanding of the technology under study and its operation mechanisms to be able to select the right set of variables. Therefore, in situations when the forecaster is not familiar with the technology under analysis, performing TFDEA could be either labor-intensive, if the forecaster would perform the system analysis on their own, or expensive, when experts are required to identify the input and output variables for the DEA model.
- Even in situations when the technology is more mature and sufficient data exists, as well as understanding of the technology, product data confidentiality can be a problem for TFDEA. TFDEA requires information on the inputs of a technology, but much of the manufacturing related information which could be used to determine technological progress, such as manufacturing costs, for example, will not be disclosed by companies. Therefore forecasters may find themselves

constrained to a limited choice of variables for which data can be acquired, which limits the possibility to investigate the full range of opportunities for technological advancement.

- It was shown that TFDEA is not able to anticipate the influence of regulation on performance parameters. This indicates that the method is very sensitive to exogenous drivers of technological change. The EV case study shows that the approach to evaluate the performance of a technology as a linear function of its inputs is an oversimplification which cannot be used for complex technologies with economic and socio-political implications.
- Using a constant ROC for forecasting is not realistic, because innovation does not occur at a regular pace. Such an assumption can be valid in situations when historical data is able to identify that the technological progress remained constant over the years and no external forces are expected to cause disruptions. If this is not the case, the forecast will be biased by the reference set used to produce it. Using as reference a year when a relatively low rate of change was recorded can lead to underestimations of future performance, as could be seen from the results of the HEV model. Alternatively, choosing a reference year with a large rate of change, may predict non-sustainable improvements in product performance.

The TFDEA method was applied in this study to obtain information on future technological progress and performance of the EV technology. The analysis conducted in this reports leads to the conclusion that the TFDEA model would not yield reliable long-term forecasts for the evolution of EV performance. Although the TFDEA results seem to be accurate enough for short term forecasting, the assumptions of the method decrease the reliability of the results.

In addition, estimating technological progress from the current state of technology is not sufficient to give an indication of which EV configuration will become dominant in the future. Due to the wide implications for different sectors of activity, the adoption of electric vehicles is expected to not depend completely on technical performance, but also on the availability of supporting technologies and reduced cost opportunities for consumers.

Recommendations

At the moment, HEVs offer superior performance compared to both BEVs and ICVs and are expected to remain a preferred technology in the near future. Especially the EREV and PHV configurations seem to have potential to act as disruptive technologies, especially for the standard hybrid configurations. Their main disadvantage is the extra weight imposed by the combined drivetrain, which will eventually pose limitations to further developments. However, despite the apparently inferior performance of BEVs compared to HEVs and the acute dependency on battery charging facilities, the need for introducing BEVs on a larger scale seems to be recognized due to different reasons of national security and environmental concerns. Therefore it can be expected that external forces will try to accelerate EV technological progress. In addition, it would be naïve to deny the importance of innovative business models and parallel technological innovations which are emerging in order to ensure a competitive market position for battery electric vehicles.

Porter et al. [45] indicate that technological changes in one technology will drive changes in other technologies. Given the current EV state of the art frontier, which is dominated mostly by hybrid vehicles of different configurations, it might be more meaningful to identify the conditions which can lean the scale towards hybrid or battery electric designs in the future. One way to do this is to perform an analysis of the impacts [45] of BEV technology.

First of all, long-lasting batteries available at reasonable cost are required to eliminate the range limitations of BEVs. Technology forecasting of battery technology advancements can offer an indication of when major improvements could be expected in the performance level of BEV. If battery advancements are slow, it is expected that the availability of a charging infrastructure will ease the requirements on the battery storage capacity decrease the consumers' concerns related to the limited range provided by the battery. At present there are two major trends for implementing such an infrastructure: fast plug-in charging stations and battery switch stations.

Fast charging stations use the same plug-in mechanism as regular power outlets, but supply a higher voltage, which means that they allow a larger volume of power to flow into the battery in a certain amount of time. This reduces the charging time from several hours (when a regular power outlet is used) to below one hour. This implementation of a fast-charging network is recommended by the Electrification Coalition [46] as part of a U.S nation-wide strategy to merge the power and the transportation sector. The alternative is a network of battery switch stations [47], where the driver can have the empty battery changed for a new one. This follows a marketing strategy to commercialize the battery as a separate service not as an integral part of the vehicle [1]. The Israeli company, the Better Place [48] has started deployment of pilot battery switch stations in several countries, such as Denmark, Israel and the Netherlands.

Regardless of the technical and economic advantages and disadvantages of the two alternatives, they both require standardized interfaces between the BEV and the charging station, as well as electricity grid capacity to accommodate a large number of BEVs on the road. To identify when charging infrastructures will be available for BEVs, an investigation of standardization tendencies for the BEVs is required. Such an investigation can be done through literature review of standardization possibilities and targets for the auto industry.

With respect to the grid capacity implications, the widespread adoption of BEVs is expected to be facilitated by the widespread of green power plants and the implementation of smart grids. The introduction of BEVs is seen as a favorable factor [46] which can improve the efficiency of intermittent green energy sources, such as wind and solar energy. The BEV batteries are seen as a potential storage alternative for the excess energy generated by wind and solar plants. One major concern with respect to the impact of a large number of vehicles plugged in to the grid at the same time is load variation [1]. However, Serra [1] and the Electrification Coalition [46] see this as an opportunity to accelerate smart electrical grid development and adoption. Smart grids rely on information and communication systems, such as smart meters, which provide real-time communication of the consumer behavior in order to improve the efficiency of the system. Deployment of BEVs on a large scale is believed to open new market opportunities for smart grid innovations. Martino [49] claims that technology indicators for market shift, such as patents or scientific publications, can give an up to three year notice before a certain technology becomes available. To identify when the necessary grid supporting technologies will be in place, a review of market shift indicators of a transition towards the smart grid could be performed.

Furthermore, experience shows that it is not always the best performing technology which becomes the market leader. Governmental support for a certain technology could be, in some cases, the showstopper for another [11, 29]. An investigation of different governmental plans and intentions is necessary to reveal market opportunities and national preferences for different EV configurations. Such plans and intentions could refer, for example, to charging infrastructure projects or announced imports of electric vehicles. It is expected that different countries will show different positions towards EV technologies, based on the national economic characteristics. Given that the transport sector is one of the largest oil consumers [50], countries which rely on oil exports will likely show resistance towards the proliferation of EVs. On the other hand, countries with large amounts of renewable energy and no proper storage possibilities, such as Sweden and Denmark [44], may encourage the adoption of EVs.

Another important disadvantage of BEVs is their high initial cost imposed by the cost of the battery. Innovative contracting and leasing schemes are developed to eliminate this obstacle. Among the strategies adopted, one notable approach is to transform the battery in a separate service [1] instead of treating it as a part of the vehicle. The buyer purchases the vehicle only, while the battery remains under the ownership of the manufacturer or the battery supplier. The battery is contracted for a monthly cost together with maintenance and support services. This strategy is meant to decreases the initial cost of the vehicle and could accelerate the penetration of EVs on the market. In order to determine how fast the widespread adoption of BEVs could take place, an analysis combining consumer research and market structure research [6] could be performed. The consumer research can be done through surveys to gather information on the expectations of different groups of users. Market structure research could be done using tools such as Porter's market forces model to identify when the necessary conditions (price, quality, charging infrastructure, etc.) to fulfill the consumers' expectation would be in place.

Moreover, it should be analyzed how the current dynamics of the car industry can impact the EV technological progress. One thing that was noticed during the data collection process is that many of the electric vehicles in the data set have been the result of collaboration between different car manufacturers. At the same time, several joint ventures between different auto makers have taken place over the past years. Joint forces between large auto makers will likely lead to knowledge spill-overs, which are recognized by economics of innovation theory to be an important driver of technological change [51, 52]. Therefore, these alliances may accelerate the course of technological progress. The potential impact of knowledge diffusion due to strategic partnerships on EV technological advancements may be very difficult to measure, but it could perhaps be evaluated based on lessons learnt from similar situations either from the car industry, or from other industries.

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Bottom line

The present study has identified that TFDEA is not a suitable method for analyzing technological progress of electric vehicle technologies. This is due to the high sensitivity to exogenous drivers and its limited capability to anticipate the introduction of potentially disruptive design configurations. These limitations are mostly a result of the assumptions that inputs and the rate of change remain constant over time.

In order to obtain an overview of development possibilities for different EV configurations a simple analysis of technological progress in not sufficient. It was pointed out that technological performance may not be the only factor responsible for a product's success. Due to the economic, environmental and political consequences, technological progress of electric vehicles is expected to be accelerated or slowed-down by different technological and context factors, such as battery technologies, available infrastructures, standardization opportunities, consumer acceptance, national interests and governmental support. Additional information on these factors is required to identify the necessary conditions, and when it is expected that the conditions are met, to be able to anticipate a potential transition towards a certain EV design. Such information can be produced through different techniques. This section indicated the use of technology forecasting and market shift indicators analysis to identify possible innovations in EV supporting technologies. Furthermore, combined analysis of consumer research and market structure analysis can help identify the market forces expected to affect further advancements of electric vehicles. In addition, monitoring government and industry plans can provide information on potential standardization opportunities and strategies meant to accelerate the adoption of BEVs.

