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Optimal deployment pathways for electric vehicles in the UK

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Abstract

Through the Climate Change Act, the UK has committed to reducing the annual emissions by 80 % relative to 1990 levels. In 2018, road transport was accountable for one-third of the national carbon dioxide emissions. Thus, a decarbonization of this sector has great potential to contribute to the national emission reduction. Battery-electric vehicles (BEVs) are currently one of the most promising technologies that can contribute to this. Compared to an internal combustion engine vehicle (ICEV) running on diesel, the BEV has shown to have lower life cycle emissions if operated on low-carbon electricity.

The objective of this thesis is to assess the optimal timing for electrifying the passenger car fleet in the UK. This implies finding the combination of BEVs and ICEVs that minimize the total greenhouse gas emissions from the fleet between 2020 and 2050, subject to given constraints. The insight is that the timing of the introduction should be seen together with future decarbonization of the electricity sector and other potential technological improvements in the vehicle technologies. Addressing the timing is necessary since the carbon budget for transitioning our society is constrained. The goal of the thesis will be achieved by applying an optimization model combined with data from life cycle assessments (LCA) and statistical databases.

Through this thesis it was shown that the deployment of BEVs in the UK is beneficial in terms of mitigating climate change, even though the electricity mix is not yet fully renewable. Since the UK electricity mix is by now clean enough for BEVs to be environmentally superior to the ICEVs, the optimal solution would be to deploy the BEVs as fast as possible. From the scenario analysis it was, however, clear that the mitigation potential is reduced if the deployment of electric vehicles are delayed or the UK fails to decarbonize the power sector.

In the short-term, meaning the next decade, it was found that the deployment of BEVs led to an increase in the annual fleet emissions, due to the higher embodied emissions in the BEV production phase. In the remaining years towards 2050, the large scale BEV deployment will contribute to reducing the annual emissions compared to a fleet of only ICEVs. In 2050, the annual direct emissions from the fleet will be reduced by 92 %, relative to 2017 levels, if the BEV deployment rate follows the path as in the main scenario and the UK successfully implements low-carbon energy sources.

Sammendrag

Storbritannia har forpliktet seg til å redusere sine klimagassutslipp med 80 % i 2050, relativt til 1990. I 2018 stod veitrafikken for en tredjedel av de nasjonal utslippene, så en avkarbonisering av denne sektoren har et stort potensiale for å bidra til at Storbritannia når sine klimamål. Storskala innføring av elektriske biler er per i dag et av de mest lovende tiltakene som kan bidra til dette. Sammenliknet med en konvensjonell bil som kjører på diesel, har elbilen lavere utslipp gjennom hele livsløpet hvis den er ladet med elektrisitet fra fornybare kilder.

Målet med denne oppgaven er å vurdere den optimale timingen for elektrifiseringen av Storbritannias bilflåte, og som en del av dette, finne kombinasjonen av elektriske og konvensjonelle biler som minimerer de totale klimagassutslippene fra flåten mellom 2020 og 2050. Storskala innføring av elbiler må sees i sammenheng med en potensiell avkarbonisering av elektrisiteten som brukes til ladning av bilen. Timingen er derfor viktig fordi karbonbudsjettet vi har til gode for å utvikle samfunnet vårt er begrenset. For å oppnå målet med oppgaven er det benyttet en optimeringsmodell, hvor denne er kombinert med data fra livssyklusanalyser og statistikk.

Gjennom oppgaven er det funnet at en innføring av elbiler i Storbritannia er fordelaktig med tanke på å redusere klimapåvirkningen fra transportsektoren. Det er også funnet at elektrisitetsmiksen i Storbritannia per i dag er ren nok til at til at en elbil har lavere livsløpsutslipp enn en dieselbil, også selv om elektrisiteten ikke kun kommer fra fornybare kilder. Den optimale løsningen vil derfor være en storskala innføring av elbiler så fort som mulig, noe som da må legges til rette for av myndighetene.

På kort sikt, noe som vil si det neste tiåret, vil en storskala innføring av elbiler føre til høyere årlige utslipp på grunn av at en elbil har høyere produksjonsutslipp enn en dieselbil. I de resterende årene vil innføringen av elbiler føre til en reduksjon av de årlige utslippene fra bilflåten, sammenliknet med en fossil bilflåte. I 2050 vil de årlige direkte utslippene fra bilflåten være redusert med 92 % sammenliknet med utslippene i 2017 fra nasjonale databaser, gitt at innføringen av elbiler skjer i henhold til det som er modellert i hovedscenarioet i oppgaven, og karbonintensiteten til elektrisiteten reduseres markant.

Preface

This master thesis is written during the spring of 2019 at the Department of Energy and Process Engineering at the Norwegian University of Science and Technology (NTNU). The thesis is the final work of my master's degree in Industrial Ecology.

I would like to thank my supervisor, Professor Anders Hammer Strømman for his guidance and feedback during this semester. I also want to thank my co-supervisor Christine Hung for useful insights and for being available for discussions and questions.

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Trondheim, July 1st 2019.

Ida Fausko Esperø

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1 Introduction

1.1 Background and motivation

Transportation facilitates the connection of people, businesses, goods and services. The transport sector is, however, the source of a substantial share of the global greenhouse gas emissions, causing a warming of the planet (Sims et al., 2014). The majority of vehicles today run on fossil fuels (EIA, 2017), contributing to climate change and local air pollution, as well as other externalities such as accidents, noise and congestion. Since the demand for transport is expected to increase in the coming years, the emissions from this sector will likely see the same trend. Therefore, to prevent further warming of the planet, and mitigating climate change, large scale implementation of vehicles with low-carbon drivetrains is needed (Sims et al., 2014). This could also contribute to improving air quality, especially in cities with heavy traffic, and reduce noise pollution.

On the contrary, future climate change may also pose a threat to our transport systems, where more frequent extreme weather events such as flooding, heat waves, droughts and storms can lead to damage of infrastructure and travel disruption (COACCH, 2018). This will also have economic effects in terms of costs, for instance related to maintenance and repairs. These costs are often referred to as the costs of inaction, since they are put upon societies due to insufficient climate change mitigation measures at an earlier stage (UNFCC, 2014).

The United Kingdom (UK) have through the Climate Change Act set a target to significantly reduce their emissions towards 2050, where the government have committed to an at least 80 % emission reduction relative to 1990 levels (DECC, 2011). This means that the UK need to reduce the annual emissions by an additional 300 Mt CO_2-eq, from today's levels, to reach this. Poor air quality is also the most significant environmental risk to public health in the UK. Through the Clean Air Strategy, the government have set goals to reduce the emissions of air pollutants such as NO_x and PMs, where road transport is a significant contributor to the emissions of both (DEFRA, 2018). In 2018, road transport was accountable for one-third of the national carbon dioxide emissions in the UK (BEIS, 2019). Thus, a decarbonization of this sector has great potential to contribute to the national emission reduction, while reducing the risk to public health.

Battery electric vehicles (BEVs) are currently one of the most promising technologies that can achieve this. Compared to an internal combustion engine vehicle (ICEV) running on diesel or gasoline, the BEV has shown to have an emission reduction potential if operated on low carbon electricity (Bauer et al., 2015; Ellingsen et al., 2016). Even though the BEVs have no tailpipe emissions during operation, there are emissions linked to the production of the lithium-ion batteries used for energy storage, as well as upstream emissions linked to the electricity generation. These factors can also outweigh the benefits of a BEV when compared to an ICEV.

Different approaches to modeling vehicle fleet compositions and the benefit of BEVs in an environmental context is found in the literature. The emission reduction potential from BEVs has so far received quite some attention in LCA literature (Bauer et al., 2015; Ellingsen et al., 2016; Hawkins et al., 2013; Pero et al., 2018), where the electric vehicle is usually compared to a fossil fueled vehicle. Ellingsen et al. (2016) assessed the life cycle emissions of BEVs and ICEVs from four different vehicle segments, looking at the change in climate change potential when the size of the vehicles is increased. Hawkins et al. (2013) also assessed different vehicle technologies based on the LCA methodology, where different battery chemistries were included for the BEV.

To achieve the highest possible emission reduction, the BEV should be produced with, and operated on, low-carbon electricity. It is therefore not evident that an electrified fleet is the best option to minimize the greenhouse gas emissions from to the transport sector at this time, due to potentially high shares of fossil fuels in the electricity mix. This is explored in the study by Casals et al. (2016) which focus on how the emissions from BEVs can vary depending on the carbon intensity of the local electricity grids and vehicle efficiency. The study considers selected countries in Europe, and the main focus is on the emissions linked to the operation of the vehicles.

At a national level, it is relevant to explore the environmental burden of different vehicle technologies regarding large scale deployment. The optimization methodology can be useful for this, and is often used in the transport sector for route planning with the goal of minimizing the operation cost or emissions. Some studies have aimed at assessing the optimal fleet composition from an environmental and economic perspective, including the emissions from the different vehicle technologies as well as the costs of vehicle acquisition, operation and maintenance. Lemme et al. (2019) assessed the optimal fleet combination in a car-sharing system with the use of an optimization model minimizing the environmental burden related to greenhouse gas emissions and local air pollution, while taking into account the economic dimension related to the costs of the emissions.

The optimization method was found to be most commonly applied to passenger cars, but other types of transport such as aviation, public transport or freight are also researched. A similar approach as Lemme et al. (2019) was taken by Ahani et al. (2016) when assessing the optimal fleet replacement from ICEVs to BEVs for an urban freight transport system. This was done by the use of an optimization model minimizing the total costs.

In addition to focusing on the optimal solution in different transport problems, various authors and organizations aim at predicting how the vehicle fleet will evolve in the future, for instance, considering different policies. The IEA have through the BLUE Map scenario modelled the global light-duty vehicle fleet towards 2050, including diesel, gasoline, hybrid, plug-in hybrid, electric and fuel cell vehicles (IEA, 2011). The same approach was taken by Fridstrøm et al. (2016), which assessed how fast technological developments with regard to passenger vehicles penetrate into the car fleet. This was done for the Norwegian fleet using a stock-flow cohort model, considering the same drivetrain technologies as the IEA.

1.2 Problem description and structure

Based on the conditions described in the previous section, there is a need to understand the potential environmental benefit of the introduction of BEVs in a fleet context and from a time perspective. The insight is that the timing of the introduction should be seen together with future decarbonization of the electricity sector and other potential technological improvements with regard to the vehicle technologies. Addressing the timing is necessary because the carbon budget for transitioning our society is constrained (Sims R. et al., 2014), meaning that different technological options should be deployed in terms of which having the best mitigation potential over its whole lifetime.

The objective of this thesis is to assess the optimal timing for the electrification of the passenger car fleet in the UK, with regard to minimizing the total greenhouse gas emissions from the fleet between 2020 and 2050. This implies finding the optimal combination of BEVs and ICEVs that fulfills this criteria, based on their respective life cycle emissions.

The goal of the thesis will be achieved by applying an optimization model combined with data from life cycle assessments (LCAs) and statistical databases. A basic version of the fleet optimization model developed at the Industrial Ecology program at NTNU is used as a starting point, and will be adapted for this thesis. Data from LCAs are used to model the emission parameters linked to the different life cycle phases of the two vehicle types. The carbon intensity of the electricity consumed is also based on the total life cycle emissions. The use of LCA data is essential to capture the total environmental burden of each technology, taking into account both upstream and direct greenhouse gas emissions. Statistical data is compiled and implemented to model the parameters related to the characteristics of the passenger car fleet in the UK.

Also, it is desirable to assess how the fleet composition is dependent on different decarbonization trajectories of the electricity sector and other technological improvements. The sensitivity of the optimal solution will be analyzed through different scenarios, where some of the key parameters are changed to assess the effect on the fleet composition and total emissions.

The thesis is divided into six sections, including this introductory chapter. Section two presents the methodology used in the thesis, including an introduction to LCA and optimization, as well as a description of the optimization model and modeling equations. Section three presents the case that will be studied and contains a description of all scenarios and parameters included in the model, as well as the corresponding data basis and assumptions. Section four presents the results for all the included scenarios. Lastly, in sections five and six, the results and uncertainties are discussed, and a conclusion is presented.

2 Methodology and model description

In this section, the methodology and tools used in the thesis are described. First, an introduction to LCA and the optimization methodology is given. Then, the method for modelling the parameters is described. Lastly, the model used for the fleet optimization is described, including all the modeling equations, parameters and variables.

2.1 Life cycle assessment

The parameters used in the optimization model in this thesis are based on LCAs. Modeling the parameters based on LCA data is beneficial to capture the full picture in terms of environmental impact of the vehicle fleet, and not only focus on direct emissions, which is often the case when comparing different vehicle technologies from a policy perspective. The objective of LCA is to perform consistent comparisons of technological systems, taking into account their total environmental impacts (Strømman, 2010).

LCA considers the entire life cycle of a product or service, from raw material extraction, through material manufacturing and energy production, to the use phase and end of life treatment (Finkbeiner et al., 2006). This is useful when comparing vehicle technologies since the powertrains are quite different, and require different inputs in terms of raw materials and energy during production.

A full scale LCA usually takes into account multiple environmental impacts, such as potential for global warming, acidification, damage to human health, and freshwater or marine eutrophication. In this thesis, the focus is on greenhouse gas emissions, and only the global warming potential is considered. The global warming potential is quantified in CO_2-equivalents, meaning that the emissions of other greenhouse gases, for instance methane (CH_4) or nitrous oxide (N_2O), also are included in the total impact.

2.2 Optimization

Optimization is an analytical method used to solve complex problems. The goal is to maximize or minimize the value of a function, describing for instance profit, costs, emissions or resource allocation, subject to given constraints. The function to be maximized or minimized is the objective function of the optimization problem. Whether the objective value is maximized or minimized depends on the formulation of the problem and the goal of the study (Luenberger et al., 2008). The objective can be expressed mathematically as a function of set decision variables and parameters (Hillier et al., 2010), where the decision variables are to be decided in the solution and parameters have predefined values.

An optimization model also contains constraints that put restrictions on the values the variables can take, and these also are expressed mathematically (Hillier et al., 2010). The constraints can be inequalities representing the upper and lower bounds on the variables or equalities describing the values of the variables. The solution to the problem is found by adjusting the values of the decision variables until a feasible or optimal solution is reached. A general minimization problem can be expressed as seen in Equation 2.1, where Z is the objective function to be minimized. Further, A, B and C are parameters and x is the decision variable. Note that the symbol used in the first constraint can be either <, = or > depending on the problem formulation. In the second constraint the x can be stated as either < 0, free or > 0, where free indicates that the decision variable both can take a positive or negative value.

$$\begin{aligned} \text{minimize} \quad & Z = C \cdot x \\ \text{subject to} \quad & A \cdot x < B \\ & x > 0 \end{aligned} \qquad 2.1$$

In order to solve the mathematical problem a solver is used to execute the optimization model. The software used in this thesis is the General Algebraic Modeling System (GAMS), which is a high-level modeling system for mathematical programming and optimization (GAMS, 2018). All equations and constraints are represented by linear relationships and the model is solved with the LP solver. The GAMS language is similar to common programming languages, and the model can be formulated in a way similar to its mathematical description. After running the model in GAMS the output file can be analyzed by the user, where all values of the variables are shown. The marginal values, or shadow price, of the equations and variables can also be assessed. Where the shadow price is describing the reduced cost of the variable or equation if the right hand side is changed.