In the light of the analysis, it is concluded that TFDEA would not be a useful forecasting tool for emerging technologies with significant economic and socio-political implications. The model could, however, provide a simple and easy to use forecasting tool for established technologies which have shown constant progress over time, given that no exogenous forces are expected to influence the technological change. Furthermore, TFDEA could be used for forecasting simple technologies whose performance can be expressed with very few attributes, and whose performance is not targeted by governmental regulation.

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Appendix A: Classification of electric vehicles

Several notations are available in the literature for the classification of electric vehicles. This is only evidence that the technology is still fairly new and a standardized nomenclature has not yet been introduced. Throughout this report, the following terminology and classification will be used.

Electric vehicles (EVs)

Electric vehicles are vehicles driven by an electric motor. This term is used without discrimination between pure-electric and hybrid electric vehicles. Electric vehicles can classified based on their propulsion system (drivetrain) architecture into battery electric vehicles (BEVs) and hybrid electric vehicles (HEVs).

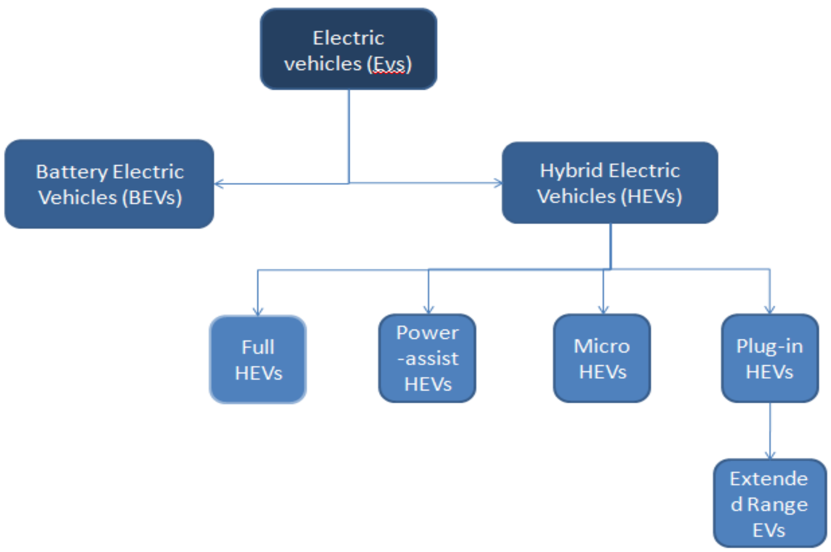

Figure 22 Electric vehicles - classification

Battery electric vehicles (BEVs)

Battery electric vehicles are fully electric vehicles, powered only by an electrochemical battery. The vehicle propulsion (VP) system of a BEV is composed of an electric motor, electronic control units (ECUs) and a simpler transmission system compared to an internal combustion vehicle (ICV). The power source in BEVs is an electrochemical battery which supplies energy for the operation of the vehicle. The electric motor delivers the traction force required to move the vehicle. The propulsion system contains the electric motor and all the auxiliary devices required to convert the electrochemical energy provided by the battery into kinetic energy at the wheels.[1, 2]

Hybrid electric vehicles (HEVs)

A hybrid electric vehicle is a vehicle which combines an electric power and a combustion power source. This category of vehicles excludes electric vehicles powered by fuel-cells and ultracapacitors. Based on the structure of the drive train, HEVs can be categorized into parallel, series and combined hybrid systems.

The drive train structure determines the level of hybridization of an HEV. Based on the level hybridization, HEVs can further classified as full (or strong) hybrids, power-assist hybrid, micro hybrid, mild hybrid, plug-in hybrids. [1, 2, 38, 39]

Parallel HEVs

The parallel HEV has both an internal combustion engine (ICE) and an electric motor. The fuel tank supplies gasoline to the engine, while a set of batteries supply power to an electric motor. Both the electric motor and the gas engine can provide propulsion power.[39]

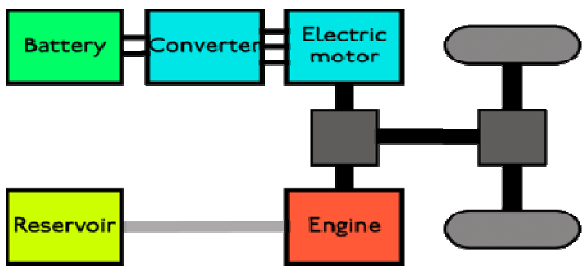

Figure 23 Parallel HEV drivetrain structure [39]

Series HEVs

A series HEV is driven by an electric motor. The ICE never powers the car directly, but drives an electric generator which charges the battery and powers the electric motor.[38]

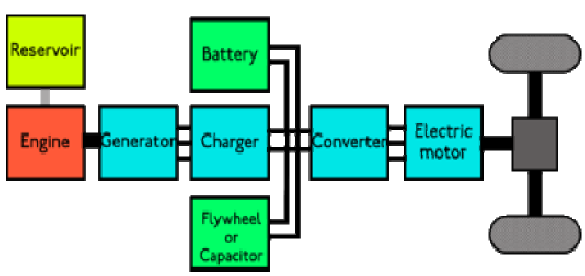

Figure 24 Series HEV drivetrain structure [39]

Combined HEVs

The combined HEV Incorporates features of both parallel and series hybrid systems. Combined HEVs maintain the parallel structure, with the difference that the ICE is also used to charge up the battery during idle periods of the vehicle. This helps increase the overall efficiency of the vehicle and diminishes the role of the regenerative breaking system.[2, 39]

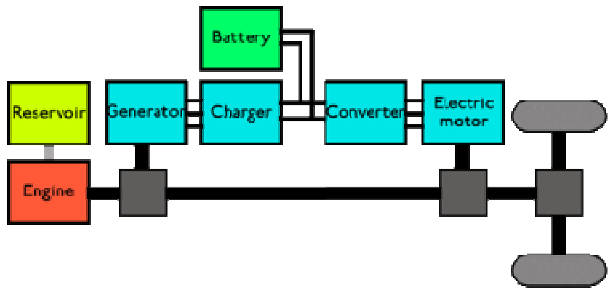

Figure 25 Combined HEV drivetrain structure [39]

Full (or strong) HEVs

A full (or strong) HEV is an HEV which can drive on electricity only for short distances at low-speed and low-acceleration, but cannot be recharged from the grid. These HEVs use a gasoline engine as the primary source of power.[1, 39]

Power-assist HEV

Power-assist HEVs on electric power alone. Power-assist HEVs use smaller electric motors and batteries because the role of these components is reduced to providing torque boosts in order to assist the internal combustion engine (ICE) during heavy acceleration. These vehicles cannot drive in electric mode.[1, 39]

Micro HEV

Micro HEVs are internal combustion vehicles (ICVs) with very small electric motors and batteries. The motor and battery are never used for the propulsion of the vehicle, they are only integrated into the vehicle for energy conservation through ICE shutdown during idle times and regenerative breaking. This configuration helps improve the energy efficiency of the vehicle, yet, micro HEVs are contested by many experts, including the ones at the Society of Automotive Engineers, because they do not fit the definition of a hybrid vehicle, which combines electric and combustion power for propulsion.[1]

Mild HEV

The mild HEV is an ambiguous term used often in advertising campaigns to define an HEV 'below' a full hybrid. The ambiguity is used with the intention to increase the credentials of the power-assist technology by associating it with the Micro HEV technology. Due to its controversy, this "mild HEV" concept will not be used as a classification criterion in the data analysis of this report.[1]

Plug-in hybrid electric vehicles (PHEV)

A plug-in hybrid electric vehicle retains the entire internal combustion engine system, but adds battery capacity to extend the operation of the electric motor. The PHEV can be driven either by an electric motor (EM) or by the internal combustion engine ICE. Also, the PHEV can recharge its battery directly from the grid in order to allow for longer driving ranges. Therefore these vehicles combine the efficiency advantages of hybridization with the opportunity to travel part-time on electricity provided by the grid, instead of only relying on the vehicle's internal recharging system.[38]

Extended range electric vehicle (EREV)

This term is used to define a sub-category of PHEVs. Unlike plug-in hybrid vehicles, which can be driven either by the EM or ICE, the EREV can be driven only by their electric motor. These vehicles are provided with a small ICE connected to a generator which recharges the battery. This structure makes it possible to use a smaller battery for a much longer range. However, since they have a fuel powered generator, these vehicles cannot be considered to be emission-free.[39]