2.3 Parameter modeling

The model contains multiple parameters describing characteristics of the UK vehicle fleet, emission intensities of the vehicles' life cycle phases and carbon intensity of the electricity used for production and operation. The parameters are modeled as generalized logistic functions, as seen in Equation 2.2. Where f(t) is the parameter value in year t, A indicates the asymptotic parameter value in 2000, B indicates the asymptotic parameter value in 2050, τ is the year of maximum gradient and r is the rate of change in the year of the maximum gradient. Using this type of function makes it possible to set upper and lower bounds on the value the parameters take in the modeling period, as well as adjusting in what year the value of the parameter has its highest increase or decrease.

$$f(t) = A + \frac{B - A}{1 + e^{-r(t-\tau)}} \qquad 2.2$$

Since this study includes forecasts over long time horizons, multiple assumptions and simplifications were made regarding the values of the parameters, which are input into the model. The values are based on statistics or scientific literature, and where sufficient sources were not available the values are based on assumptions. The A and B values for the different parameters have been the focus throughout the thesis and will be described for each parameter in section 3. The r is usually set based on the relative change between A and B and is not discusses in the following section. The τ is usually decided based on the fit of the parameter values in each year to current and historical data, or used to differentiate between different technologies and regions in terms of technology maturity or predicted development.

2.4 Description of the optimization model

The optimization model used in this thesis is a vehicle fleet optimization model developed at the Industrial Ecology department at NTNU. The model was used as a basis and some elements were added to customize the model for the purpose of the thesis. This includes separating the emissions from battery production from the rest of the BEV production and adding more parameters for the carbon intensity of the electricity mixes in different countries. A new restriction to the allowed growth in the BEV market share was also added, to make sure the introduction rate of BEVs was realistic.

The objective in this thesis is to minimize the total greenhouse gas emissions from the passenger car fleet in the UK between 2020 and 2050. The overarching goal is to find the combination of drivetrain technologies in each year, i.e. number of battery electric vehicles (BEVs) and internal combustion engine vehicles running on diesel (ICEVs), that fulfill this objective based on their respective life cycle emissions.

The sets and corresponding indices, parameters and variables included in the model are shown below. Recall that the parameters are required inputs to the model with predefined values for the whole modeling period. Each parameter will be described more in detail in section three, together with the assigned value and assumptions, where the respective sections are stated on the right hand side in the list below. Note that some of the parameters listed below also are defined with additional superscript in the equations to explicitly state a drivetrain component or life cycle phase.

Sets

T	Set of years in the whole modeling period, T = {2000, 2001, 2002, … , 2050}
I	Subset of years in the vehicle stock initialization period, I = {2000, 2001, 2002, … , 2020}
O	Subset of years in the vehicle stock optimization period, O = {2020, 2021, 2002, … , 2050}
A	Set of vehicle age classes, A = {0, 1, 2, … , 20}
K	Set of drivetrain technologies, K = {ICEV, BEV}

Indices

t	Index for year, $t \in T, I, O$		
a	Index for vehicle age class, $a \in A$		
k	Index for drivetrain technology, $k \in K$		

Parameters

α_a	Share of vehicles of age *a* in the initial vehicle stock	3.5.2	[%]
β_a	Share of vehicles of age *a* scrapped each year	3.5.2	[%]
$C_{t,k}^{PROD}$	Emission intensity of producing a vehicle with drivetrain *k* in year *t*	3.3.1	[kg CO_2-eq/veh]
$C_{t,k}^{CNST}$	Constant emission term of producing a vehicle with drivetrain *k* in year *t*	3.3.1	[kg CO_2-eq/veh]
$C_{a,t,k}^{OPER}$	Emission intensity of operating a vehicle with drivetrain *k* of age *a* in year *t*	3.3.3	[kg CO_2-eq/km]
$C_{t,k}^{EOL}$	Emission intensity of EOL treatment of a vehicle with drivetrain *k* in year *t*	3.3.4	[kg CO_2-eq/veh]
CI_t	Carbon intensity of the electricity mix in year *t*	3.4	[kg CO_2-eq/kWh]
D_t	Annual driving distance per vehicle in year *t*	3.5.1	[km/veh]
$\epsilon_{t,k}$	Electricity requirement of producing a vehicle with drivetrain *k* in year *t*	3.3.1	[kWh/veh]
$I_{a,t,k}^{OPER}$	Energy consumption of operating a BEV of age *a* in year *t*	3.3.3	[kWh/km]
V_t	Vehicle stock size in year *t*	3.5.1	[veh]
R_1, R_2	Shape parameters used in the constraint for BEVs added	3.5.3	[%]

Variables

Z	Objective function to be minimized: Total emissions from the vehicle fleet	[kg CO_2-eq]
$A_{a,t,k}$	Number of vehicles with drivetrain *k* at age *a* added to the fleet in year *t*	[veh]
$LC_{t,k}^{TOT}$	Total life cycle emissions from the vehicle fleet with drivetrain *k* in year *t*	[kg CO_2-eq]
$LC_{t,k}^{PROD}$	Total production emissions of vehicles with drivetrain k added in year *t*	[kg CO_2-eq]
$LC_{t,k}^{OPER}$	Total emissions from operating the vehicles with drivetrain *k* in the fleet in year *t*	[kg CO_2-eq]
$LC_{t,k}^{EOL}$	Total emissions from the EOL treatment of vehicles with drivetrain *k* removed in year *t*	[kg CO_2-eq]
$R_{a,t,k}$	Number of vehicles with drivetrain *k* at age *a* removed from the fleet in year *t*	[veh]
$S_{a,t,k}$	Number of vehicles with drivetrain *k* at age *a* in the fleet in year *t*	[veh]
$\Delta S_{t,k}$	Number of vehicles in the fleet with drivetrain *k* in year *t* relative to the previous year	[veh]

2.4.1 Objective function and emission modeling

The objective function to be minimized in the optimization model, Z, is the sum of the total life cycle fleet emissions, $LC_{t,k}^{TOT}$, for all years t and all drivetrain technologies k, in the period from 2020 to 2050 (Equation 2.3).

$$min\, Z = \sum_t \sum_k LC_{t,k}^{TOT}, \qquad \forall\ t \in\ O, k \in K \tag{2.3}$$

The total fleet emissions in year t for each drivetrain technology k is the sum of the emissions from all three life cycle phases, $\mathrm{LC_{t,k}^{PROD}}$, $\mathrm{LC_{t,k}^{OPER}}$ and $\mathrm{LC_{t,k}^{EOL}}$, in the optimization period (Equation 2.4).

$$LC_{t,k}^{TOT} = LC_{t,k}^{PROD} + LC_{t,k}^{OPER} + LC_{t,k}^{EOL}, \qquad \forall\ t \in\ O, k \in\ K \tag{2.4}$$

The equations for calculating the total emissions from each life cycle phase are dependent on the dynamics of the vehicle stock, which will be explained in more detail in section 2.4.2. The production emissions for drivetrain technology k in year t, $\mathrm{LC}_{t,k}^{\mathrm{PROD}}$, is dependent on the vehicles with drivetrain k added in year t, $\mathrm{A_{a,t,k}}$, and the emission intensity of producing all vehicle components for drivetrain k in year t, $\mathrm{C_{t,k}^{PROD}}$ (Equation 2.5).

$$LC_{t,k}^{PROD} = \sum_a \left(A_{a,t,k} \cdot C_{t,k}^{PROD}\right), \qquad \forall\ t \in\ O, k \in K \tag{2.5}$$

The parameter $\mathrm{C_{t,k}^{PROD}}$ is calculated differently for the BEV and ICEV. For the BEV the emissions are dependent on both the production of the battery and the production of rest of the vehicle. Each element is also split up into a constant emission term, $\mathrm{C_{t,k}^{CNST}}$, and the electricity requirement during production, $\epsilon_{\mathrm{t,k}}$ (Equation 2.6). The production emissions for the ICEV are only dependent on the production of the vehicle, i.e. the constant emission term and the electricity requirement (Equation 2.7). The electricity requirements are multiplied with the carbon intensity of the electricity mix, $\mathrm{CI_t}$, to calculate the emissions, where the superscript indicates the production region.

$$C_{t,k}^{PROD} = (C_{t,k}^{CNST,BATT} + CI_t^{ASIA} \cdot \epsilon_{t,k}^{BATT}) + (C_{t,k}^{CNST,VEH} + CI_t^{EUR} \cdot \epsilon_{t,k}^{VEH}), \qquad \forall\, t \in O, k = BEV \tag{2.6}$$

$$C_{t,k}^{PROD} = C_{t,k}^{CNST,VEH} + CI_t^{EUR} \cdot \epsilon_{t,k}^{VEH}, \qquad \forall\, t \in\ O, k = ICEV \tag{2.7}$$

The total operation emissions from drivetrain technology k in year t, $\mathrm{LC_{t,k}^{OPER}}$, is calculated from the number of vehicles of each drivetrain in the fleet in the given year, $\mathrm{S_{a,t,k}}$, the emission intensity of driving each vehicle, $\mathrm{C_{a,t,k}^{OPER}}$, and the total operational distance in year $\mathrm{D_t}$ (Equation 2.8). Note that the emission intensity of the operation also will depend on the age of the vehicles.

$$LC_{t,k}^{OPER} = \sum_a \left(S_{a,t,k} \cdot C_{a,t,k}^{OPER} \cdot D_t\right), \qquad \forall\ t \in\ O, k \in K \tag{2.8}$$

The operation emissions from the BEV are dependent on the energy consumption per kilometer driven, $\mathrm{I_{a,t}^{OPER}}$, and carbon intensity of the electricity in the UK in year t, $\mathrm{CI_t^{UK}}$ (Equation 2.9).

$$C_{a,t,k}^{OPER} = I_{a,t,k}^{OPER} \cdot CI_t^{UK}, \qquad \forall\ t \in\ O, k = BEV \tag{2.9}$$

The total emissions from the EOL treatment of drivetrain technology k in year t , $LC_{t,k}^{EOL}$, is calculated from the sum of vehicles removed from the stock in year t of all ages, $R_{a,t,k}$, and the emission intensity of the EOL for each vehicle, $C_{t,k}^{EOL}$ (Equation 2.10).

$$LC_{t,k}^{EOL} = \sum_a (R_{a,t,k} \cdot C_{t,k}^{EOL}), \qquad \forall\ t \in\ O, k \in K \tag{2.10}$$

2.4.2 Vehicle stock dynamics

The model is split into two time periods, an initialization period and an optimization period. The purpose of the initialization period is to establish a vehicle fleet that resembles the historic and current fleet in the UK. In this thesis the fleet is assumed to only contain ICEVs between 2000 and 2020. The amount of BEVs is seen as negligible because the fleet currently contains only 0.15 % of BEVs (DfT, 2018e). From 2020 and towards 2050 the fleet composition is optimized and the model will decide the optimal combination of BEVs and ICEVs in order to minimize the emissions over the whole period. The equations calculating the different aspects of the fleet dynamics are essentially the same as in both periods, with some exceptions which will be explained in further detail later in this section.

Initialization period

The vehicle demand in each year is driven by a parameter based on historical data and predicted future growth of the vehicle stock, V_t. In the first year of the initialization period, the age distributed vehicle stock, $S_{a,t,k}$, is determined by the parameter defining the total number of vehicles in the fleet, and an age distribution parameter, α_a (Equation 2.11). The age distribution parameter is describing the share of vehicles in the fleet at age a, and is based on statistical data averaged over 15 years. In the whole initialization period the fleet consists of ICEVs only, and the equations are therefore only valid for drivetrain technology k = ICEV. For the case of k = BEV the value of the equations are equal to zero, meaning no BEVs are added, removed or present in the fleet when t ∈ I.

$$S_{a,t.k} = V_t \cdot \alpha_a, \qquad \forall\ t = 2000 \in I, k = ICEV \tag{2.11}$$

In the remaining years of the initialization period the stock of vehicles with drivetrain technology k of age a, in year t is given by the size of the stock in the previous year, plus the new vehicles added to the stock, $A_{a,t,k}$, minus the vehicles that are assumed scrapped and therefore removed from the stock, $R_{a,t,k}$ (Equation 2.12).

$$S_{a,t,k} = S_{a-1,t-1,k} + A_{a,t,k} - R_{a,t,k}, \qquad \forall\, t \neq 2000 \in I\,, k = ICEV \tag{2.12}$$

All vehicles added to the fleet are assumed to be new, and are therefore assigned to age class 0. The number of vehicles added are based on the change in vehicle stock, $\Delta S_{t,k}$, and the total vehicles removed from the stock in the previous year (Equation 2.13). Where the change in vehicle stock is calculated from the vehicle stock size parameter, taking the difference between the current and previous year (Equation 2.14). The vehicles removed from the stock, $R_{a,t,k}$, are dependent on a parameter describing the share of vehicles in the stock of different age classes that are scrapped, β_a (Equation 2.15). The scrapping parameter is based on a cumulative normal distribution function, which was used to calculate the vehicle death rate for each given age.

$$A_{a,t,k} = \Delta S_{t,k} + \sum_{a} R_{a,t-1,k}\,, \qquad \forall\, t \in I\,, k = ICEV \tag{2.13}$$

$$\Delta S_{t,k} = V_t - V_{t-1}, \qquad \forall\, t \in I\,, k = ICEV \tag{2.14}$$

$$R_{a,t,k} = S_{a-1,t,-1,k} \cdot \beta_{a-1}, \qquad \forall\, t \in I, k = ICEV \tag{2.15}$$

Optimization period

In the optimization period, the change in vehicle stock, vehicle stock size, vehicles added and vehicles removed are calculated in the same way as in the initialization period (Equations 2.12 through 2.15). The only differences are the conditions of validity, where in the optimization period the equations are valid for $t \in O$ and $k \in K$.

Since the fleet now consist of both ICEVs and BEVs, it is the sum of the ICEVs and BEVs in the fleet that has to fulfil the total vehicle demand given by the parameter V_t (Equation 2.16).

$$\sum_{a}\sum_{k} S_{a,t,k} = V_t, \qquad \forall\, t \in O, k \in K \tag{2.16}$$

The total number of BEVs and ICEVs added in the optimization period also has to be balanced in terms of the total number of vehicles that are removed from the fleet and the calculated stock growth (Equation 2.17).

$$\sum_{k} A_{a,t,k} = \sum_{k}\left(\Delta S_{t,k} + \sum_{a} R_{a,t-1,k}\right), \qquad \forall\, t \in O, k \in K \tag{2.17}$$

An additional constraint is included to restrict the number of BEVs added in each year to provide a realistic growth in the BEV stock (Equation 2.18). The parameters R_1 and R_2 are percentages that can be adjusted in order to obtain the desired BEV introduction rate. R_1 denotes the annual growth relative to the size of the BEV fleet in the previous year. R_2 denotes the additional growth relative to the total fleet size, and is included to start the BEV introduction if the BEV stock in the previous year is zero.

$$A_{a,t,k} \leq (1 + R_1) \cdot A_{a,t-1,k} + R_2 \cdot S_{a-1,t,-1,k}, \qquad \forall\, t \in O, k = BEV \qquad 2.18$$

3 Case description and data

This section contains a description of the scenarios modeled, as well as a description of the different parameters, data sources and assumptions made. First, the vehicles modelled are presented, followed by a description of the main storylines of the scenarios. Then, each parameter is presented together with their respective values and assumptions. The life cycle emissions parameters for the vehicles and electricity mixes are presented first, followed by the parameters linked to the vehicle fleet in the UK. In total, this section is quite long, but this is seen as necessary in order to give a thorough explanation of the parameters and the corresponding data basis.

An overview of all input parameters and respective values for the main scenario can be seen in Table B.1 in the appendix, while the relative parameter changes in the other scenarios can be seen in Table 3.1 in this section. The uncertainties linked to the parameter values and assumptions are discussed in section 5.1.

3.1 Vehicles modelled

The optimization model includes two vehicle technologies; Battery-electric vehicles (BEVs) and internal combustion engine vehicles (ICEVs). The model only includes one vehicle segment, and it is chosen to model a medium-sized vehicle. The past years the sales of small and medium-sized vehicles have increased in the UK, while the sale of larger cars has stagnated (SMMT, 2018b). Modelling a medium-sized vehicle is therefore chosen to model a vehicle that represents the average in the fleet.

The main difference comparing the two drivetrains is that the BEV uses electricity stored in an onboard battery pack to power an electric motor that provides propulsion, while the ICEV has an engine and a fuel tank. The vehicle fleet in the UK has historically been dominated by gasoline vehicles. In the past years, however, it is seen that the gasoline sales are declining while the sales of diesel cars are increasing (DfT, 2018e). The ICEV modeled in this thesis is, therefore, assumed to be a diesel car. Other differences are the cost of both buying and operating the vehicles. BEVs usually have a higher purchasing price, but on the other hand, they are cheaper to fuel and maintain (IEA, 2018c). Another evident difference is that the BEV has no tailpipe emissions, while the ICEV, which is dependent on the combustion of fossil fuels, will emit greenhouse gases during its whole lifetime.

For the BEV it is chosen to model a 42 kWh battery since this is assumed representative for today's medium-sized vehicles. When the first commercially available BEVs were launched the battery size was usually in the range 16 to 24 kWh, which can be deemed representative for a medium sized vehicle in that period. The battery sizes have since increased to meet the demand for longer range BEVs. Thus, 30 to 60 kWh can be deemed as a more common battery size for a medium-sized vehicle today. An overview of previous and current BEV models and corresponding battery sizes can be seen in Table C.3 in the appendix.

3.2 Scenario description

The purpose of the scenarios included in this study is to assess how the fleet composition would change if a variety of parameters in the model were changed. Besides, it is desirable to see how the annual and cumulative emissions in the period 2020 to 2050 are changing relative to main scenario. The storylines of the various scenarios will be described here, while the exact values for the different parameters are described in the respective parameter subsection later.

Main scenario

The main scenario is based on statistical data and current trends and is used as a basis for the adjustments made in the other scenarios. In this scenario, all maximum gradients of change regarding ICEV lifecycle emissions are set to 2025 since the ICEV technology is seen as more mature than the BEV technology (IEA, 2018c). The maximum gradients of change for the BEV life cycle emissions are set to 2030. The introduction rate of the BEVs is modeled so that the UK can reach its goal of an electric market share of 50 % in 2030. Regarding production, the battery is assumed to be produced in Japan, China or South Korea and the other vehicle components are assumed to be produced in Europe. It is further assumed that the UK successfully decarbonizes the power sector, leading to a carbon intensity of 110 g CO_2-eq/kWh in 2050.

Sustainable transport (ST) scenario

In the ST scenario, it is assumed that a behavioral change among the UK population, as well as policies introduced by the government, will change the way people travel. Travel demand management can be done through strategies and policies that reduce the population's need for driving, for instance, through promoting other modes of transport, congestion pricing, parking management and road tolls (Mashayekh et al., 2011). This scenario includes a substantial modal shift to other transport modes, such as bus, rail, walking or cycling. Since the dependency on a personal vehicle is decreasing, the growth in the vehicle stock is assumed slower than in the main scenario. Since more people are choosing public transport, the annual driving distance is also expected to have a higher annual decrease. Also, a switch towards larger shares of biofuels in the diesel is contributing to bringing down the operation emission from the ICEVs. This is seen to happen due to stronger enforcement of the Renewable Transport Fuel Obligation by the UK government, which is setting goals for fuel producers in terms of the share of renewable fuels produced. The obligation is intended to reduce greenhouse gas emissions from fuels used in road vehicles (DfT, 2018b). It is assumed that all ICEVs after 2020 run on biodiesel, which has a lower carbon intensity than regular diesel (Edwards et al., 2014).

Battery electric success (BE-S) scenario

In the BE-S scenario it is desirable to see what would happen if the improvements of the battery electric technology are more significant and happening faster than what is assumed in the main scenario. This includes 20 % lower emission intensities of battery production, BEV operation and end-of-life treatment in 2050, relative to the main scenario. In addition, multiple policies favoring BEVs are successfully implemented leading to a higher introduction rate of electric vehicles. The introduction rate is following the most positive trajectory by the Department for Transport, with an electric market share of 70 % in 2030 (DfT, 2018c).

Delayed action (DA) scenario

The DA scenario explores what would happen if the improvements of the technologies for BEVs are delayed and will have the steepest decrease in the life cycle emission parameters in 2035 instead of 2030. The emission intensities of battery production, energy consumption during operation and emissions from end-of-life treatment will then be higher in 2050, and a 20 % increase relative to the main scenario is assumed. In addition, due to few successful policies favoring BEVs, the electric car sales will increase at a slower rate than in the main scenario. Here, the introduction rate is modeled after the slowest introduction rate predicted by the Department for Transport, where the share of BEVs of new car sales in 2030 is 30 % (DfT, 2018c).

Production location (PL) scenario

The PL scenario explores what would happen if the production of the vehicles and battery was set to different regions. This will then affect the production emissions since the carbon intensity of the electricity varies between countries (Moro et al., 2018). It is assumed that the production of the battery and the rest of the vehicle happens in the same country, as opposed to the main scenario where the production farcicalities are situated in different countries. The first case, PL-A, explores the case of importing the cars from Asia, the second case, PL-E, includes production in Europe and the last case, PL-N, explores how moving the production of both cars and batteries to Norway, which has almost 100 % renewable electricity, would affect the optimal solution.

ICEV light-weighting (LW) scenario

The LW scenario assumes that the ICEVs are light-weighted. This assumption is affecting two things; the emission intensity of the vehicle production and the fuel consumption during operation. Since light-weighting the vehicles means substituting materials such as steel with aluminum or magnesium, this will increase the production emissions since the upstream emissions embodied in the lighter materials are higher (Kim et al., 2013). On the other hand, the benefit of reducing the weight is lower fuel consumption, hence lower emissions from the operation of the vehicles (Sims et al., 2014). The benefit of improved fuel economy versus increased emissions from production is dependent on multiple factors, for instance, the share of material substituted, choice of substitution material and vehicle lifetime (Kelly et al., 2015; Kim et al., 2013; Raugei et al., 2015). This scenario is therefore based on a very simplified case, where it is assumed that decreasing the weight of the ICEV leads to an improvement of 6 % in fuel economy (Lewis et al., 2014). Since the parameter describing the emissions during ICEV operation is not dependent on the fuel consumption in the model it is assumed that the emissions will have the same percentage reduction as the fuel consumption. It is further assumed, based on Raugei et al. (2015) that the production emissions due to the use of lighter materials will increase by 10 % relative to the main scenario.

UK electricity trajectory (EL) scenario

Different trajectories for decarbonizing the UK electricity is included in the EL scenario. This scenario explores how the carbon intensity of the electricity used during BEV operation is affecting the optimal fleet composition and total emissions. The carbon intensity of the electricity in the main scenario is here seen as an optimistic future state. Different cases of higher final carbon intensities are explored where in the first case, EL-0, it is assumed that the carbon intensity will not see a reduction and stagnate at today's level. In the rest of the cases EL-30, EL-50 and EL-70, it is assumed that the carbon intensity will be 30 %, 50 % and 70 % lower than today's level, respectively.

Scenario overview

Table 3.1 shows the key aspects that are affected by the assumptions in each scenario. The changes in the parameters are given relative to the main scenario, where = indicates that the parameter is unaffected, ⇑ indicates that the parameter value is increasing and ⇓ indicates that the parameter value is decreasing. Note that not all parameters are included in the table, but that changes for instance in the electricity mixes will affect the other parameters and are therefore assigned to these.

Table 3.1 – Overview of the parameters changed in the various scenario. The changes are given relative to the main scenario, where = denotes that the parameter is unaffected, ⇑ denotes that the parameter value is increasing and ⇓ denotes that the parameter value is decreasing

	Vehicle fleet size	Annual operating distance	ICEV production	ICEV operation	ICEV EOL	BEV production	BEV operation	BEV EOL
ST	⇓	⇓	=	⇓	=	=	=	=
BE-S	=	=	=	=	=	⇓	⇓	⇓
DA	=	=	=	=	=	⇑	⇑	⇑
PL-A	=	=	⇑	=	=	⇑	=	=
PL-E	=	=	=	=	=	⇓	=	=
PL-N	=	=	⇓	=	=	⇓	=	=
LW	=	=	⇑	⇓	=	=	=	=
EL	=	=	=	=	=	=	⇑	=

3.3 Life cycle emission intensities

Life cycle emissions from a vehicle are comprised of three phases: production, operation and end-of-life. The production phase includes manufacturing of the vehicles, as well as the battery for the BEVs. Both the vehicle and battery production are split up into two parts, where the first part is the electricity consumption during manufacture and the second part is a constant emission term. The electricity consumption is linked to the carbon intensity of the electricity mix in the respective production location to estimate the emission burden for this part. Note that the constant emissions also change during the modeling period, but is denoted as constant due to the fact that they are not dependent on the electricity mix.

During the modeling of the life cycle parameters in this thesis the question has usually not been *if* the emission intensity for a given parameter will decrease or not, but *how much* it will decrease. Since it is virtually infeasible to estimate this in any exact way, the future emission intensities are often based on assumptions. When available, the reductions have been based on trends seen in data from automotive manufacturer or projections from government reports. The focus has been on making sure the developments of the two drivetrain technologies were reasonable relative to one another, as well as benchmarking the parameter values to results from literature in the current decade.

It is chosen to base the life cycle emission parameters on the study by Ellingsen et al. (2016), and it is assumed that these values are representative for the current decade. The results from Ellingsen et al. (2016) were compared to other studies in literature and from the industry. Both the results for the ICEV and the BEV are in the range of the average from what is found in industry reports and other studies. An overview of the results from reviewed LCA studies can be seen in Table C.1 and Table C.2 in the appendix.

3.3.1 Production of the vehicles (excluding battery pack)

For the ICEV, the production of the vehicle includes all components needed to produce a fully functional vehicle. For the BEV the production of the battery pack is not included in this section, but the impacts from producing all other vehicle components are assigned to this parameter. The electricity requirement includes all electricity used during the production phase at the factory, for instance, processing of vehicle parts and vehicle assembly. The constant emission term comprises all other non-electricity related emissions, such as the use of other fuels and gases for heat in the factory and upstream emissions linked to the materials used.

Electricity use

To estimate the electricity used to produce the vehicles, given by parameter $\epsilon_{t,k}^{\mathrm{VEH}}$, sustainability reports from Volkswagen, Nissan, BMW and Daimler were assessed. The stated energy consumption in kWh per produced vehicle can be seen in Table 3.2. It is assumed that these values are representative for the production of an ICEV since most of the car models produced by these manufacturers are ICEVs. For all manufacturers the energy consumption per vehicle produced has been decreasing over the years, with an annual reduction of between 1.6 and 4.6 %. It is assumed that this reduction is representative for the previous decade, and the average of 3.4 % is used to estimate the energy consumption in 2000. The average energy consumption in 2010 was 2953 kWh. Extrapolating this back to 2000 results in an energy consumption of 4000 kWh per vehicle.

Table 3.2 – Energy consumption for producing one vehicle given in kWh per vehicle, and average decrease in the energy consumption for the different manufacturers given in percent per year. [1] Volkswagen AG (2018), [2] Nissan Motor Corporation (2014, 2018b), [3] BMW Group (2018), [4] Daimler AG (2017).

	VW [1]	Nissan [2]	BMW [3]	Daimler [4]	Average
2010	2519	2490		3850	2953
2011		2200		3730	2965
2012		2300		3710	3005
2013		2190	2360	3490	2680
2014		1870	2250	3240	2452
2015		1860	2190	3060	2370
2016	2090	1800	2210	2990	2272
2017	2068	1680	2170	3070	2247
2018	2037				2037
Average decrease	2.7 % p.a.	4.6 % p.a.	1.6 % p.a.	2.9 % p.a.	3.4 % p.a.

Further, Nissan states that around 50 % of the energy used in their manufacturing process is electricity (Nissan Motor Corporation, 2014), which results in an electricity consumption of 2000 kWh. This is assumed to be representative for the production of an ICEV in the main scenario in 2000. As mentioned in the scenario description it is assumed that the weight reduction will increase the production emissions by 10 % in the LW scenario. It is assumed that the electricity consumption will increase by the same amount, leading to an electricity consumption of 2200 kWh. The electricity requirement parameter for the ICEV production can be seen in Figure 3.1a.

The BEV without the battery pack is relatively similar to the ICEV. As a simplification one can say that the main difference between the two are that the ICEV has an internal combustion engine and a fuel tank, while the BEV has an electric motor and a battery pack. Of the components mentioned it is the electric motor that has the highest associated production emissions, not considering the battery pack (Bauer et al., 2015; Hawkins et al., 2013). Since no data were obtained of the differences in electricity consumption during production it is assumed that the BEV production electricity is similar to the ICEV. The electricity requirement parameter for the BEV production can be seen in Figure 3.1b.

To estimate the electricity consumption in manufacturing in 2050 the lowest annual decrease found in industry reports of 1.6 % is used, and this rate of reduction is assumed to 2025. From 2025 to 2050 the decrease is assumed to slow down to 1 % per year, resulting in a total electricity consumption for producing the vehicles of 900 kWh in 2050 in the main scenario. In the battery electric success (BE-S) scenario it is assumed that electricity consumption for producing a BEV in 2050 is 20 % lower than in the main scenario (720 kWh), while in the DA scenario it is assumed that the consumption is 20 % higher (1080 kWh). In addition, the highest gradient of change in the DA scenario is set to 2035, compared to 2030 in the two other scenarios.

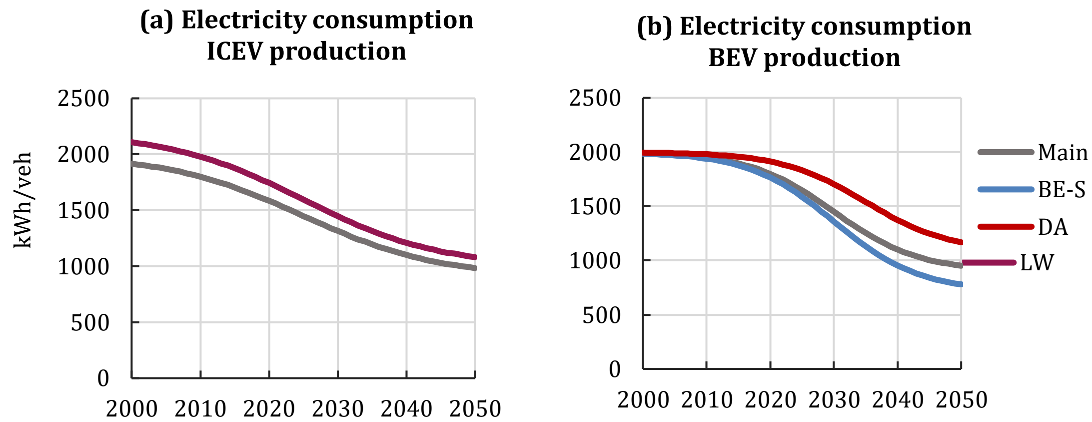

Figure 3.1a-b – Electricity requirement of producing the ICEV and BEV shown in kWh per vehicle produced. The chart for the ICEV is showing the main and light-weighting (LW) scenarios, while the chart for the BEV is showing the main, battery electric success (BE-S) and delayed action (DA) scenarios.