Appendix B: DEA Macro

```
Sub DEA()

‘this Macro is meant to automate the DEA model runs such that all efficiency scores are calculated and the lambdas are recorded.

'declare dmu as integer

Dim dmu As Integer

‘NumberOfDMUs is the number of vehicles in one run

For dmu = 1 To NumberOfDMUs

'set the value of cell E2 equal to dmu

Range("E2") = dmu

'run the Solver model. the user finish is set to true so that the dialogue box does not appear

SolverSolve UserFinish:=True

'place the efficiency in column T, starting with row 2

Range("T" & dmu + 1) = Range("F3")

'select the cells containing the optimal lambdas (S2 onwards)

Range("lambdas").Select

'copy the selected lambdas and paste them to row dmu+1 starting with row V

Selection.Copy

Range("V" & dmu + 1).Select

Selection.PasteSpecial Paste:=xlPasteValues, Transpose:=True

Next dmu


End Sub
```

Appendix C: EVs and HEVs specifications

Table 29 EV specifications

#	Product	year	type	Weight	Output power	Battery capacity	Acceleration rate	CO2	Fuel economy	Electric range
1	EV-Plus	1997	EV	1620	49	26	9.80			190
2	Prius (1st gen.)	1997	HEV	1240	50	1.7	7.46	135	17.54	
3	Tino Hybrid	2000	HEV	1500	83	0.6	8.20	182	23	
4	Prius (2nd gen.)	2000	HEV	1640	57	1.7	7.97	120	19.23	
5	Civic Hybrid 1st gen.	2001	HEV	1290	69	0.85	7.04	137	20	
6	Alphard Hybrid	2003	HEV	2100	96	4.4	8.33	173	17.2	
7	Escape Hybrid	2004	HEV	1656	116	1.8	10.32	174	13.6	
8	Tango	2005	EV	1300	42	34	24.15			241
9	Happy Messenger EV	2005	EV	1050	20	13	3.60			100
10	Lexus RX400h	2005	HEV	1960	200	1.8	12.76	192	12	
11	Civic Hybrid 2nd gen	2005	HEV	1260	82	0.86	7.63	129	17	
12	Highlander Hybrid	2005	HEV	2160	200	1.3	12.76	165	12.5	
13	Venturi Fetish	2006	EV	1225	180	28	22.47			350
14	Mercury Mariner Hybrid	2006	HEV	1664	115	1.8	8.98	110	14	
15	Camry Hybrid	2006	HEV	1550	140	1.59	11.28	180	14.3	
16	Lexus GS450h	2006	HEV	1890	253	1.5	18.65	186	14.2	
17	Estima Hybrid	2006	HEV	2020	140	1.59	9.26	127	20	
18	Altima Hybrid	2006	HEV	1573	147	30	13.29	160	14	
19	Smart fortwo el. drive 1st gen	2007	EV	730	30	13.2	9.23			110
20	Chevrolet Tahoe Hybrid	2007	HEV	3220	247	1.8	10.91	366	9.5	
21	Kluger Hybrid	2007	HEV	1890	200	1.3	12.76	173.5	11	
22	Lexus LS600h/hL	2007	HEV	2340	327	1.3	17.54	219	12.2	
23	Tribute Hybrid	2007	HEV	1668	115	8.5	11.28	173	13.5	
24	GMC Yukon Hybrid	2007	HEV	2388	247	1.8	12.28	108	9.26	

#	Product	year	type	Weight	Output power	Battery capacity	Acceleration rate	CO2	Fuel economy	Electric range
25	Tesla Roadster	2008	EV	1235.1	215	56	26.11			394
26	Crown Hybrid	2008	HEV	1840	220	1.3	8.70	173	15.8	
27	Cadillac Escalade Hybrid	2008	HEV	2527	275	1.8	9.09	256	9.5	
28	F3DM	2008	PHEV	1540	125	20	9.52	130	12.8	
29	Subaru Plug-in Stella	2009	EV	1010	47	9	7.73			80
30	Venturi Fetish	2009	EV	1125	180	45	22.47			290
31	Smart fortwo el. drive 2nd gen	2009	EV	730	20	16.5	14.64			135
32	Think city	2009	EV	1038	34	23	7.69			160
33	A5 BSG	2009	HEV	1290	95	5.2	7.87	158	15	
34	Lexus RX450h	2009	HEV	2130	220	2.4	13.47	148	18.8	
35	ML450 Blue HV	2009	HEV	2150	250	2.4	12.60	185	10.2	
36	Prius (3rd gen.)	2009	HEV	1350	100	1.3	9.60	111	20.4	
37	S400 Hybrid/ Hybrid Long	2009	HEV	1980	220	0.9	13.89	190	11.2	
38	Mercury Milan Hybrid	2009	HEV	1691	142	1.4	11.55	108	17.3	
39	Lexus HS250h	2009	HEV	1640	187	1.98	11.55	163	23	
40	Avante/ Elantra LPI	2009	HEV	1297	99	1.4	10.21	99	17.8	
41	Forte LPI	2009	HEV	1297	83.85	0.95	14.06	99	17.2	
42	ActiveHybrid X6	2009	HEV	2580	357	2.4	17.96	231	8	
43	SAI	2009	HEV	1590	140	4.4	11.55	105	23	
44	i-Miev (G Grade)	2010	EV	1100	25	16	10.00			180
45	Benni Mini EV	2010	EV	950	20	19.2	8.20			105
46	Zotye 2008 EV	2010	EV	1200	27	25	8.05			200
47	Zotye 5008 EV	2010	EV	1200	11	32	7.14			200
48	Mercedes-Benz A-class E-Cell	2010	EV	1325	70	36	10.91			200
49	Riich M1 EV	2010	EV	1050	30	20.16	7.14			160
50	REVAi	2010	EV	665	13	9.6	5.71			80
51	Leaf	2010	EV	1520	80	24	8.40			160
52	Peugeot iOn	2010	EV	1080	47	16	10.00			160

#	Product	year	type	Weight	Output power	Battery capacity	Acceleration rate	CO2	Fuel economy	Electric range
53	C-Zero	2010	EV	1110	50	16	6.67			150
54	Auris HSD	2010	HEV	1320	98	1.3	8.85	90	29	
55	CR-Z	2010	HEV	1160	91	0.85	9.24	117	25.8	
56	F3DM PHEV	2010	PHEV	1560	125	20	9.24	63	12.82	
57	Touareg HV	2010	HEV	2240	279	1.7	15.38	193	12.2	
58	Audi Q5	2010	HEV	1730	176	1.3	14.08	159	14.3	
59	Jeep Patriot EV	2010	PHEV	1410	150	35	12.05	50	12.5	
60	Besturn B50	2010	PHEV	1285	76	18	7.14	70	13.3	
61	ActiveHybrid 7 Series	2010	Mild-HEV	1720	342	0.4	20.41	219	9.4	
62	Lincoln MKZ Hybrid	2010	HEV	1632	142	1.5	11.15	109	16	
63	Fit/ Jazz Hybrid	2010	HEV	1130	75	20	8.26	104	22.73	
64	Sonata HV	2010	HEV	1568	155	1.4	14.70	170	15.73	
65	Cayenne S HV	2010	HEV	2240	275	16	14.71	193	11.1	
66	Fuga Hybrid/ Infiniti M35h	2010	HEV	2135	268	1.4	18.65	162	14.3	
67	Chevrolet Volt	2010	PHEV	1715	111	16	10.78	52.5	14.88	
68	Chery QQ3 EV	2011	EV	1050	12	10.8	15.38			80
69	Twizy Z.E.	2011	EV	450	15	7	9.66			100
70	Inizio R	2011	EV	1406	175	40.32	16.37			241
71	Inizio RT	2011	EV	1633	175	96.78	13.61			402
72	Inizio RTX	2011	EV	1769	290	80.64	28.41			321
73	I-Miev (M Grade)	2011	EV	1070	25	10.5	8.12			120
74	Like G-grade	2011	EV	1130	25	16	8.12			180
75	Like M-grade	2011	EV	1090	25	10.5	8.12			120
76	BMW Active E	2011	EV	1800	125	32	10.73			160
77	BYD e6	2011	EV	2295	75	48	6.90			300
78	Electric C30	2011	EV	1347	82	24	8.78			144
79	Wave II, S model	2011	EV	1020	47	33.6	8.05			241
80	Wave II, SE model	2011	EV	1065	47	40.3	7.61			321