Constant emission term

According to ACEA (2019) the total CO_2 emissions per car produced dropped by 30.1 % between 2008 and 2017. This reflects the manufacturer's effort to bring the overall emissions down, and it is likely that they will continue to strive for this in the future. The constant emission term, given by parameter $C_{t,k}^{CNST,VEH}$, is estimated by taking the total production emissions from Ellingsen et al. (2016) and subtracting the emissions linked to the electricity consumption, assuming an average European electricity mix of 521 g CO_2-eq/kWh.

Ellingsen et al. (2016) estimated the total emissions from producing an ICEV to 4500 kg CO_2-eq. Assuming approximately 800 kg CO_2-eq can be allocated to the electricity use yields a constant emission term of 3700 kg CO_2-eq in the main scenario. For the ICEV it is further assumed that the constant production emissions will decrease by 10 %, in line with Bauer et al. (2015), resulting in a constant emissions term of 3400 kg

CO_2-eq in 2050. Fitting the 2000 value to the other values stated yields production emissions of approximately 3900 kg CO_2-eq per ICEV in the main scenario. In the LW scenario, where the ICEVs are assumed to be light weighted, the switch from less steel and more aluminum will lead to higher production emissions (Kim et al., 2013). As mentioned in the scenario description, it is assumed that the light-weighting will increase the production emissions by 10 %, leading to constant emissions of 4300 kg CO_2-eq per produced vehicle in 2050. The constant emission term parameter for the ICEV can be seen in Figure 3.2a.

Ellingsen et al. (2016) estimated the production emissions for the BEV, excluding battery pack, to 6500 kg CO_2-eq. Subtracting the share allocated to the electricity yields a constant emission term of 5700 kg CO_2-eq. The production emissions are assumed to decline 18 % in the main scenario, also in line with Bauer et al. (2015), resulting in a constant emission term of 4670 kg CO_2-eq per BEV in 2050. Fitting the 2000 value to the other values stated yields production emissions of approximately 5800 kg CO_2-eq per BEV. In the BE-S scenario and DA scenario the values in 2050 are assumed to change in the same way as for the electricity consumption, i.e. a decrease and increase by 20 %. Resulting in 3700 kg CO_2-eq and 5600 kg CO_2-eq for the BEVs produced in the BE-S scenario and DA scenario, respectively. This can be seen in Figure 3.2b.

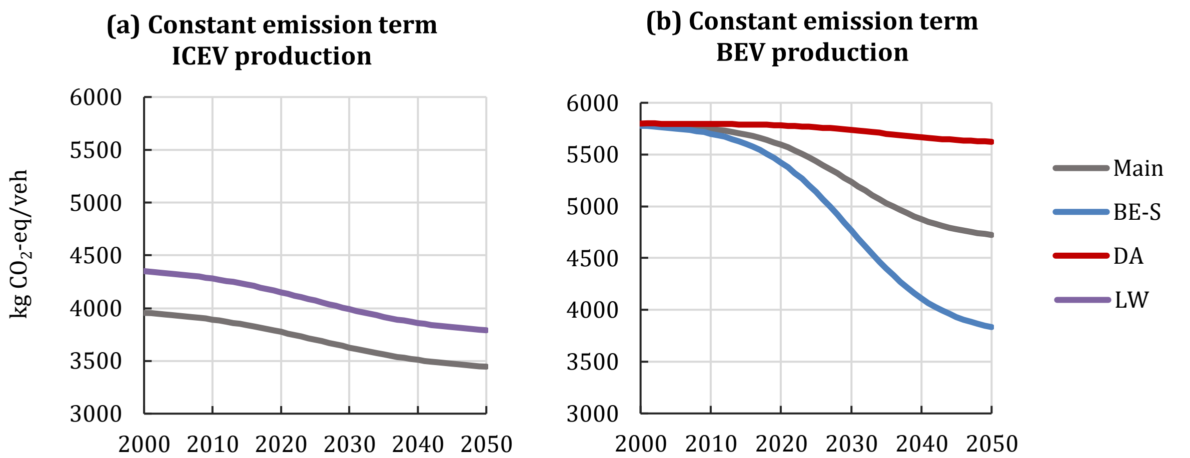

Figure 3.2a-b – Constant emission parameter for producing the ICEV and BEV, given in kilo CO_2-equivalents per vehicle produced. The chart for the ICEV is shown in the main and the light-weighting (LW) scenarios, while the chart for the BEV is showing the main, battery electric success (BE-S) and delayed action (DA) scenarios.

3.3.2 Production of battery pack

Emissions from battery production account for 30 to 40 % of the total BEV production emissions (Ellingsen et al., 2018). The battery pack is modelled separately since it is likely that it is produced in another region than the rest of the vehicle. The battery production is also split up into an electricity requirement and a constant emission term.

Electricity consumption

It is estimated that around 50 % of the emissions linked to the battery production are caused by the use of energy during battery cell manufacture (Ellingsen et al., 2014; Kim et al., 2016). The main driver for energy consumption during cell manufacture is the operation of the dry rooms that are required to assure the quality of the battery cells (Ellingsen et al., 2014). The energy used to operate the dry rooms depend on the throughput of the factory, i.e. if the factory produces batteries close to its capacity or not. Lower throughput than capacity will lead to a higher energy consumption per battery produced and vice versa (Dunn et al., 2015).

The energy consumption in battery production, given by parameter $\epsilon_{t,k}^{BATT}$, is estimated to be between 147 and 464 kWh per kWh battery by Ellingsen et al. (2018). The lower value represents a state-of-the art production facility, while the higher value represents a smaller scale factory, which is in line with the differences described by Dunn et al. (2015). Further, Ellingsen et al. (2018) state that electricity accounts for around 57 % of the energy used. This is used as an approximation in this study since few of the other studies in literature stated the share of electricity consumed. Applying the lowest value from Ellingsen et al. (2018) for the production of a 42 kWh battery pack yields an electricity consumption of approximately 3500 kWh, which is assumed to be representative for the production in the current decade.

The price of the lithium ion battery packs has decreased in the past decade, and is predicted to continue decreasing in the coming years (Nykvist et al., 2015; Philippot et al., 2019; Tesla Motors, 2014). This can be used as an indication of for instance the energy used in the production process, and it is assumed the energy consumption has been following the same trend. A decline in electricity consumption of 1 % per year is assumed in the main scenario, resulting in a requirement of 2900 kWh per battery in 2050. Fitting the 2000 value yields 3700 kWh per battery produced. In the BE-S and DA scenarios the electricity requirements are assumed to be 20 % lower and higher than in the main scenario in 2050, respectively. This results in an electricity requirement of 2320 kWh in the BE-S scenario and 3480 kWh in the DA scenario. The parameter values in the different scenarios for the electricity requirement can be seen in Figure 3.3a.

Constant emission term

The constant term for the battery production, given by parameter $C_{t,k}^{CNST,BATT}$, is estimated in the same way as the constant term for the production of the rest of the vehicle. The emissions linked to the electricity consumption were compared to the results from Ellingsen et al. (2016) for the whole battery pack of 42 kWh, where the emissions were found to 4900 kg CO_2-eq. Assuming an average Asian electricity mix of 900 g CO_2-eq/kWh, since the battery is assumed to be produced in either China, South Korea or Japan, yields electricity related emissions of around 3000 kg CO_2-eq. This results in constant emissions of approximately 1900 kg CO_2-eq in the current decade. The constant emission term of the battery production can be seen in

Figure 3.3b. Further, assuming the constant emission term has had and will have a slower decrease than the electricity consumption, of 0.5 % reduction per year, results in 2000 kg CO_2-eq in 2000 and 1700 kg CO_2-eq in 2050. In the BE-S scenario it is assumed that the values will be 20 % lower and in the DA scenario the values will be 20 % higher in 2050, leading to 1360 kg CO_2-eq and 1950 kg CO_2-eq, respectively.

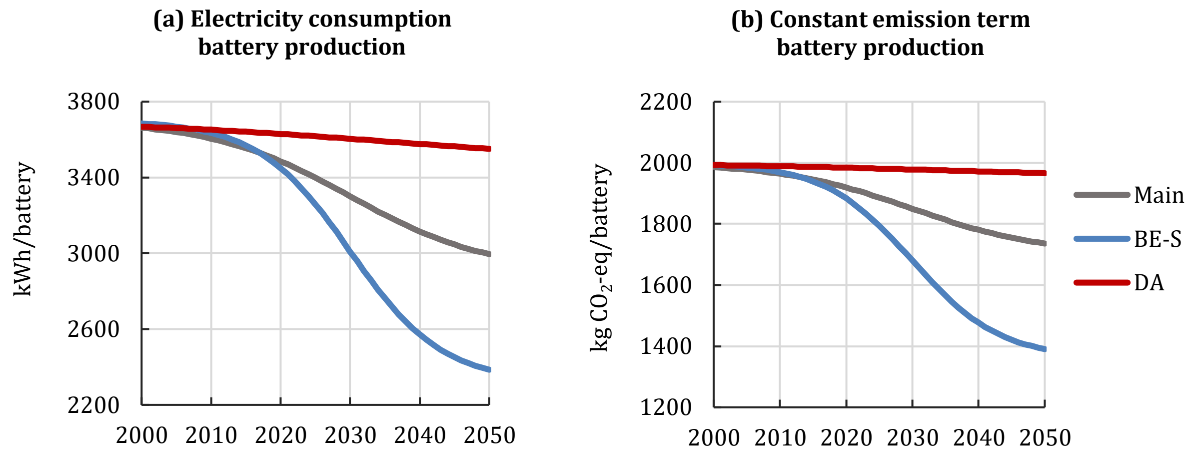

Figure 3.3a-b –Electricity consumption and constant emission term parameters for battery production, shown in kWh and kilo CO_2-eq per battery, respectively. Both charts show the main, battery electric success (BE-S) and delayed action (DA) scenario.

3.3.3 Operation

The operation is usually the largest contributor of emissions over the vehicle life cycle, and the emission burden is dependent on the vehicles' fuel or energy consumption. The fuel or energy consumption of the vehicles is again depend on various factors, for instance driving pattern and speed, road gradient, rolling resistance, vehicle design and weight, as well as drivetrain efficiency. As inputs to the operation phase in the model, the emission intensity of driving the ICEV, given by parameter $C^{OPER}_{a,t,k}$, and the energy consumption of the BEV per km, given by parameter $I^{OPER}_{a,t,k}$, are established. The emissions from the BEV will also be dependent on the carbon intensity of the electricity used to charge the vehicle.

The BEV drivetrain is quite efficient, with an efficiency of between 80 and 90 % (Sims et al., 2014). There are however some potential for improvements with regard to the energy density of the battery and battery lifetime, which may increase the efficiency in the future (Ellingsen et al., 2018). The efficiency of the ICEV is limited by the thermodynamic properties of the internal combustion engine, which has an efficiency of 20 to 35 % (Sims et al., 2014). Potential improvement in efficiency of the ICEV is more dependent on vehicle light-weighting and improvements in rolling resistance and aerodynamics, where these improvements could yield a potential fuel consumption reduction of 25 % (Sims et al., 2014).

The fuel and energy consumption of the ICEV and BEV are based on the report by Edwards et al. (2014), for the European Commission. Their calculations consider the New European Driving Cycle (NEDC) and the results are said to represent the most widespread passenger vehicles in Europe, which is of the C-segment. The whole well-to-wheel consumption and emissions are estimated, meaning that both production of the fuel or electricity, and combustion of the fuel is taken into account.

Edwards et al. (2014) estimates the emission intensity of an ICEV to 0.15 kg CO_2-eq/km in 2010, while the energy consumption of the BEV is estimated to 0.14 kWh/km. In the main scenario light-weighting of the vehicles is not taken into account, but improvements in other factors such as aerodynamics and the drivetrains are considered. It is further predicted by Edwards et al. (2014) that the ICEV emission intensity will be reduced to 0.11 kg CO_2-eq/km in 2020 and beyond, and the future BEV energy consumption is estimated to 0.11 kWh/km. These values are assumed to be representative for the operation of the vehicles in 2050. As a previous state in 2000, both values are estimated from fitting the curve to the value stated for 2010, which yields an emission intensity of 0.16 kg CO_2-eq/km for the ICEV and 0.15 kWh/km for the BEV. The operational parameters can be seen in Figure 3.4a and b.

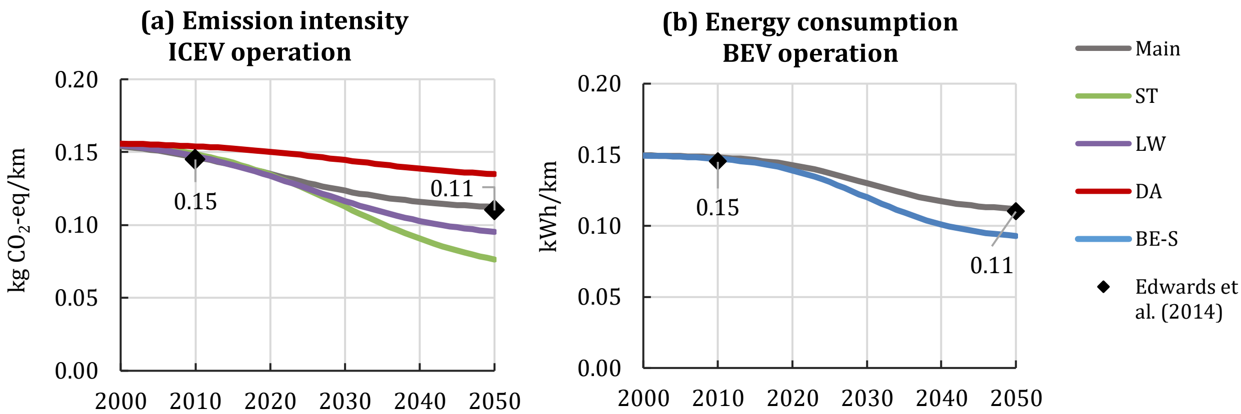

Figure 3.4a-b – Parameters for the emissions intensity of ICEV operation and energy consumption during BEV operation, shown in kilo CO_2-eqivalents and kWh per kilometer, respectively.

3.3.4 End-of-life

In the end-of-life phase (EOL) the vehicles are usually recycled or parts of the vehicles can be reused. Reuse is the highest hierarchy in product recovery and materials or whole components are reused in either the same product or other applications. If the vehicle, or parts of it, are recycled the used materials are collected, sorted and later reprocessed to be used in new products. Both reuse and recycling contribute to reducing the use of primary raw material, which can contribute to reducing the overall environmental impact. In the UK, 85 % of the weight of end-of-life vehicles are either reported to be recycled or reused (Eurostat, 2019a). The li-ion battery used in the BEV is usually handled separately in the EOL phase (Dunn et al., 2015).

In contrast to the production and operation phase, the EOL phase contributes to a small share of the life cycle emissions. The emissions linked to EOL, given by parameter $C^{EOL}_{t,k}$, are also dependent on what kind of recycling method that is used and a lot of studies often leave out this phase due to lack of available data (Ellingsen et al., 2018). The recycling practices also vary between countries. Comparing the EOL treatment of ICEVs and BEVs the latter usually has a higher impact in terms of greenhouse gas emissions due to the lithium-ion battery. Recycling of the battery components can however in some cases contribute to lowering the total impact of the battery production, since the use of secondary recovered material instead of primary materials may be less emission intensive (Dunn et al., 2015).

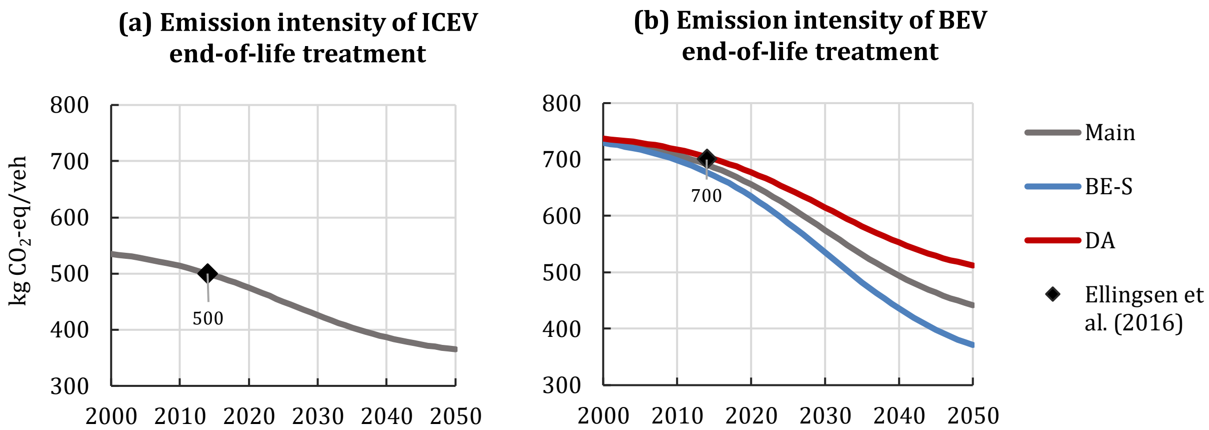

Figure 3.5a-b – Development of the parameter describing the emissions from the EOL treatment of the BEV and ICEV.

Ellingsen et al. (2016) estimates the emissions from the EOL phase for a medium sized vehicle to 700 kg CO_2-eq for a BEV and 500 kg CO_2-eq for an ICEV. An additional green energy scenario is modelled by Ellingsen et al. (2016), where the EOL of the BEV is estimated to 400 kg CO_2-eq. It is stated that this scenario is not aiming at predicting the future emissions intensities of the BEV life cycle phases, but rather give an indication of where we can hope to land the emissions given that the electricity mix is fully renewable. Nevertheless, since the EOL phase modelled in this thesis is not dependent on the carbon intensity of the electricity, the green scenario is used as an estimation of the impact from the EOL phase for the BEV in 2050 in the main scenario. In the BE-S and DA scenarios the EOL emissions are following the same path as the other BEV parameters in the scenarios, with a reduction and increase of 20 %, respectively. This can be seen in Figure 3.5b.

It is assumed that the improvements in the EOL phase of ICEVs will decrease less than for the BEV, which is modelled with an decrease of 43 %. It is assumed that the emissions intensity for the ICEV treatment will see a reduction of 30 %, leading to an emission intensity of 350 kg CO_2-eq per vehicle in 2050 in the main scenario, as seen in Figure 3.5a. Having established the current and future state of the EOL treatment, the values for 2000 are estimated from fitting the curves to match the points mentioned above. This yields an emission intensity of 750 kg CO_2-eq per BEV and 550 kg CO_2-eq per ICEV in the main scenario.

3.4 Carbon intensity of the electricity

To capture that the production of the vehicles, production of the battery pack and operation of the BEV is happening at different locations, three different electricity mixes are included in the model. The emissions from electricity generation depend on multiple factors, for instance electricity demand, fuels used for electricity generation and the thermal efficiency of the system (Ang & Goh, 2016). An energy system based on coal as the primary fuel will have a much higher carbon intensity compared to an energy system with only renewables (Turconi et al., 2013).

Different countries with different energy systems will therefore have different carbon intensities, where the carbon intensity represents the emissions in kg CO_2-equivalents per kilowatt hour of electricity (e.g. consumed). The emissions per kilowatt hour will depend on where in the electricity pathway the carbon intensity is calculated. Even though the amount of emissions are the same, the losses increase along the pathway, leading to a higher carbon intensity towards final consumption (Moro et al., 2018). All the electricity mixes described in this subsection include the upstream emissions linked to construction of the power plants, and distribution and transmission of the electricity. The carbon intensity is given at low voltage, representing the final consumption at the user.

All carbon intensities included in this subsection are benchmarked against the study by Itten et al. (2014), which is based on data from 2008. Here, the carbon intensity of the electricity is estimated for multiple countries, including all of the ones relevant for this study. It is also seen as reasonable to use the values from Itten et al. (2014) as a basis since the same methodology was used for all calculations. Statistics of the historic sources for electricity generation was collected from the IEA (2018a). Since no data of the carbon intensity was available for the year 2000, the carbon intensity is based on a simplified assumption that a previously higher share of fossil fuels in the energy mix means that the carbon intensity was higher, and vice versa. The carbon intensities in 2050 were based on governmental plans and goals regarding the future state of the respective energy systems, as well as scientific literature if available.

3.4.1 Electricity in the UK

Since the BEVs are operated in the UK and charged with electricity from the national grid an electricity mix reflecting this was established, given by parameter $\mathrm{CI}_t^{\mathrm{UK}}$. The UK energy system has historically relied on primary fuels such as coal and natural gas, with a 73 % fossil share in 2000 and 48 % fossil share in 2016 (IEA, 2018a). In the past decade, renewable sources such as wind and solar power have been introduced to a larger extent, and most of the coal power is substituted by natural gas, as seen in Figure 3.6. Even though natural gas is a fossil fuel it has a lower carbon intensity when compared to coal (Moro et al., 2018; Turconi et al., 2013), and can therefore contribute to bringing down the emissions. In addition, the UK depend on nuclear power, as well as some imports, mainly from France (Itten et al., 2014). Nuclear power has a low carbon intensity and can in terms of emissions be compared to renewable sources (Turconi et al., 2013).

Based on data from 2008 the carbon intensity of the UK electricity mix was found to be 690 g CO_2-eq/kWh by Itten et al. (2014). While Moro et al. (2018) estimates the carbon intensity to 630 g CO_2-eq/kWh, based on data from 2013. This decrease in carbon intensity can be seen in relation to the higher shares of nuclear power and renewables in 2013 as well as a decrease in the share of fossil fuels. In 2000 the share of fossil fuels and renewables were slightly lower compared to 2008, while the share of nuclear power was slightly higher. Since both nuclear power and renewables have lower carbon intensity per kWh generated than fossil fuels such as coal and natural gas (Turconi et al., 2013), it is assumed that the carbon intensity of the UK electricity in 2000 was in line with what was estimated by Itten et al. (2014).

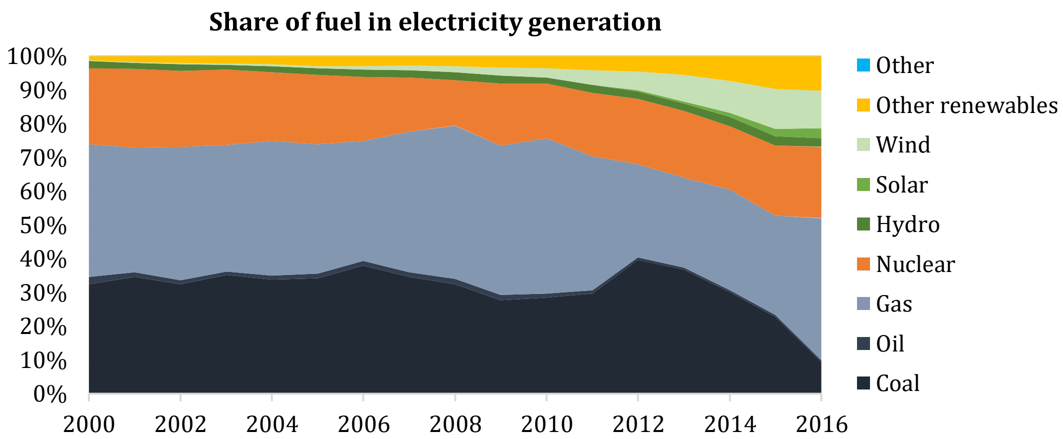

Figure 3.6 – Shares of different fuels as input into electricity generation averaged in the United Kingdom from 2000 to 2016 (IEA, 2018a).

The use of fossil fuels for electricity generation in the UK peaked in 2010, and the government is now focusing on promoting low-carbon electricity, with a focus on renewable energies, nuclear energy and coal and natural gas combined with carbon capture and storage (CCC, 2018; IEA, 2012). In addition, the government have committed to phase out unabated coal by 2025 (CCC, 2018) and it is projected that the direct emissions from the power sector will be 90 % lower in 2050 compared to current levels (DfT, 2018c).

The estimated carbon intensity of the electricity in 2050 is based on the assumption that the UK will successfully phase out coal and implement low-carbon technologies and CCS, which brings the carbon intensity down substantially. Studies from literature that assess scenarios for the future of UK electricity estimate the carbon intensity in a low-carbon economy to between 90 and 120 g CO_2-eq/kWh in 2050

(Hammond et al., 2013; Hammond et al., 2017; Stamford et al., 2014). The differences in the carbon intensities reflect different policy assumptions and predicted energy demand. Nevertheless, all projections include a mix of nuclear power, renewables such as wind and solar and successful implementation of CCS technology.

In the main scenario the carbon intensity in 2050 is based on the average from the presented literature and assumed to be 110 g CO_2-eq/kWh. The development of the parameter can be seen in Figure 3.7. In the EL scenario four different cases are included, where each case represents a higher final carbon intensity in 2050. The trajectories included are based on a given reduction compared to today's level, and the reductions assessed range from 0 to 70 % reduction.

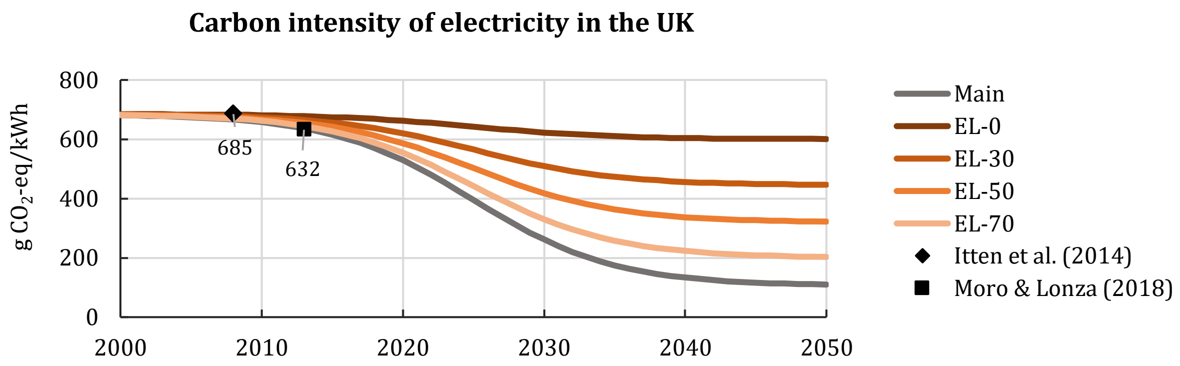

Figure 3.7 – Development of the parameter for the carbon intensity of the electricity mix in the UK in the main and EL scenarios, given in grams of CO_2-equivalents per kWh.

3.4.2 Electricity in Europe

The UK was the fourth biggest manufacturer of passenger cars in the EU in 2017 (ACEA, 2018a). Cars are also both the most exported and imported goods in the UK (OEC, 2017a, 2017b), and 80 % of the passenger cars made in the UK are exported (ACEA, 2018b). In terms of imports, 88 % of the cars imported in 2017 came from Europe (OEC, 2017b). It is therefore reasonable to assume that many of the vehicles on UK roads are not produced within the economy, but imported from Europe. To reflect this in the model it is assumed that the electricity used to produce the ICEVs and BEVs (excluding battery pack) is of European origin. This is represented by parameter CI_t^{EUR} in the model.

Historically, Europe has been somewhat dependent on fossil fuels such as coal and natural gas for electricity generation, with a fossil share of 54 % in 2000. However, compared to the UK, Europe has had higher shares of renewables in the electricity mix (IEA, 2018a). In addition, Europe is also dependent on a substantial share of nuclear power. The trend seen the last decade shows the fossil share is decreasing and the renewable contribution is increasing, as seen in Figure 3.8. The share of nuclear power in the electricity mix has seen a small decrease in the same period.

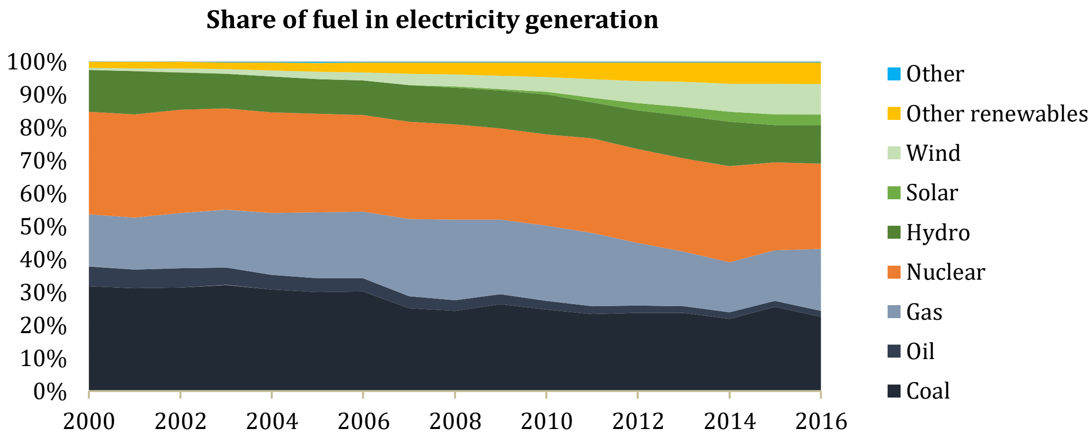

Figure 3.8 – Shares of different fuels as input into electricity generation in Europe from 2000 to 2016 (IEA, 2018a).

As a future strategy, the European Commission is seeking to maximize the deployment of renewable energy technologies to fully decarbonize Europe's energy supply (European Commission, 2018). In the main scenario it is assumed the carbon intensity of European electricity will reach the same level as the UK , and the carbon intensity in 2050 is set to 110 g CO_2-eq/kWh, as seen in Figure 3.9.

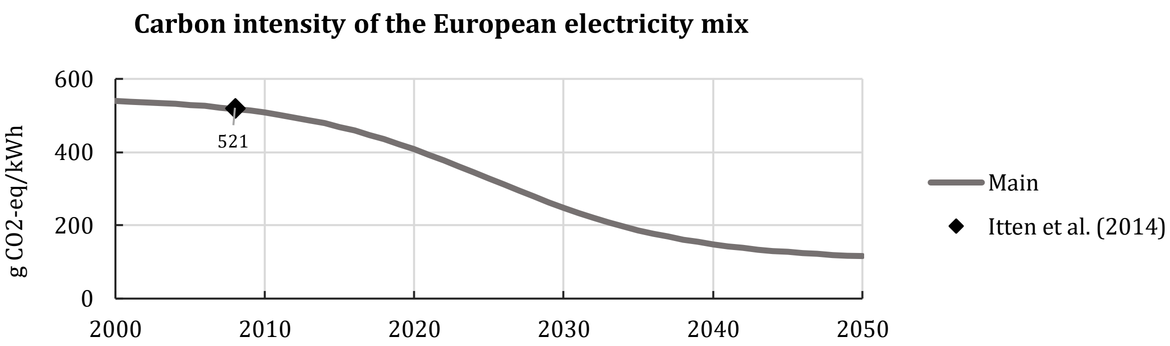

Figure 3.9 – Development of the parameter for the carbon intensity of the average European electricity mix in the main scenario, given in grams of CO_2-equivalents per kWh.