#	Product	year	type	Weight	Output power	Battery capacity	Acceleration rate	CO2	Fuel economy	Electric range
81	Beijing C30DB	2011	EV	1540	47	20.2	7.81			150
82	Ray ev	2011	EV	1185	50	16.4	6.29			138
83	Aqua	2011	HEV	1134	73.5	0.93	9.35	111	35.4	
84	Lexus CT200h	2011	HEV	1420	99	1.3	9.71	89	26.3	
85	Civic Hybrid 3rd gen	2011	HEV	1302	82	0.94	9.60	109	18.86	
86	Prius alpha	2011	HEV	1480	100	1.3	10.00	100	31	
87	3008 Hybrid4	2011	HEV	1660	200	1.1	11.36	99	26	
88	Fit Shuttle Hybrid	2011	HEV	1190	76	0.6	7.52	120	25	
89	Karma S	2011	PHEV	2400	194	20	16.67	83	22.1	
90	Buick Regal eAssist	2011	Mild-HEV	1641	153	0.5	12.05	129	11.05	
91	Prius v	2011	HEV	1485	100	1.3	9.51	132	14	
92	Freed/ Freed Spike Hybrid	2011	HEV	1380	73	0.82	6.29	95	21.6	
93	Optima K5 HV	2011	HEV	1583	153	30	10.54	158	15.3	
94	Fluence Z.E.	2012	EV	1543	70	22	7.30			185
95	Coda Sedan	2012	EV	1670	100	31	11.36			144
96	Focus Electric	2012	EV	1644	107	23	10.73			120
97	RAV4 EV	2012	EV	1829	80	41.8	13.80			160
98	Fit EV	2012	EV	1475	123	20	10.62			200
99	e6 Premier	2012	EV	2020	75	48	12.08			300
100	Zoe Z.E.	2012	EV	1400	70	22	12.35			160
101	Prius PHV	2012	PHEV	1490	100	4.4	8.82	41	61	
102	Ampera	2012	EREV	1715	110	16	11.11	40	83	
103	ActiveHybrid 5 Series	2012	HEV	1980	250	6.75	16.67	155	13.6	
104	Prius c	2012	HEV	1134	73.5	0.93	9.35	111	17.85	
105	Lexus GS450h (2013 MY)	2012	HEV	1865	253	1.8	16.95	137	12.3	
106	Insight	2012	HEV	2747	73	0.6	9.42	96	27.2	

Appendix D: Efficiency scores HEVs

Table 30 Efficiency scores HEVs

#	Product	Year	Φ_'97	Φ_'00	Φ_'01	Φ_'03	Φ_'04	Φ_'05	Φ_'06	Φ_'07	Φ_'08	Φ_'09	Φ_'10	Φ_'11	Φ_'12
1	Prius 1st gen	1997	1	1	1	1	1	1	1	1	1	1	1	1	1
2	Tino Hybrid	2000		1	1	1	1	1	1	1	1	1	1	1	1.17
3	Prius 2nd gen	2000		1	1	1	1	1	1	1	1	1	1	1	1
4	Civic Hybrid 1st gen	2001			1	1	1	1	1	1	1	1	1	1	1.30
5	Alphard Hybrid	2003				1	1	1	1	1	1	1	1	1	1.41
6	Escape Hybrid	2004					1	1	1.08	1.08	1.08	1.15	1.15	1.15	1.33
7	Lexus RX400h	2005						1	1.14	1.14	1.14	1.15	1.15	1.15	1.28
8	Civic Hybrid 2nd gen	2005						1	1.00	1.00	1.00	1.12	1.12	1.28	1.41
9	Highlander Hybrid	2005						1	1	1	1	1	1	1	1.20
10	Mercury Mariner Hybrid	2006							1	1	1	1	1.04	1.07	1.39
11	Camry Hybrid	2006							1.11	1.11	1.11	1.23	1.23	1.26	1.34
12	Lexus GS450h	2006							1	1	1	1	1	1	1
13	Estima Hybrid	2006							1	1	1	1	1	1	1.38
14	Altima Hybrid	2006							1	1	1	1.11	1.11	1.18	1.18
15	Chevrolet Tahoe Hybrid	2007								1	1	1	1	1	1
16	Kluger Hybrid	2007								1.08	1.08	1.15	1.15	1.15	1.27
17	Lexus LS600h/hL	2007								1	1	1	1	1	1
18	Tribute Hybrid	2007								1	1	1.08	1.08	1.17	1.25
19	GMC Yukon Hybrid	2007								1	1	1	1	1	1.05
20	Crown Hybrid	2008									1.21	1.22	1.25	1.41	1.65
21	Cadillac Escalade Hybrid	2008									1.34	1.36	1.36	1.37	1.68
22	F3DM	2008									1.08	1.25	1.38	1.52	1.55
23	A5 BSG	2009										1.37	1.50	1.61	1.76
24	Lexus RX450h	2009										1	1	1	1.16
25	ML450 Blue HV	2009										1.22	1.23	1.24	1.31
26	Prius 3rd gen	2009										1	1.16	1.18	1.29
27	S400 Hybrid/ Hybrid Long	2009										1	1	1	1.17
28	Mercury Milan Hybrid	2009										1	1	1.00	1.18
29	Lexus HS250h	2009										1	1.01	1.10	1.26
30	Avante/ Elantra LPI	2009										1	1.07	1.09	1.22
31	Forte LPI	2009										1	1	1	1
32	ActiveHybrid X6	2009										1	1	1	1

#	Product	Year	Φ_'97	Φ_'00	Φ_'01	Φ_'03	Φ_'04	Φ_'05	Φ_'06	Φ_'07	Φ_'08	Φ_'09	Φ_'10	Φ_'11	Φ_'12
33	SAI	2009										1	1	1.08	1.25
34	Auris HSD	2010											1	1	1.13
35	CR-Z	2010											1	1.07	1.14
36	F3DM PHEV	2010											1.18	1.19	1.35
37	Touareg HV	2010											1.05	1.05	1.11
38	Audi Q5	2010											1.04	1.04	1.13
39	Jeep Patriot EV	2010											1	1	1.06
40	Besturn B50	2010											1	1	1.14
41	ActiveHybrid 7 Series	2010											1	1	1
42	Lincoln MKZ Hybrid	2010											1.05	1.07	1.23
43	Fit/ Jazz Hybrid	2010											1.01	1.12	1.28
44	Sonata HV	2010											1.03	1.03	1.07
45	Cayenne S HV	2010											1.10	1.22	1.22
46	Fuga Hybrid/ Infiniti M35h	2010											1	1	1.00
47	Chevrolet Volt	2010											1	1	1.10
48	Aqua	2011												1	1
49	Lexus CT200h	2011												1	1.11
50	Civic Hybrid 3rd gen	2011												1.12	1.19
51	Prius alpha	2011												1	1.06
52	3008 Hybrid4	2011												1	1.07
53	Fit Shuttle Hybrid	2011												1	1.09
54	Karma S	2011												1	1
55	Buick Regal eAssist	2011												1	1
56	Prius v (USA)	2011												1.26	1.41
57	Freed/ Freed Spike Hybrid	2011												1	1.03
58	Optima K5 HV	2011												1.45	1.48
59	Prius PHV	2012													1
60	Ampera	2012													1
61	ActiveHybrid 5 Series	2012													1.10
62	Prius c	2012													1.13
63	Lexus GS450h (2013 MY)	2012													1.03
64	Insight	2012													1

Appendix E: Efficiency scores BEVs

Table 31 Efficiency scores BEVs

#	Product	year	type	Φ_'97	Φ_'05	Φ_'06	Φ_'07	Φ_'08	Φ_'09	Φ_'10	Φ_'11	Φ_'12
1	EV-Plus	1997	EV	1	1	1	1	1	1	1	1	1
2	Happy Messenger EV	2005	EV		1	1	1	1	1	1	1.32	1.32
3	Tango	2005	EV		1	1	1	1	1	1	1	1
4	Venturi Fetish	2006	EV			1	1	1	1	1	1	1
5	Smart fortwo electric drive 1st gen	2007	EV				1	1	1	1.12	1.32	1.32
6	Tesla Roadster	2008	EV					1	1	1	1	1
7	Subaru Plug-in Stella	2009	EV						1	1	1	1
8	Smart fortwo e- drive 2g	2009	EV						1	1	1.01	1.01
9	Think city	2009	EV						1.09	1.29	1.37	1.37
10	Venturi Fetish	2009	EV						1.12	1.12	1.12	1.12
11	REVAi	2010	EV							1	1.09	1.09
12	Benni Mini EV	2010	EV							1.28	1.52	1.52
13	C-Zero	2010	EV							1.16	1.24	1.24
14	Riich M1 EV	2010	EV							1.22	1.28	1.28
15	Leaf	2010	EV							1	1.23	1.28
16	Peugeot iOn	2010	EV							1.11	1.15	1.15
17	i-Miev (G Grade)	2010	EV							1	1	1
18	Zotye 2008 EV	2010	EV							1	1.03	1.03
19	Zotye 5008 EV	2010	EV							1	1	1
20	Mercedes-Benz A-class	2010	EV							1.29	1.42	1.42
21	Chery QQ3 EV	2011	EV								1	1
22	Twizy Z.E.	2011	EV								1	1
23	I-Miev (M Grade)	2011	EV								1.00	1.00
24	Like M-grade	2011	EV								1	1
25	Ray ev	2011	EV								1.27	1.31
26	Electric C30	2011	EV								1.59	1.59
27	Beijing C30DB	2011	EV								1	1
28	BMW Active	2011	EV								1	1

#	Product	year	type	Φ_'97	Φ_'05	Φ_'06	Φ_'07	Φ_'08	Φ_'09	Φ_'10	Φ_'11	Φ_'12
29	Like G-grade	2011	EV								1	1
30	Inizio R	2011	EV								1.31	1.32
31	Wave II, S model	2011	EV								1.18	1.18
32	BYD e6	2011	EV								1	1
33	Inizio RTX	2011	EV								1	1
34	Wave II, SE model	2011	EV								1	1
35	Inizio RT	2011	EV								1	1
36	Focus Electric	2012	EV									1
37	Coda Sedan	2012	EV									1.14
38	RAV4 EV	2012	EV									1
39	Zoe Z.E.	2012	EV									1.06
40	Fluence Z.E.	2012	EV									1
41	Fit EV	2012	EV									1
42	e6 Premier	2012	EV									1

Apendix F: Efficiency scores HEVs and BEVs combined

Table 32Efficiency scores EVs & BEVs

#	Product	year	type	ϕ_'97	ϕ_'00	ϕ_'01	ϕ_'03	ϕ_'04	ϕ_'05	ϕ_'06	ϕ_'07	ϕ_'08	ϕ_'09	ϕ_'10	ϕ_'11	ϕ_'12
1	EV-Plus	1997	EV	1	1	1	1	1	1	1	1	1	1	1	1	1.55
2	Prius 1st gen	1997	HEV	1	1	1	1	1	1	1	1	1	1	1	1	1
3	Tino Hybrid	2000	HEV		1	1	1	1	1	1	1	1	1	1	1	1.17
4	Prius 2nd gen	2000	HEV		1	1	1	1	1	1	1	1	1	1	1	1
5	Civic Hybrid 1st gen	2001	HEV			1	1	1	1	1	1	1	1	1	1	1.3
6	Alphard Hybrid	2003	HEV				1	1	1	1	1	1	1	1	1	1.49
7	Escape Hybrid	2004	HEV					1	1	1.09	1.09	1.09	1.15	1.16	1.16	1.36
8	Tango	2005	EV						1	1	1	1	1	1	1	1
9	Happy Messenger EV	2005	EV						1	1	1	1	1	1	4.54	4.54
10	Lexus RX400h	2005	HEV						1.01	1.14	1.14	1.14	1.15	1.2	1.2	1.29
11	Civic Hybrid 2nd gen	2005	HEV						1	1	1	1	1.12	1.12	1.28	1.41
12	Highlander Hybrid	2005	HEV						1	1	1	1	1	1	1	1.24
13	Venturi Fetish	2006	EV							1.03	1.03	1.03	1.03	1.05	1.05	1.05
14	Mercury Mariner	2006	HEV							1	1	1	1	1.04	1.07	1.4
15	Camry Hybrid	2006	HEV							1.11	1.11	1.11	1.23	1.24	1.27	1.34
16	Lexus GS450h	2006	HEV							1	1	1	1	1	1	1
17	Estima Hybrid	2006	HEV							1	1	1	1	1	1	1.38
18	Altima Hybrid	2006	HEV							1.05	1.05	1.05	1.16	1.18	1.33	1.48
19	Smart fortwo 1st gen	2007	EV								1	1	1.49	1.49	1.81	1.81
20	Chevrolet Tahoe	2007	HEV								1	1	1	1	1	1
21	Kluger Hybrid	2007	HEV								1.08	1.08	1.15	1.19	1.19	1.29
22	Lexus LS600h/hL	2007	HEV								1	1	1	1	1	1
23	Tribute Hybrid	2007	HEV								1.14	1.14	1.17	1.18	1.24	1.41
24	GMC Yukon Hybrid	2007	HEV								1	1	1	1	1	1.06
25	Tesla Roadster	2008	EV									1	1	1	1	1
26	Crown Hybrid	2008	HEV									1.21	1.22	1.25	1.41	1.65
27	Cadillac Escalade	2008	HEV									1.34	1.36	1.36	1.37	1.68
28	F3DM	2008	PHEV									1.09	1.25	1.4	1.53	1.77
29	Subaru Plug-in Stella	2009	EV										1.67	1.67	2.04	2.04
30	Venturi Fetish	2009	EV										1.12	1.12	1.12	1.12

#	Product	year	type	ϕ_'97	ϕ_'00	ϕ_'01	ϕ_'03	ϕ_'04	ϕ_'05	ϕ_'06	ϕ_'07	ϕ_'08	ϕ_'09	ϕ_'10	ϕ_'11	ϕ_'12
31	Smart fortwo 2g	2009	EV										1	1	1.2	1.2
32	Think city	2009	EV										2.24	2.3	2.62	2.62
33	A5 BSG	2009	HEV										1.37	1.52	1.61	1.82
34	Lexus RX450h	2009	HEV										1	1	1	1.21
35	ML450 Blue HV	2009	HEV										1.22	1.34	1.34	1.4
36	Prius 3^{rd} gen	2009	HEV										1	1.16	1.18	1.29
37	S400 Hybrid	2009	HEV										1	1	1	1.18
38	Mercury Milan	2009	HEV										1	1	1	1.19
39	Lexus HS250h	2009	HEV										1	1.01	1.12	1.26
40	Avante/ Elantra LPI	2009	HEV										1	1.07	1.09	1.22
41	Forte LPI	2009	HEV										1	1	1	1
42	ActiveHybrid X6	2009	HEV										1	1	1	1
43	SAI	2009	HEV										1	1	1.08	1.26
44	i-Miev (G Grade)	2010	EV											1	1.75	1.75
45	Benni Mini EV	2010	EV											1.28	2.16	2.16
46	Zotye 2008 EV	2010	EV											1.6	2.16	2.21
47	Zotye 5008 EV	2010	EV											1	1	1
48	Mercedes-Benz A	2010	EV											2.2	2.23	2.23
49	Riich M1 EV	2010	EV											2.04	2.67	2.67
50	REVAi	2010	EV											1	2.38	2.38
51	Leaf	2010	EV											2.33	2.34	2.49
52	Peugeot iOn	2010	EV											1.63	1.81	1.81
53	C-Zero	2010	EV											2.51	2.74	2.74
54	Auris HSD	2010	HEV											1	1	1.13
55	CR-Z	2010	HEV											1	1.07	1.14
56	F3DM PHEV	2010	PHEV											1.18	1.19	1.39
57	Touareg HV	2010	HEV											1.12	1.13	1.17
58	Audi Q5	2010	HEV											1.08	1.08	1.14
59	Jeep Patriot EV	2010	PHEV											1	1	1.1
60	Besturn B50	2010	PHEV											1	1	1.25
61	ActiveHybrid 7 Series	2010	Mild-HEV											1	1	1
62	Lincoln MKZ Hybrid	2010	HEV											1.05	1.07	1.24
63	Fit/ Jazz Hybrid	2010	HEV											1.01	1.13	1.62
64	Sonata HV	2010	HEV											1.04	1.05	1.07

#	Product	year	type	ϕ_'97	ϕ_'00	ϕ_'01	ϕ_'03	ϕ_'04	ϕ_'05	ϕ_'06	ϕ_'07	ϕ_'08	ϕ_'09	ϕ_'10	ϕ_'11	ϕ_'12
65	Cayenne S HV	2010	HEV											1.18	1.28	1.29
66	Fuga Hybrid	2010	HEV											1	1	1
67	Chevrolet Volt	2010	PHEV											1	1	1.14
68	Chery QQ3 EV	2011	EV												1	1
69	Twizy Z.E.	2011	EV												1	1
70	Inizio R	2011	EV												1.51	1.51
71	Inizio RT	2011	EV												1.79	1.8
72	Inizio RTX	2011	EV												1	1
73	I-Miev (M Grade)	2011	EV												1.93	1.93
74	Like G-grade	2011	EV												2.14	2.15
75	Like M-grade	2011	EV												1.93	1.93
76	BMW Active E	2011	EV												1.75	1.83
77	BYD e6	2011	EV												1	1.8
78	Electric C30	2011	EV												2.48	2.48
79	Wave II, S model	2011	EV												2.99	2.99
80	Wave II, SE model	2011	EV												3.19	3.19
81	Beijing C30DB	2011	EV												1.31	2.1
82	Ray ev	2011	EV												2.92	2.92
83	Aqua	2011	HEV												1	1
84	Lexus CT200h	2011	HEV												1	1.11
85	Civic Hybrid 3rd gen	2011	HEV												1.12	1.19
86	Prius alpha	2011	HEV												1	1.06
87	3008 Hybrid4	2011	HEV												1	1.07
88	Fit Shuttle Hybrid	2011	HEV												1	1.09
89	Karma S	2011	PHEV												1	1
90	Buick Regal eAssist	2011	Mild-HEV												1	1
91	Prius v (USA)	2011	HEV												1.26	1.41
92	Freed/ Freed Spike	2011	HEV												1	1.03
93	Optima K5 HV	2011	HEV												1.5	1.78
94	Fluence Z.E.	2012	EV													2.71
95	Coda Sedan	2012	EV													1.77
96	Focus Electric	2012	EV													1.88