3.4.3 Electricity in China, Japan and South Korea

Around 80 % of the batteries for electric vehicles today are produced in Asia, namely China, Japan and South Korea (Ellingsen et al., 2018; Zenglein et al., 2018). It is therefore assumed that the battery packs for the BEVs are produced in one of these countries. An average carbon intensity reflecting the emissions from the electricity generation in these countries is therefore established, given by parameter CI_t^{ASIA}.

Both China, Japan and South Korea have fossil fuel dependent energy systems, especially on coal. The share of fossil fuels has been quite stable the past decades, as seen in Figure 3.10. China has had both a strong population growth as well as economic growth the past years, leading to a great increase in the energy demand, where this demand has mainly been met by increasing the electricity generated from coal power (IEA, 2018a). The share of nuclear power seen in the average is mainly due to electricity from Japan and South Korea. However, after the Fukushima accident in Japan in 2011 the majority of the nuclear power plants in the country were closed and electricity generation substituted by coal power. The main renewable energy source in the countries' average is hydro power, which has had an increasing contribution to the electricity generation in the past years. There has also been an increase in other low-carbon technologies such as solar power, wind power and other renewables (IEA, 2018a).

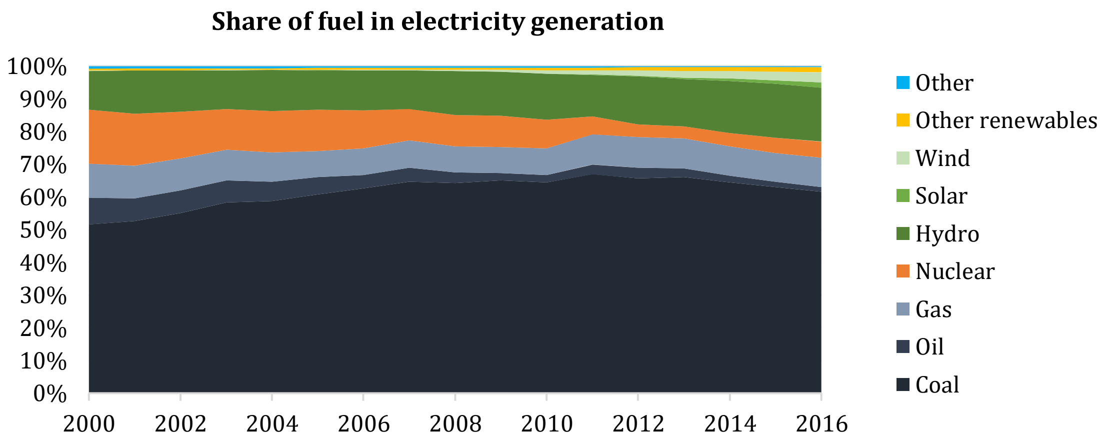

Figure 3.10 – Shares of different fuels as input into electricity generation averaged for China, South Korea and Japan from 2000 to 2016 (IEA, 2018a).

The carbon intensities for the electricity in China, Japan and South Korea has been estimated to 1230, 680 and 710 g CO_2-eq/kWh, respectively, by Itten et al. (2014). The average of the three electricity mixes, approximately 870 g CO_2-eq/kWh, is used as a basis for modeling the electricity used for battery production. Ang and Su (2016) found that the carbon intensity in both Japan and South Korea had an average annual increase of 1.3 % between 1990 and 2013, while the carbon intensity in China had an annual decrease of approximately 1 % in the same period. Even though the share of fossil energy sources in the average electricity mix was slightly lower in 2000 compared to 2008, as seen in Figure 3.10, it is assumes that the carbon intensities estimated by Itten et al. (2014) is representative for 2000.

The Ministry of Trade, Industry and Energy in South Korea has developed a national plan for the long-term electricity supply and demand. The plan contains regulations that promote energy efficiency as well as goals for the future sources for electricity generation (MOTIE, 2017). South Korea aims at producing more power from renewable energy sources and natural gas, while reducing their dependency on coal and nuclear power. In 2030 it is predicted that 20 % of their electricity will come from renewable sources, 19 % from natural gas, 36 % from coal and 24 % from nuclear power (MOTIE, 2017).

Japan's energy plan also set targets with regard to reducing their emissions from the power sector. They aim at setting reduction targets that are comparable with the EU and implementing a policy program that promotes wider introduction of renewable energies. In 2030 it is projected that the energy mix could consist of 23 % renewable energy, 21 % nuclear power, 27 % natural gas, 26 % coal and 3 % oil (METI, 2015). In order to reduce the emissions from the non-renewable energy sources, Japan also aims at increasing the efficiency of their fossil power plants (METI, 2015).

China has a vision for how their energy system should look towards 2050, where main points are that the system should be clean, low-carbon and efficient (CNREC, 2018). In addition, China aims at reducing their dependency on fossil fuels, particularly coal, as much as possible, while substituting it with renewable sources. Furthermore, the China National Renewable Energy Centre presents a future scenario predicting how the power generation mix could look like in 2050. This mix consists of 87 % renewable energies, 5 % coal power, 6 % nuclear power and a small amount of other energy sources such as oil, natural gas and geothermal (CNREC, 2018).

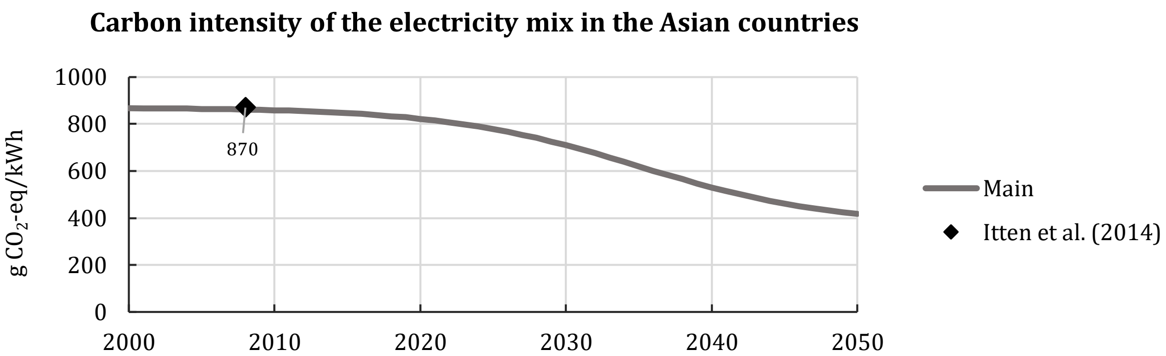

Figure 3.11 – Development of the carbon intensity of the average electricity mix in China, South Korea and Japan for the main scenario, given in grams of CO_2-equivalents per kWh.

Generally, one can see that all the three Asian countries have set goals to reduce their dependency on fossil power, as well as implementing more renewables. Even though some of the goals are quite ambitious, for instance for China, it is assumed that the average carbon intensity of the electricity mix in 2050 will be higher than what is assumed for the UK and Europe. This is also consistent with the predicted development by the International Energy Agency (IEA, 2019b), and is seen as realistic due to the substantial shares of fossil fuels in the current electricity mixes. In addition it is also assumed that the decarbonization of the average carbon intensity will happen later than in the European countries, and the maximum gradient of changed is set in 2035.

In the main scenario it is assumed that the decrease in carbon intensity will be faster than what was found by Ang and Su (2016) due to the current focus on implementation of renewable energies in the three countries. With a reduction of 2 % per year the carbon intensity is assumed to approximately 370 g CO_2-eq/kWh in 2050. The development of the parameter for the carbon intensity can be seen in Figure 3.11.

3.4.4 Electricity based on renewable sources

A fourth carbon intensity is included in the model in order to model a low-carbon electricity in the PL-N scenario. This carbon intensity is based on the Norwegian electricity mix, which consists of more than 98 % renewables, mainly hydro power (IEA, 2018a). The carbon intensity of the Norwegian electricity is also based on the study by Itten et al. (2014), which estimates the carbon intensity to 50 g CO_2-eq/kWh. Substantial shares of hydro power in Norway's electricity mix has been persistent for decades, so the carbon intensity estimated by Itten et al. (2014) is assumed to be representative in 2000.

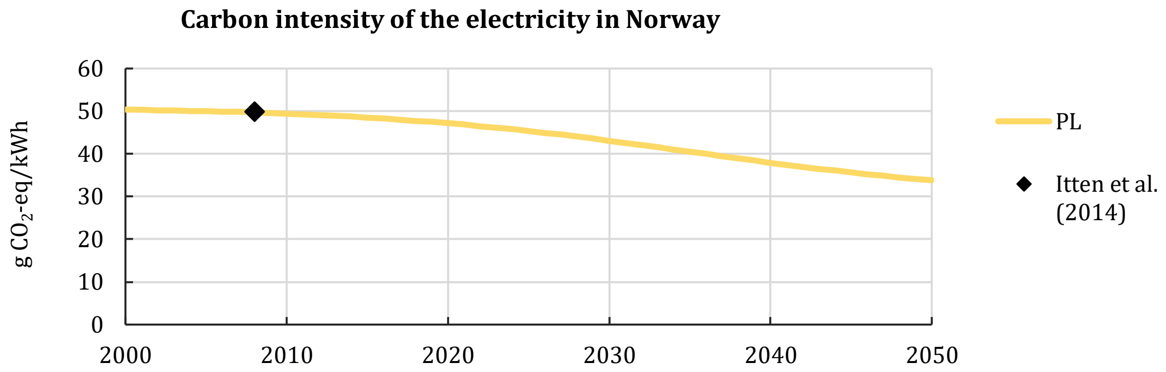

Figure 3.12 – Development of the parameter for the carbon intensity of the electricity in Norway used in the production location (PL) scenario, shown in grams of CO_2-equivalents per kWh.

The carbon intensity can be further reduced by introducing larger shares of other renewables with less upstream emissions, for instance wind power, which has a carbon intensity of 21 g CO_2-eq/kWh (Ecoinvent Centre, 2010). Assuming a higher share of wind power in the Norwegian electricity mix towards 2050, the final carbon intensity is set to 30 g CO_2-eq/kWh.

3.5 Vehicle fleet characteristics

This subsection describes the parameters linked to the UK vehicle fleet. Statistical data of different aspects of the vehicle fleet was collected from the UK Department for Transport (DfT, 2018d, 2018f). This data is comprised of the total number of licensed passenger cars at the end of the year and the total kilometrage driven per year by the passenger car fleet. In addition, statistical data describing the historic and predicted population in the UK was collected from the Office for National Statistics in order to estimate the number of vehicles per capita (ONS, 2018). An overview of the historic statistical data can be seen in Table A.1 in the appendix.

3.5.1 Vehicle fleet size and annual operating distance

Data of the passenger car fleet in the UK was only available from year 2014 to 2017, while data of the fleet in Great Britain (GB) was available from 1994 to 2017 (DfT, 2018f). From the data one can see that the fleet in the UK contains approximately 1 million more vehicles than the fleet in GB, and it is assumed that this holds for all years. The passenger car fleet in the UK, given by parameter V_t, is estimated to 25.4 million cars in 2000 and 32.2 million cars in 2017. This further translates to 431 and 488 cars per 1000 capita in 2000 and 2017, respectively (DfT, 2018f; ONS, 2018). As mentioned in section two, it is assumed that all of the vehicles in the passenger car fleet are ICEVs, since the current share of BEVs is deemed negligible (DfT, 2018e).

Car ownership has earlier been seen to vary with affluence and social standing. However, a decoupling of these factors has been seen the past years (Lansley, 2016). There are also claims that the car ownership in UK has reached its peak, and is predicted to level off in the next decades (Goodwin et al., 2013; Headicar, 2013). This trend can also be seen in statistics, where the car ownership per capita increased 15.7 % between 1997 and 2007, but only 3.1 % between 2007 and 2017 (DfT, 2018f; ONS, 2018).

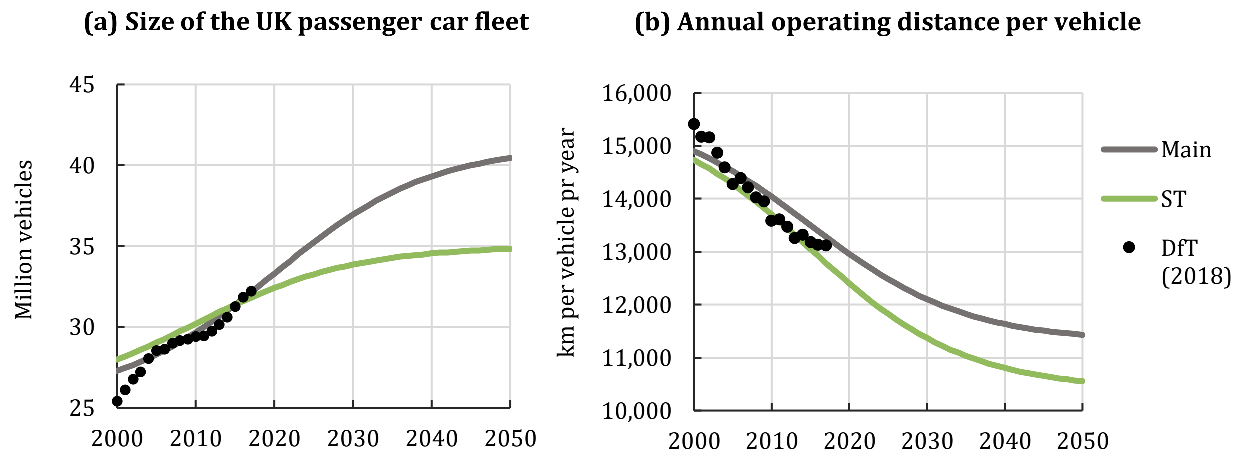

Figure 3.13a-b – Development of the vehicle stock parameter (a) and annual driving distance per vehicle (b) in the main and sustainable transport (ST) scenario. The dotted line shows the trend in the statistics from the Department for Transport (2018).

In the main scenario the size of the passenger car fleet in 2050 is based on the assumption that the number of cars per capita will follow the same trend as in the past decade, where the average increase per year was 0.28 %. This results in 535 cars per 1000 capita in 2050. Combining this with the population projection of 77 million inhabitants (Eurostat, 2019b) results in 41.2 million cars in 2050. In the sustainable transport

(ST) scenario a modal shift towards public transport like bus and rail is predicted, leading to a smaller future vehicle stock. It is assumed that the number of vehicles per capita will stabilize at the current level, which is consistent with the trend seen in more developed countries (Hao et al., 2016), resulting in 35 million vehicles in 2050. The differences in the vehicle fleet size parameters used as input in the main and ST scenario can be seen in Figure 3.13a.