#	Product	year	type	ϕ_'97	ϕ_'00	ϕ_'01	ϕ_'03	ϕ_'04	ϕ_'05	ϕ_'06	ϕ_'07	ϕ_'08	ϕ_'09	ϕ_'10	ϕ_'11	ϕ_'12
97	RAV4 EV	2012	EV													1.24
98	Fit EV	2012	EV													2.03
99	e6 Premier	2012	EV													1.22
100	Zoe Z.E.	2012	EV													1.66
101	Prius PHV	2012	PHEV													1
102	Ampera	2012	EREV													1
103	ActiveHybrid 5 Series	2012	HEV													1.12
104	Prius c	2012	HEV													1.13
105	Lexus GS450h	2012	HEV													1.05
106	Insight	2012	HEV													1

Appendix G: Results

HEV forecast verification

Table 33 Verification of HEV model predictions for 2010 based on 2009 data

#	Product	Type	Year	ϕ_2010	Acceleration rate	CO2	Fuel economy
34	Auris HSD	HEV	2010	1	8.85	90	29
35	CR-Z	HEV	2010	1	9.24	117	25.8
36	F3DM PHEV	PHEV	2010	1.18	9.24	63	12.82
37	Touareg HV	HEV	2010	1.05	15.38	193	12.2
38	Audi Q5	HEV	2010	1.04	14.08	159	14.3
39	Jeep Patriot EV	PHEV	2010	1	12.05	50	12.5
40	Besturn B50	PHEV	2010	1	7.14	70	13.3
41	ActiveHybrid 7 Series	Mild-HEV	2010	1	20.41	219	9.4
42	Lincoln MKZ Hybrid	HEV	2010	1.05	11.15	109	16
43	Fit/ Jazz Hybrid	HEV	2010	1.01	8.26	104	22.73
44	Sonata HV	HEV	2010	1.03	14.70	170	15.73
45	Cayenne S HV	HEV	2010	1.10	14.71	193	11.1
46	Fuga Hybrid/ Infiniti M35h	HEV	2010	1	18.65	162	14.3
47	Chevrolet Volt	PHEV	2010	1	10.78	52.5	14.88
		Conservative frontier 2010			**7.36**	**222.53**	**9.14**
		Aggressive frontier 2010			**21.19**	**106.54**	**24.00**

Table 34 Verification of HEV model predictions for 2011 based on 2009 data

#	Product	Type	Year	ϕ_2011	Acceleration rate	CO2	Fuel economy
48	Aqua	HEV	2011	1	9.35	111	35.4
49	Lexus CT200h	HEV	2011	1	9.71	89	26.3
50	Civic Hybrid 3rd gen	HEV	2011	1.12	9.60	109	18.86
51	Prius alpha (7)	HEV	2011	1	10.00	100	31
52	3008 Hybrid4	HEV	2011	1	11.36	99	26
53	Fit Shuttle Hybrid	HEV	2011	1	7.52	120	25
54	Karma S	PHEV	2011	1	16.67	83	22.1
55	Buick Regal eAssist	Mild-HEV	2011	1	12.05	129	11.05
56	Prius v	HEV	2011	1.26	9.51	132	14
57	Freed/ Freed Spike Hybrid	HEV	2011	1	6.29	95	21.6
58	Optima K5 HV	HEV	2011	1.45	10.54	158	15.3
		Conservative frontier 2011			**7.26**	**238.48**	**9.01**
		Aggressive frontier 2011			**20.31**	**105.11**	**25.05**

Table 35 Verification of HEV model predictions for 2012 based on 2009 data

#	Product	Type	Year	ϕ_2012	Acceleration rate	CO2	Fuel economy
59	Prius PHV	PHEV	2012	1	8.82	41	61
60	Ampera	EREV	2012	1	11.11	40	83
61	ActiveHybrid 5 Series	HEV	2012	1.10	16.67	155	13.6
62	Prius c	HEV	2012	1.13	9.35	111	17.85
63	Lexus GS450h (2013 MY)	HEV	2012	1.03	16.95	137	12.3
64	Insight	HEV	2012	1	9.42	96	27.2
		Conservative frontier 2012			**7.16**	**248.86**	**8.89**
		Aggressive frontier 2012			**21.20**	**103.69**	**26.14**

Verification of BEV model predictions

Table 36 Verification of BEV model predictions for 2011 based on 2010 data

#	Product	Type	Year	ϕ_2011	Acceleration rate	Range
21	Chery QQ3 EV	2011	EV	1	15.38	80
22	Twizy Z.E.	2011	EV	1	9.66	100
23	I-Miev (M Grade)	2011	EV	1	8.12	120
24	Like M-grade	2011	EV	1	8.12	120
25	Ray EV	2011	EV	1.27	6.29	138
26	Electric C30	2011	EV	1.59	8.78	144
27	Beijing C30DB	2011	EV	1	7.81	150
28	BMW Active E	2011	EV	1	10.73	160
29	Like G-grade	2011	EV	1	8.12	180
30	Inizio R	2011	EV	1.31	16.37	241
31	Wave II, S model	2011	EV	1.18	8.05	241
32	BYD e6	2011	EV	1	6.90	300
33	Inizio RTX	2011	EV	1	28.41	321
34	Wave II, SE model	2011	EV	1	7.61	321
35	Inizio RT	2011	EV	1	13.61	402

	Acceleration rate	Range
Conservative frontier 2012	7.68	79.47
Aggressive frontier 2012	26.64	402.07

Table 37 Verification of BEV model predictions for 2012 based on 2010 data

#	Product	Type	Year	ϕ_2012	Acceleration rate	Range
36	Focus Electric	2012	EV	1	10.73	120
37	Coda Sedan	2012	EV	1.14	11.36	144
38	RAV4 EV	2012	EV	1	13.80	160
39	Zoe Z.E.	2012	EV	1.06	12.35	160
40	Fluence Z.E.	2012	EV	1	7.30	185
41	Fit EV	2012	EV	1	10.62	200
42	e6 Premier	2012	EV	1	12.08	300

	Acceleration rate	Range
Conservative frontier 2012	7.63	78.94
Aggressive frontier 2012	27.19	410.30

EV combined forecasts verification

Table 38Verification of combined model predictions for 2010 based on 2009 data

#	Product	Type	Year	ϕ_2010	acceleration rate	CO2	Fuel economy	Range
44	i-Miev (G Grade)	2010	EV	1.00	10.00	0	0	180
45	Benni Mini EV	2010	EV	1.28	8.20	0	0	105
46	Zotye 2008 EV	2010	EV	1.60	8.05	0	0	200
47	Zotye 5008 EV	2010	EV	1.00	7.14	0	0	200
48	Mercedes-Benz A-class E-Cell	2010	EV	2.20	10.91	0	0	200
49	Riich M1 EV	2010	EV	2.04	7.14	0	0	160
50	REVAi	2010	EV	1.00	5.71	0	0	80
51	Leaf	2010	EV	2.33	8.40	0	0	160
52	Peugeot iOn	2010	EV	1.63	10.00	0	0	160
53	C-Zero	2010	EV	2.51	6.67	0	0	150
54	Auris HSD	2010	HEV	1.00	8.85	90	29	0
55	CR-Z	2010	HEV	1.00	9.24	117	25.8	0
56	F3DM PHEV Low-carbon Version	2010	PHEV	1.18	9.24	63	12.82	0
57	Touareg HV	2010	HEV	1.12	15.38	193	12.2	0
58	Audi Q5	2010	HEV	1.08	14.08	159	14.3	0
59	Jeep Patriot EV	2010	PHEV	1.00	12.05	50	12.5	0
60	Besturn B50	2010	PHEV	1.00	7.14	70	13.3	0
61	ActiveHybrid 7 Series	2010	Mild-HEV	1.00	20.41	219	9.4	0
62	Lincoln MKZ Hybrid	2010	HEV	1.05	11.15	109	16	0
63	Fit/ Jazz Hybrid	2010	HEV	1.01	8.26	104	22.73	0
64	Sonata HV	2010	HEV	1.04	14.70	170	15.73	0
65	Cayenne S HV	2010	HEV	1.18	14.71	193	11.1	0
66	Fuga Hybrid/ Infiniti M35h	2010	HEV	1.00	18.65	162	14.3	0
67	Chevrolet Volt	2010	PHEV	1.00	10.78	52.5	14.88	0
		Conservative frontier 2010			6.72	257.75	8.83	104.90
		Aggressive frontier 2010			30.73	102.99	27.07	463.71

Table 39 Verification of combined model predictions for 2011 based on 2009 data

#	Product	Year	Type	ϕ_2010	acceleration rate	CO2	Fuel economy	Range
68	Chery QQ3 EV	2011	EV	1.00	15.38	0	0	80
69	Twizy Z.E.	2011	EV	1.00	9.66	0	0	100
70	Inizio R	2011	EV	1.51	16.37	0	0	241
71	Inizio RT	2011	EV	1.79	13.61	0	0	402
72	Inizio RTX	2011	EV	1.00	28.41	0	0	321
73	I-Miev (M Grade)	2011	EV	1.93	8.12	0	0	120
74	Like G-grade	2011	EV	2.14	8.12	0	0	180
75	Like M-grade	2011	EV	1.93	8.12	0	0	120
76	BMW Active E	2011	EV	1.75	10.73	0	0	160
77	BYD e6	2011	EV	1.00	6.90	0	0	300
78	Electric C30	2011	EV	2.48	8.78	0	0	144
79	Wave II, S model	2011	EV	2.99	8.05	0	0	241
80	Wave II, SE model	2011	EV	3.19	7.61	0	0	321
81	Beijing C30DB	2011	EV	1.31	7.81	0	0	150
82	Ray EV	2011	EV	2.92	6.29	0	0	138
83	Aqua	2011	HEV	1.00	9.35	111	35.4	0
84	Lexus CT200h	2011	HEV	1.00	9.71	89	26.3	0
85	Civic Hybrid 3rd gen	2011	HEV	1.12	9.60	109	18.86	0
86	Prius alpha 7 seats	2011	HEV	1.00	10.00	100	31	0
87	3008 Hybrid4	2011	HEV	1.00	11.36	99	26	0
88	Fit Shuttle Hybrid	2011	HEV	1.00	7.52	120	25	0
89	Karma S	2011	PHEV	1.00	16.67	83	22.1	0
90	Buick Regal eAssist	2011	Mild-HEV	1.00	12.05	129	11.05	0
91	Prius v (USA)	2011	HEV	1.26	9.51	132	14	0
92	Freed/ Freed Spike Hybrid	2011	HEV	1.00	6.29	95	21.6	0
93	Optima K5 HV	2011	HEV	1.50	10.54	158	15.3	0
		Conservative frontier 2011			6.40	303.35	8.42	100.03
		Aggressive frontier 2011			36.16	98.21	31.86	545.75

Table 40 Verification of combined model predictions for 2012 based on 2009 data

#	Product	Type	Year	ϕ	acceleration rate	CO2	Fuel economy	Range
94	Fluence Z.E.	2012	EV	2.71	7.30	0	0	185
95	Coda Sedan	2012	EV	1.77	11.36	0	0	144
96	Focus Electric	2012	EV	1.88	10.73	0	0	120
97	RAV4 EV	2012	EV	1.24	13.80	0	0	160
98	Fit EV	2012	EV	2.03	10.62	0	0	200
99	e6 Premier	2012	EV	1.22	12.08	0	0	300
100	Zoe Z.E.	2012	EV	1.66	12.35	0	0	160
101	Prius PHV	2012	PHEV	1.00	8.82	41	61	0
102	Ampera	2012	EREV	1.00	11.11	40	83	0
103	ActiveHybrid 5 Series	2012	HEV	1.12	16.67	155	13.6	0
104	Prius c	2012	HEV	1.13	9.35	111	17.85	0
105	Lexus GS450h	2012	HEV	1.05	16.95	137	12.3	0
106	Insight	2012	HEV	1.00	9.42	96	27.2	0
		Conservative frontier 2012			6.11	357.01	8.03	95.39
		Aggressive frontier 2012			42.56	93.66	37.49	642.30

Appendix H: Dominant peer technologies

Table 41 SOA frontier and dominant peers in 2012

#	Product	Year	Type	Φ_'12	Φ_'11	Peer 1	Peer 2	Peer 3	Peer 4	Peer 5
1	EV-Plus	1997	EV	1.55	1	Tango 0.42	Insight 0.40	Zotye 500 0.18		
2	Prius 1 gen	1997	HEV	1	1	1.00				
3	Tino Hybrid	2000	HEV	1.17	1	Insight 0.97	Active 0.02	Aqua 0.01		
4	Prius 2gen	2000	HEV	1	1					
5	Civic Hybrid 1st gen	2001	HEV	1.30	1	Insight 0.68	Prius 2st G 0.19	Aqua 0.11	Forte LPI 0.02	
6	Alphard Hybrid	2003	HEV	1.49	1	Insight 0.62	Lexus GS450h 0.12	Forte LPI 0.11	Tango 0.08	Ampera 0.06
7	Escape Hybrid	2004	HEV	1.36	1.16	Forte LPI 0.51	Insight 0.26	Fuga 0.2	Tango 0.03	
8	Tango	2005	EV	1	1					
9	Happy Messenger EV	2005	EV	4.54	4.54	Chery 0.82	Tango 0.12	Forte LPI 0.06		
10	Lexus RX400h	2005	HEV	1.29	1.20	Fuga 0.64	Forte LPI 0.18	Insight 0.16	Tango 0.02	
11	Civic Hybrid 2nd gen	2005	HEV	1.41	1.28	Insight 0.67	Forte LPI 0.29	Prius PHV 0.04		
12	Highlander Hybrid	2005	HEV	1.24	1		Fuga 0.65	Insight 0.28	Forte LPI 0.07	
13	Venturi Fetish	2006	EV	1.05	1.05	Tango 0.82	Active 0.18			
14	Mercury Mariner Hybrid	2006	HEV	1.40	1.07	Forte LPI 0.37	Insight 0.24	Prius PHV 0.21	Fuga 0.16	Ampera 0.01
15	Camry Hybrid	2006	HEV	1.34	1.27	Forte LPI 0.54	Lexus GS450h 0.33	Insight 0.10	Ampera 0.03	
16	Lexus GS450h	2006	HEV	1	1					
17	Estima Hybrid	2006	HEV	1.38	1	Insight 0.43	Lexus GS450h 0.34	Prius PHV 0.16	Forte LPI 0.06	
18	Altima Hybrid	2006	HEV	1.48	1.33	Ampera 0.36	Tango 0.34	Inizio RTX 0.16	Active 0.09	Fuga 0.07
19	Smart fortwo e 1st gen	2007	EV	1.81	1.81	Chery 0.65	Tango 0.18	Forte 0.17		

#	Product	Year	Type	Φ_'12	Φ_'11	Peer 1	Peer 2	Peer 3	Peer 4	Peer 5
20	Chevrolet Tahoe Hybrid	2007	HEV	1	1					
21	Kluger Hybrid	2007	HEV	1.29	1.19	Fuga 0.64	Forte LPI 0.24	Insight 0.12		
22	Lexus LS600h/hL	2007	HEV	1	1					
23	Tribute Hybrid	2007	HEV	1.41	1.24	Forte LPI 0.29	Insight 0.23	Fuga 0.22	Tango 0.20	Ampera 0.06
24	GMC Yukon Hybrid	2007	HEV	1.06	1	Insight 0.45	Activ 0.36	Prius PHV 0.13	Fuga 0.06	
25	Tesla Roadster	2008	EV	1.00	1.00	Tango 0.53	Inizio RTX 0.47			
26	Crown Hybrid	2008	HEV	1.65	1.41	Active 0.46	Insight 0.30	Prius PHV 0.21	Aqua 0.03	
27	Cadillac Escalade Hybrid	2008	HEV	1.68	1.37	Active 0.43	Insight 0.29	LexusLS 600h 0.21	Fuga 0.04	Ampera 0.02
28	F3DM	2008	PHEV	1.77	1.53	Ampera 0.52	Tango 0.32	Active 0.15	Inizio RTX 0.01	
29	Subaru Plug-in Stella	2009	EV	2.04	2.04	Chery 0.45	Forte LPI 0.44	Tango 0.11		
30	Venturi Fetish	2009	EV	1.12	1.12	Tango 0.76	Inizio RTX 0.24			
31	Smart fortwo electric 2nd gen	2009	EV	1.20	1.20	Chery 0.74	Tango 0.25	Forte LPI 0.01		
32	Think city	2009	EV	2.62	2.62	Tango 0.56	Chery 0.37	Forte LPI 0.07		
33	A5 BSG	2009	HEV	1.82	1.61	Forte LPI 0.73	Ampera 0.17	Lexus GS450h 0.05	Tango 0.05	
34	Lexus RX450h	2009	HEV	1.21	1	Fuga 0.71	Insight 0.16	Ampera 0.07	Prius PHV 0.04	Lexus GS450h 0.03
35	ML450 Blue HV	2009	HEV	1.40	1.34	Fuga 0.83	Ampera 0.06	Insight 0.06	Karma S 0.01	
36	Prius 3rd gen	2009	HEV	1.29	1.18	Forte LPI 0.5	Insight 0.21	Prius PHV 0.13	Aqua 0.09	Active 0.07
37	S400 Hybrid	2009	HEV	1.18	1	Fuga 0.39	Active 0.26	Insight 0.24	Forte 0.11	