Data of the total passenger car kilometrage was only available for GB and the average kilometrage per car is therefore estimated based on the GB fleet size. It is assumed that this estimate is representative for car use in the UK. The total passenger car road traffic reported in 2000 and 2017 was 376 and 409 billion km, respectively (DfT, 2018d). This results in an annual operation distance, given by parameter D_t, of approximately 15 700 km in 2000 and 13 100 km in 2017, where the operating distance is calculated by dividing the total kilometers driven by the total number of vehicles. It is assumed that the trend in the decreasing annual driving distance will continue. The number of trips per person has also been decreasing since 2000, supporting these findings (DfT, 2018a). Between 1997 and 2007 the annual decrease was 1 %, while between 2007 and 2017 the annual decrease was 0.7 %. This suggests that while the annual kilometrage is decreasing it may also decrease at a lower rate in the future.

In the main scenario the decrease in kilometers driven is assumed to continue at the current rate of 0.7 % annually towards 2030. Then it is assumed that the decline will slow down with an annual decrease of 0.3 % towards 2050. This results in approximately 11 300 km driven per vehicle in 2050, as seen in Figure 3.13b. In the ST scenario it is assumed that the way we use our vehicles will change, and due to the modal shift towards public transport the vehicles in the stock will also drive less distance per year. The annual kilometers driven is assumed to follow the trend seen the past decade with a 0.7 % reduction per year, resulting in 10 400 km driven per vehicle in 2050.

3.5.2 Vehicle age distribution and lifetime

The age distribution of the vehicle stock, i.e. the share of vehicles in the stock of different age classes, is based on statistical data from the Department for Transport (DfT, 2018f). Historic data containing the number of vehicles in the GB fleet at different ages was collected and an average distribution is used in the model. Since the data was not available for the UK is assumed that the age distribution of the GB fleet is representative for the UK fleet. An average age distribution from year 2000 to 2017 is used. Since the model only accounts for vehicles up to 20 years the cars older are left out of the average. This does however not exclude many vehicles, since 97 % of the vehicles in the fleet are between 1 and 20 years (DfT, 2018f). The normalized age distribution used to set the initial age distribution of the UK vehicle fleet, given by parameter α_a, can be seen in Figure 3.14a.

The probability of a vehicle being scrapped at a certain age is derived using a normal distribution given by Equation 3.1. Where the parameter a is the age of the vehicle, the parameter μ is the average vehicle lifetime and the parameter σ is the standard deviation, all given in years. The share of vehicles exiting the stock at each age is given by the cumulative probability of being scrapped up to that age.

$$f(a, \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(a-\mu)^2}{2\sigma^2}} \tag{3.1}$$

The average vehicle age at scrapping in the UK is 14 years (SMMT, 2018a), the μ is therefore set to 14 and a standard deviation of 4 years is used. This yields the probability of a vehicle being scrapped at a given age as seen in Figure 3.14b and the share of vehicles in the stock scrapped at a given age, given by parameter β_a, as seen in Figure 3.14c. At age 20 it is assumed that all vehicles are scrapped since this is the maximal age set in the model and it is not possible for vehicles above this age to persist in the stock. Note that this is however not included in Figure 3.14c.

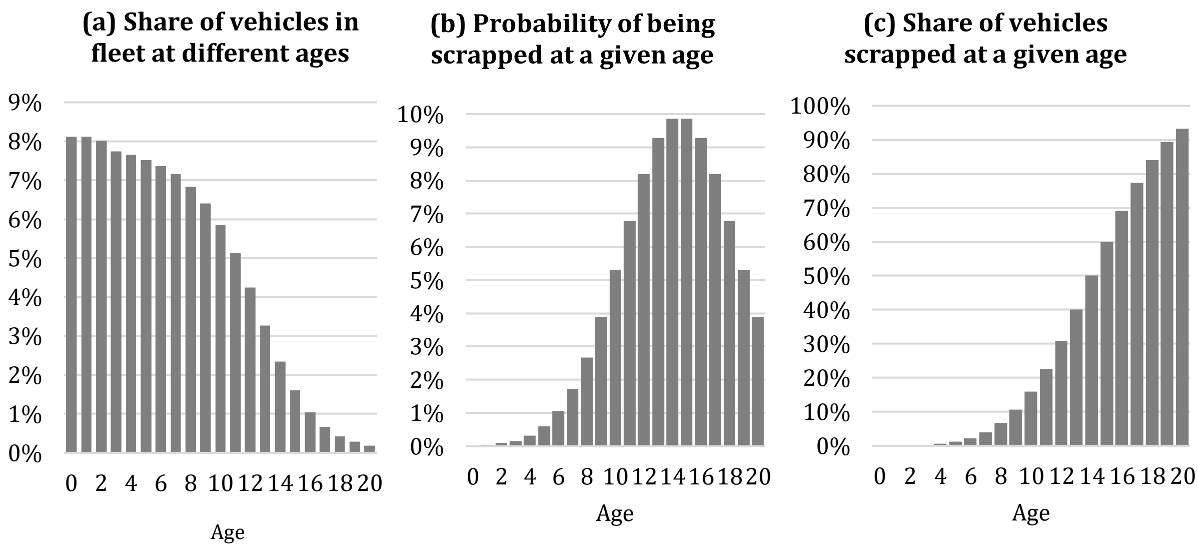

Figure 3.14a-c – Age distribution of the UK vehicle fleet based on an average over 15 years from statistical data (a), probability of a vehicle being scrapped at a given age calculated with an average lifetime of 14 years and standard deviation of 4 years (b), and the share of vehicles leaving the fleet each year in the given age classes (c).

3.5.3 Introduction rate of BEVs

The UK has through the EV30@30 campaign committed to a goal of reaching 30 % sales share of electric vehicles, including passenger cars, vans, buses and trucks, by 2030 (IEA, 2018b). In terms of only passenger cars, the government has a separate goal, aiming at a market share of at least 50 % by 2030 (DfT, 2018c). Today, the purchase price of a BEV is higher than for the ICEV, which currently one of the limiting factor to the uptake of electric vehicles (IEA, 2018c). The introduction of BEVs is therefore largely dependent on policy measures, where financial incentives to facilitate the acquisition of BEVs and reducing their operational costs are key examples of successful measures (IEA, 2018c). The UK government has established a grant for low emission vehicles, where the buyers get a discount of up to 20 % on the purchasing price of the vehicles that are eligible (UK Government, 2019). However, poor provision of charging infrastructure is currently one of the greatest barriers of growth in the BEV market in the UK, and the charging network is lacking geographic coverage and size (BEIS, 2018).

As descried in the methodology section, a restriction on the number of BEVs added to the vehicle stock in each year is included in the model (Equation 2.18). This is seen as necessary to prevent the model from dramatically switching all new car sales from ICEVs to BEVs from one year to another, if this happens to be most beneficial in terms of minimizing the emissions. It is seen as more realistic that the shift will happen gradually, with an increasing share of BEVs sold each year. Recall that this restriction is dependent on two shape parameters, R_1 and R_2, where R_1 is linked to the number of BEVs added to the fleet in the previous year and R_2 is linked to the total number of vehicles in the fleet.

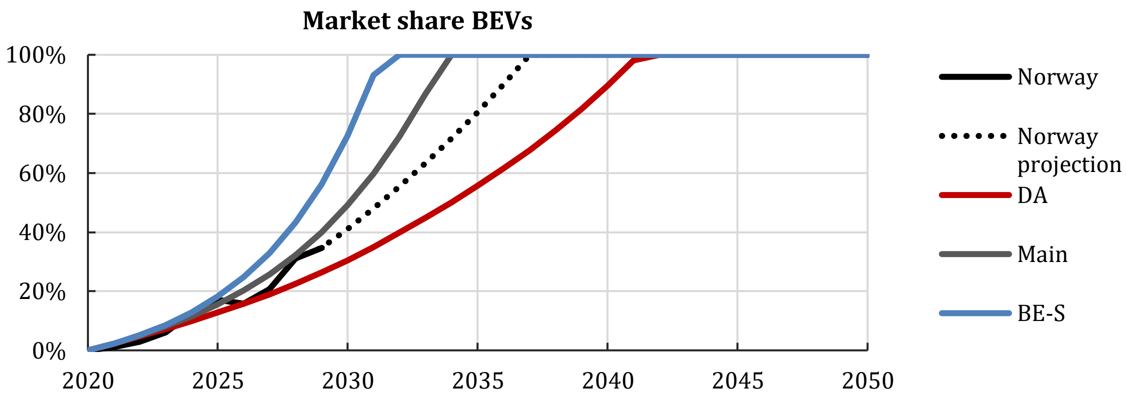

Figure 3.15 – Share of battery electric vehicles of total vehicles sales for the main, battery electric success (BE-S) and delayed action (DA) scenarios. The development of the Norwegian battery electric sales is used to provide a reference of a possible path.

Norway is currently one of the countries with the highest share of BEVs in new car sales, and provides an example of how the shift towards an electrified vehicle fleet may look like. Statistics of the historic BEV sales in Norway was collected from 2010 to 2018 (Norsk Elbilforening, 2018; SSB, 2018). Based on these numbers, a future projection is made assuming an exponential growth. The historic data is together with the projection used as a reference for how the BEV introduction could look like in the UK. The trend seen in Norway is plotted from 2020 in Figure 3.15 together with the market share developments assumed in the main, DA and BE-S scenario.

In the main scenario it is assumed that the UK achieves the goal of reaching a 50 % share of BEVs in the vehicle sales by 2030. In terms of the constraint restricting the additions of BEVs, the parameters R_1 and R_2

are set to 17 % and 0.2 %, respectively. In the battery electric success (BE-S) scenario it is assumed that the sale of BEVs will be more successful than in the main scenario, and that the share of BEV in the total vehicles added will follow almost the same pattern as seen in Norway. The parameters R_1 and R_2 are set to 25 % and 0.2 %, respectively. In the delayed action (DA) scenario it is assumed that the sale of BEVs will be slower than in the main scenario, and it will take longer time before all the new vehicles sold are electric. The parameters R_1 and R_2 are set to 7 % and 0.2 %, respectively.

4 Results and analysis

The results from the optimization model are presented in this section. First, the results from the main scenario are presented and analyzed. This includes the breakdown of the emissions from all life cycle phases to provide some insight before presenting the optimal vehicle stock composition and fleet dynamics. Further, the total vehicle stock emissions are presented. Finally, the results from the rest of the scenarios are presented and compared to the main scenario, with a focus on stock composition and emissions.

4.1 Main scenario

The main scenario aimed at modeling a realistic development of the vehicle stock, technologies and electricity mixes, and was based on trends, current literature, statistics and governmental goals. The results in the main scenario will be described more in detail than the other scenarios to provide an understanding of the dynamics in the model and how the final emissions are dependent on the inflow and outflow of the different vehicle technologies, as well as the stock composition.

4.1.1 Life cycle emissions

The life cycle emissions from the two drivetrain technologies are compared in terms of which year the vehicles are produced to provide a fair comparison. The lifetime of the vehicles are affecting the total environmental burden substantially due to the emissions from the operation phase. Since the annual driving distance is modelled as a parameter that is decreasing each year it means that the vehicles produced in 2000 are likely to have a longer lifetime than the vehicles produced in 2040.

In this comparison, the vehicles are assumed to be driven for 14 years since this is the average vehicle age in the UK (SMMT, 2018a). The annual operating distance is held constant and set to 13 000 km, which currently is the average annual driving distance in the UK (DfT, 2018d). The emission values from the production of the vehicles and battery pack are taken from the production year. The fuel or energy efficiency is also taken from this year and held constant throughout the lifetime. The operation emissions from the ICEV will therefore be the same in each year, while the emissions from the BEV operation will change since the carbon intensity of the electricity is decreasing. The emissions from the EOL are taken from 14 years after the production year, since the vehicles are assumed to enter this phase later. The comparison of the ICEV and BEV life cycle emissions for the different production years can be seen in Figure 4.1, where the dashed line represents the trajectory of the carbon intensity of the electricity mix in the UK.

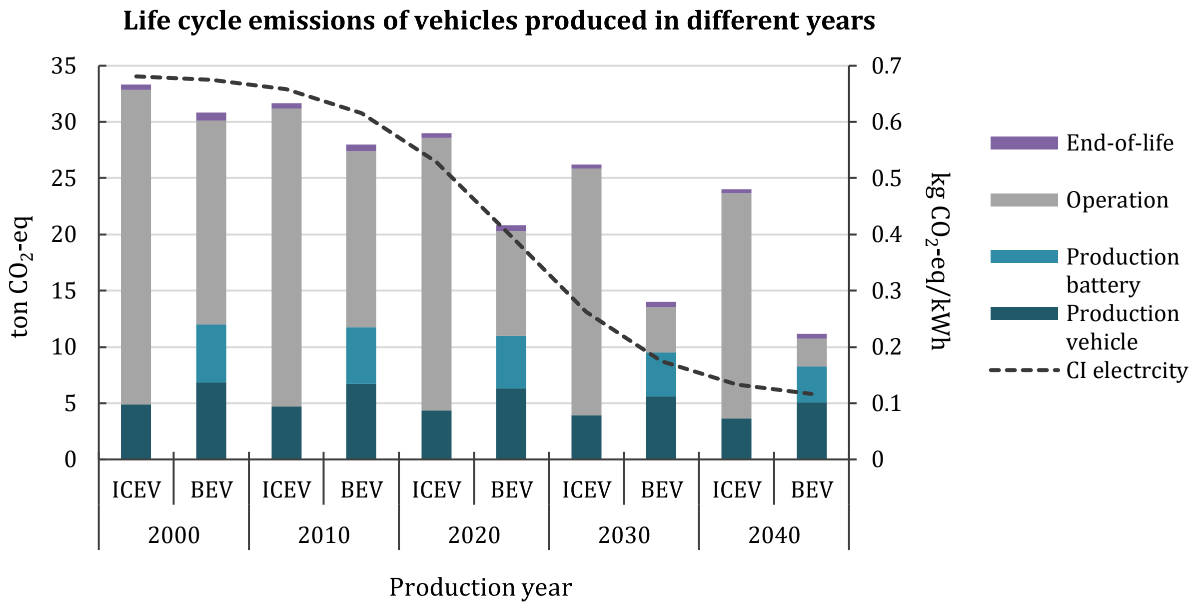

Figure 4.1 – Comparison of the total life cycle emissions from the ICEVs and BEVs for different production years. The total emissions are broken down into the life cycle phases and shown in tons of CO_2-eq on the left hand axis. The dashed line represents the carbon intensity of the electricity in the UK, shown in kg CO_2-eq per kWh on the right hand axis.

Comparing the life cycle emissions from the vehicles produced in the same year the BEV has a 7 to 54 % lower impact, and the ICEV has the higher associated emissions in all production years. This is mainly due to its operation phase, which is contributing to more than 80 % of the emissions during the vehicle's lifetime. For the production of the vehicles one can see that the BEV has more than double the emissions compared to the ICEV, which is mainly because of the additional emissions linked to the production of the battery pack. In terms of the EOL phase, this is contributing to a small share of the total life cycle emissions for both drivetrain technologies.

When comparing the different production years one can see that the emissions from the vehicles with the same drivetrain also are decreasing each decade. This is mainly due to the vehicles becoming more energy or fuel efficient, as well as the electricity mix becoming less carbon intensive, as seen from the dashed line in Figure 4.1. One can here see that the reduced carbon intensity is contributing to a substantial reduction in the emissions linked to the BEV operation. This also leads to the gap between the life cycle emissions of the ICEV and BEV increasing each decade. Overall, one can here argue that the BEV is a more environmentally sound alternative in terms of reduced greenhouse gas emissions, regardless of the carbon intensity of the electricity used for charging being high in for instance 2000 and 2010.