#	Product	Year	Type	Φ_'12	Φ_'11	Peer 1	Peer 2	Peer 3	Peer 4	Peer 5
38	Mercury Milan Hybrid	2009	HEV	1.19	1.00	Forte LPI 0.35	Insight 0.26	Fuga 0.18	Prius PHV 0.14	Active 0.09
39	Lexus HS250h	2009	HEV	1.26	1.12	Prius PHV 0.31	Active 0.23	Fuga 0.21	Forte LPI 0.19	Insight 0.05
40	Avante/ Elantra LPI	2009	HEV	1.22	1.09	Forte LPI 0.67	Insight 0.18	Prius PHV 0.15		
41	Forte LPI	2009	HEV	1	1					
42	ActiveHybrid X6	2009	HEV	1	1					
43	SAI	2009	HEV	1.26	1.08	Forte LPI 0.46	Fuga 0.28	Ampera 0.21	Insight 0.04	Tango 0.01
44	i-Miev (G Grade)	2010	EV	1.75	1.75	Chery 0.67	Tango 0.25	Forte LPI 0.07		
45	Benni Mini EV	2010	EV	2.16	2.16	Chery 0.73	Tango 0.27			
46	Zotye 2008 EV	2010	EV	2.21	2.16	Tango 0.46	Chery 0.34	Zotye 500 0.18	Insight 0.02	
47	Zotye 5008 EV	2010	EV	1	1					
48	Mercedes-Benz A-class E-Cell	2010	EV	2.23	2.23	Tango 0.93	Inizio RTX 0.06	Active 0.02		
49	Riich M1 EV	2010	EV	2.67	2.67	Chery 0.5	Tango 0.43	Forte LPI 0.07		
50	REVAi	2010	EV	2.38	2.38	Chery 0.69	Twizy ZE 0.31			
51	Leaf	2010	EV	2.49	2.34	Tango 0.69	Insight 0.16	Fuga 0.14	Karma S 0.02	
52	Peugeot iOn	2010	EV	1.81	1.81	Tango 0.37	Forte LPI 0.33	Chery 0.3		
53	C-Zero	2010	EV	2.74	2.74	Tango 0.38	Forte LPI 0.37	Chery 0.25		
54	Auris HSD	2010	HEV	1.13	1	Insight 0.70	Prius PHV 0.18	Active 0.06	Aqua 0.05	
55	CR-Z	2010	HEV	1.14	1.07	Aqua 0.43	Insight 0.38	Active 0.06	Prius PHV 0.02	Forte LPI 0.1
56	F3DM PHEV	2010	PHEV	1.39	1.19	Ampera 0.88	Inizio RTX 0.06	Active 0.03	Tango 0.03	

#	Product	Year	Type	Φ_'12	Φ_'11	Peer 1	Peer 2	Peer 3	Peer 4	Peer 5
57	Touareg HV	2010	HEV	1.17	1.13	Fuga 0.68	Lexus LS600h 0.07	Insight 0.04	Ampera 0.01	
58	Audi Q5	2010	HEV	1.14	1.08	Fuga 0.51	Forte LPI 0.39	Insight 0.1		
59	Jeep Patriot EV	2010	PHEV	1.10	1	Ampera 0.87	Inizio RTX 0.13			
60	Besturn B50	2010	PHEV	1.25	1	Prius PHV 0.73	Zotye 500 0.2	Chery 0.06		
61	ActiveHybrid 7 Series	2010	Mild-HEV	1	1					
62	Lincoln MKZ Hybrid	2010	HEV	1.24	1.07	Forte LPI 0.39	Fuga 0.18	Prius PHV 0.17	Insight 0.17	Active 0.1
63	Fit/ Jazz Hybrid	2010	HEV	1.62	1.13	Ampera 0.62	Chery 0.31	Tango 0.07		
64	Sonata HV	2010	HEV	1.07	1.05	Forte LPI 0.49	Lexus GS450h 0.43	Insight 0.07	Tango 0.01	
65	Cayenne S HV	2010	HEV	1.29	1.28	Fuga 0.32	Active 0.29	Karma S 0.24	Inizio RTX 0.12	Ampera 0.02
66	Fuga Hybrid/ Infiniti M35h	2010	HEV	1	1					
67	Chevrolet Volt	2010	PHEV	1.14	1	Ampera 0.84	Tango 0.07	Fuga 0.05	Insight 0.04	
68	Chery QQ3 EV	2011	EV	1	1					
69	Twizy Z.E.	2011	EV	1	1					
70	Inizio R	2011	EV	1.51	1.51	Tango 0.71	Inizio RTX 0.20	Active 0.09		
71	Inizio RT	2011	EV	1.80	1.79	Inizio RTX 0.52	Tango 0.35	Insight 0.16		
72	Inizio RTX	2011	EV	1	1					
73	I-Miev (M Grade)	2011	EV	1.93	1.93	Chery 0.79	Forte LPI 0.16	Tango 0.05		
74	Like G-grade	2011	EV	2.15	2.14	Chery 0.67	Tango 0.26	Forte LPI 0.06	Insight 0.02	
75	Like M-grade	2011	EV	1.93	1.93	Chery 0.79	Forte LPI 0.16	Tango 0.05		
76	BMW Active E 1 Series	2011	EV	1.83	1.75	Tango 0.35	Insight 0.30	Inizio RTX 0.21	Karma S 0.14	

#	Product	Year	Type	Φ_'12	Φ_'11	Peer 1	Peer 2	Peer 3	Peer 4	Peer 5
77	BYD e6	2011	EV	1.80	1	Insight 0.81	Tango 0.16	Inizio RTX 0.03		
78	Electric C30	2011	EV	2.48	2.48	Tango 0.69	Lexus GS450h 0.16	Forte LPI 0.14		
79	Wave II, S model	2011	EV	2.99	2.99	Tango 0.99	Active 0.01			
80	Wave II, SE model	2011	EV	3.19	3.19	Tango 0.98	Inizio RTX 0.02			
81	Beijing C30DB	2011	EV	2.10	1.31	Tango 0.46	Insight 0.35	Zotye 500 0.11	Chery 0.08	
82	Ray ev	2011	EV	2.92	2.92	Tango 0.4	Forte LPI 0.36	Chery 0.24		
83	Aqua	2011	HEV	1	1					
84	Lexus CT200h	2011	HEV	1.11	1	Insight 0.53	Forte LPI 0.31	Prius PHV 0.16		
85	Civic Hybrid 3rd gen	2011	HEV	1.19	1.12	Insight 0.50	Forte LPI 0.45	Prius PHV 0.05		
86	Prius alpha	2011	HEV	1.06	1	Aqua 0.41	Insight 0.27	Prius PHV 0.14	Active 0.08	Forte LPI 0.1
87	3008 Hybrid4	2011	HEV	1.07	1	Insight 0.55	Active 0.26	Prius PHV 0.14	Aqua 0.05	
88	Fit Shuttle	2011	HEV	1.09	1					
89	Karma S	2011	PHEV	1	1					
90	Buick Regal eAssist	2011	Mild-HEV	1	1					
91	Prius v	2011	HEV	1.41	1.26	Forte LPI 0.69	Insight 0.15	Fuga 0.09	Prius PHV 0.05	Ampera 0.01
92	Freed/ Freed Spike Hybrid	2011	HEV	1.03	1	Insight 0.91	Prius 1 0.05	Prius PHV 0.04		
93	Optima K5 HV	2011	HEV	1.78	1.50	Ampera 0.43	Tango 0.27	Inizio RTX 0.17	Active 0.13	
94	Fluence Z.E.	2012	EV	2.71		Tango 0.64	Insight 0.24	Fuga 0.08	Forte LPI 0.04	
95	Coda Sedan	2012	EV	1.77		Tango 0.49	Insight 0.28	Inizio RTX 0.16	Karma S 0.06	

#	Product	Year	Type	Φ_'12	Φ_'11	Peer 1	Peer 2	Peer 3	Peer 4	Peer 5
96	Focus Electric	2012	EV	1.88		Tango 0.54	Karma S 0.22	Insight 0.16	Fuga 0.13	
97	RAV4 EV	2012	EV	1.24		Insight 0.50	Tango 0.41	Inizio RTX 0.09		
98	Fit EV	2012	EV	2.03		Tango 0.57	Lexus GS450h 0.32	Forte LPI 0.06	Fuga 0.05	
99	e6 Premier	2012	EV	1.22		Insight 0.65	Tango 0.30	Inizio RTX 0.05		
100	Zoe Z.E.	2012	EV	1.66		Tango 0.64	Forte LPI 0.21	Insight 0.08	Fuga 0.07	
101	Prius PHV	2012	PHEV	1						
102	Ampera	2012	EREV	1						
103	ActiveHybrid 5 Series	2012	HEV	1.12		Fuga 0.75	Ampera 0.09	Active 0.08	Tango 0.05	Inizio RTX 0.03
104	Prius c	2012	HEV	1.13		Insight 0.54	Forte LPI 0.30	Prius 1st G 0.14	Prius PHV 0.02	
105	Lexus GS450h	2012	HEV	1.05		Fuga 0.60	Active 0.22	Forte LPI 0.09	Prius PHV 0.04	Ampera 0.04
106	Insight	2012	HEV	1						