Since the production of the BEV has a higher associated impact, it may however take some years before it reaches the breakeven point compared to the ICEV. The breakeven point is defined as when the cumulative emissions of the two drivetrain technologies are equal. A comparison of the breakeven points for the production years 2010, 2020, 2030 and 2040 can be seen in Figure 4.2, where the BEV is represented by the green line and ICEV by the blue line. The vehicles produced in 2000 and 2010 break even after approximately 10 years, so only the curve for the vehicle produced in 2010 is shown in the figure. The vehicles produced in 2020 break even after between 7 and 8 years, while for the vehicles produced in 2030 break even after 5 years. For the vehicles produced in 2040 it takes only 3 years before the BEV provides an emission reduction compared to the ICEV. If the vehicle lifetime however is less than the respective values for the different production years, one could argue that the ICEV would be a better option in terms of emission reduction. The BEV would then not have managed to compensate for the higher production emissions.

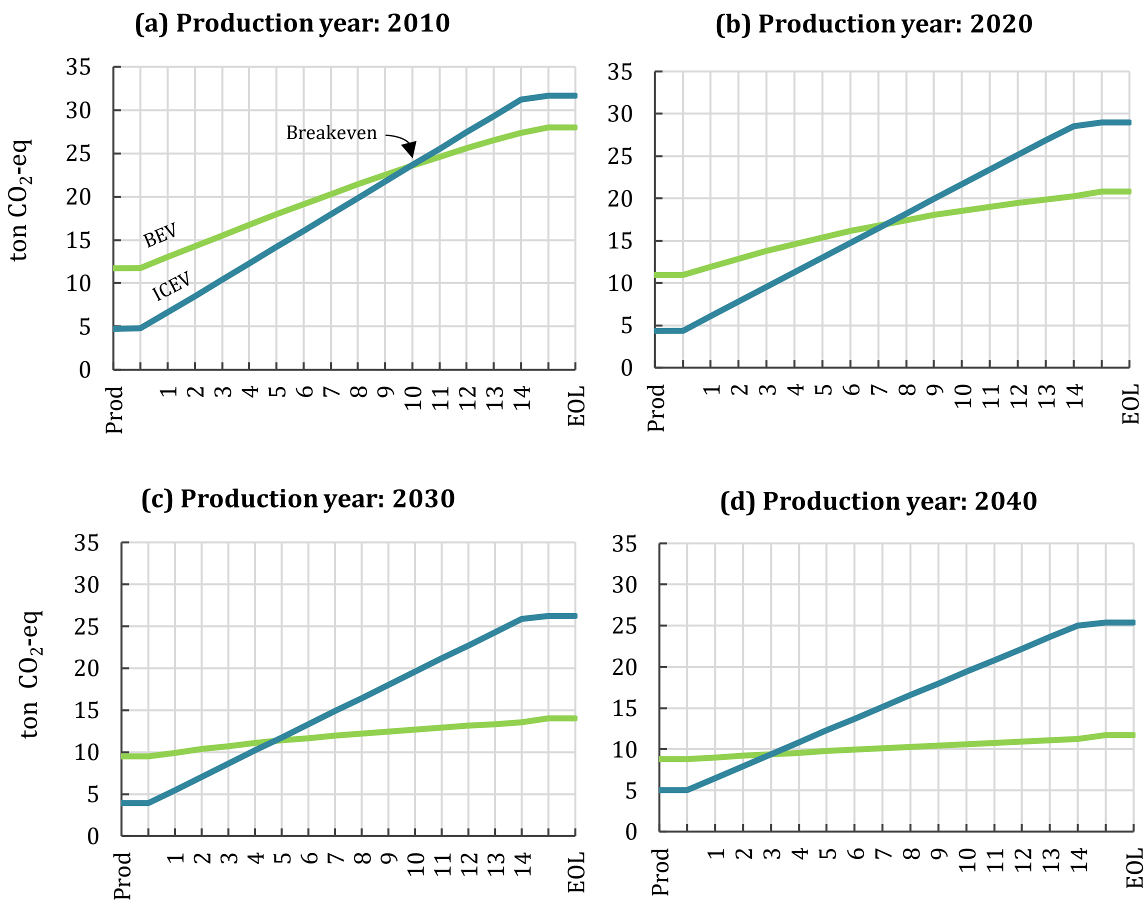

Figure 4.2a-d – Comparison of breakeven point of ICEVs and BEVs produced in different years. The y-axis shows the associated emissions in tons of CO_2-eq and the x-axis shows the life cycle phases, where the operation is shown as the vehicle age.

In the model the lifetime in terms of kilometers driven will vary depending on the production year since the scrapping rate for a given vehicle age class is constant and the annual kilometrage is decreasing each year. This means that a vehicle produced in year 2000 has a higher probability of having a longer lifetime in terms of kilometers driven than a vehicle produced in 2030, which implies that the less energy efficient vehicles are driving longer distances, hence contributing to more pollution.

4.1.2 Vehicle stock dynamics and optimal fleet composition

The optimal fleet composition is dependent on the stock dynamics of the model, i.e. the numbers of vehicles with different drivetrain technologies that enter or leave the vehicle fleet each year. The vehicles added to the fleet are shown in Figure 4.3a, given in million vehicles. In the beginning of the optimization period the majority of the vehicles added are ICEVs and the BEV sales are increasing slowly. However, after some years, the BEV is gaining market, reaching a 50 % share in 2030. By 2034 all new vehicles added to the optimized fleet are electric. Looking at the vehicles removed in Figure 4.3b, one can see that mostly ICEVs are exiting the stock until 2035. After this, the BEV fleet also starts to age and the share of BEV exiting the stock is increasing. This is also due to the increasing numbers of BEVs entering the fleet at an earlier stage.

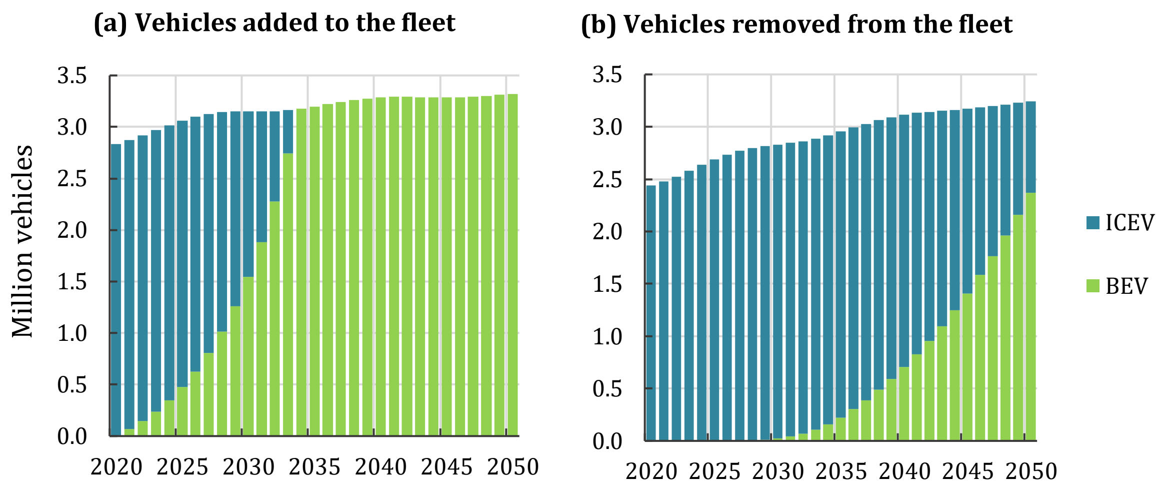

Figure 4.3a-b – Vehicles added to the vehicle stock and vehicles removed from the stock, shown in million vehicles. The bars are split up into the different drivetrain technologies.

The optimal combination of ICEVs and BEVs in the UK vehicle fleet is the one that fulfills the objective of minimizing the total emissions from the vehicle fleet between 2020 and 2050. The optimal stock composition can be seen in Figure 4.4 where the red field represents ICEVs and the green field represents BEVs. Here one can see that the transition from a fleet based on ICEVs only to a mixed fleet is happening gradually. It is optimal to introduce BEVs from the first year of the optimization period and from 2020 to 2030 the BEV stock is increasing slowly, while in the later years the BEV stock is increasing at a faster rate. BEVs are starting to dominate the fleet after 2035, where the electric share is 50 %.

The optimal fleet in 2050 is almost 100 % electric, but still contains around thousand ICEVs, even though the last ICEVs entered the fleet in 2033. The share of ICEVs still present in the stock is due to the lifetime of the vehicles, which in the model is set to a maximum lifetime of 20 years, with an average age of 14 years. So, even though the lock-in time of personal vehicles is relatively short compared to the lifetime of other larger infrastructure systems, it may take some years for a full fleet turnover to be achieved.

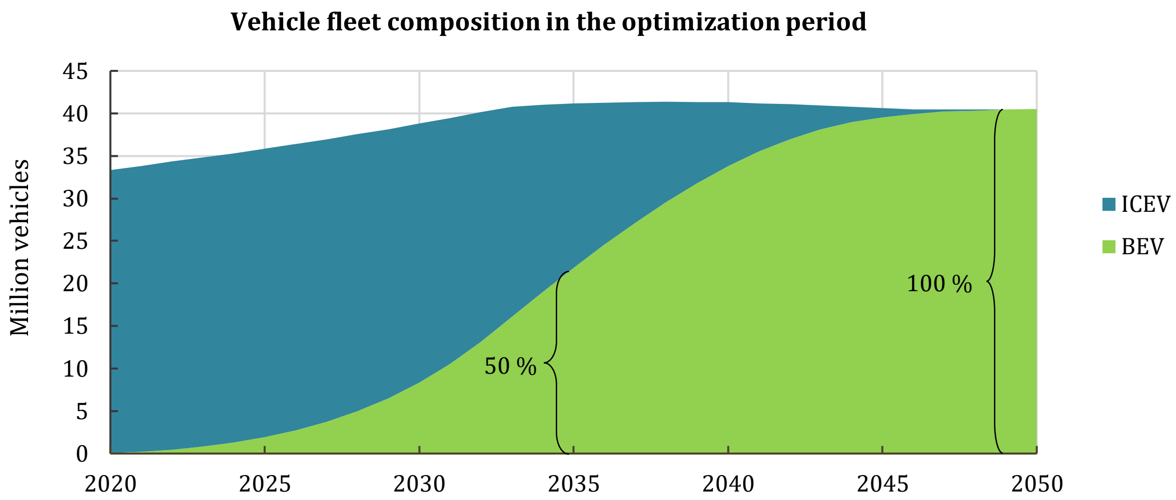

Figure 4.4 – Optimal vehicle fleet composition in the optimization period, shown from year 2020 to 2050, given in million vehicles.

4.1.3 Vehicle fleet emissions

The objective function value for the optimized vehicle fleet, i.e. the total emissions from the vehicle fleet between 2020 and 2050, is found to be 1.94 Gt CO_2-equivalents. As a reference, the cumulative direct emissions from the passenger cars in the UK between 1990 and 2017 was 2.07 Gt CO_2-eq (Jones et al., 2019). Recall that the objective function value represents the emissions from both production, operation and end-of-life treatment. The annual emissions from the optimization period can be seen in Figure 4.5, given in mega tons of CO_2-eq. The chart is split into emissions from the ICEV stock and BEV stock, and shows the source of the emissions in terms of life cycle. The dotted line represents the emissions from the fleet if no BEVs were introduced, further referred to as the ICEV baseline.

In the first 15 years of the optimization period the emissions from the mixed ICEV and BEV fleet are slightly higher compared to the ICEV baseline. This can be explained by the higher production emissions from the BEVs that are introduced to the stock compared to the ICEVs in the baseline. In the later years the annual emissions are dropping below the baseline, even though the vehicle fleet size increases. This relative reduction is due to the BEVs having lower operation emissions than the ICEV, combined with the shift from an ICEV to BEV dominated fleet.

In 2050, the annual emissions from the mixed fleet are 47 % lower than for the ICEV baseline. The drop in the annual emissions is caused by two factors; the stock dynamics and the reduction in emissions related to the vehicles' life cycle. Regarding stock dynamics the number of BEVs added is increasing, while vehicles removed from the stock mostly are ICEVs. Even though the BEVs have higher production emissions than the ICEVs, the fleet now benefits from the lower operation emissions that the BEVs provide.

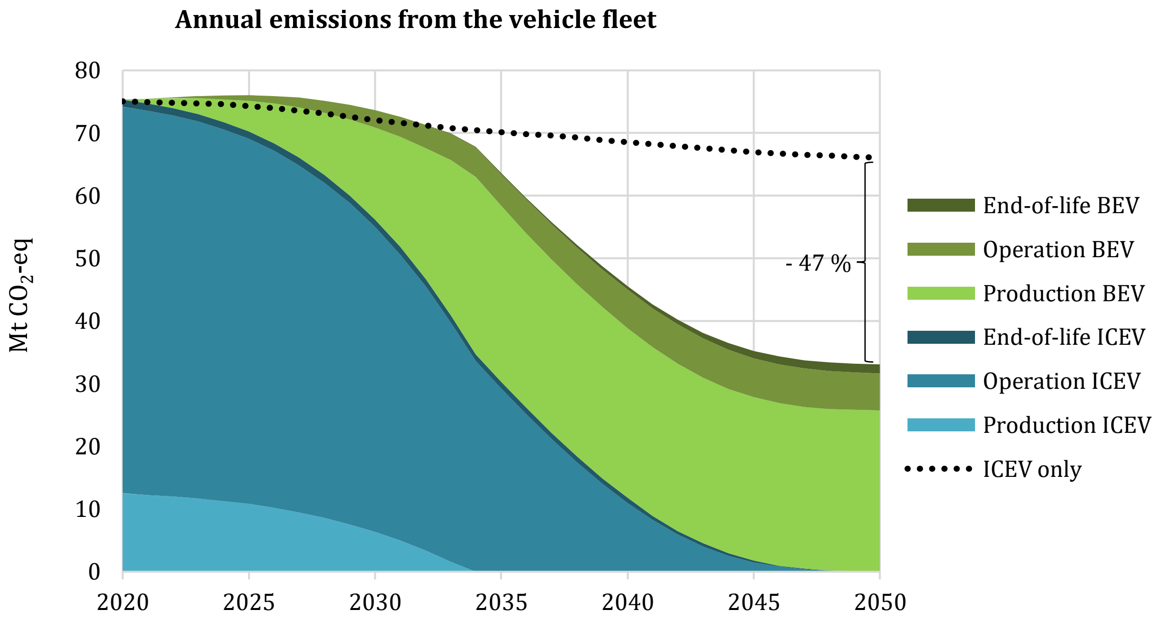

Figure 4.5 – Total greenhouse gas emissions from the optimized vehicle fleet with a mix of both ICEVs and BEVs. The graph shows the annual emissions given in mega tons of CO_2-equivalents. The dotted and dashed lines are included as references, representing the annual emissions of a fleet consisting of only ICEVs and BEVs, respectively.

Recall from Figure 4.1 that the gap between the operation emissions from the vehicles with different drivetrain technologies produced in the same year is increasing each decade, making it more beneficial in terms of emission reduction to switch from ICEVs to BEVs. The removal of the vehicles of older age classes, regardless of drivetrain technology, and replacing them with more fuel or energy efficient vehicles will also contribute to bringing the overall emissions down over the whole period. The operation phase accounts for 82 % of the total emissions from the fleet in 2020, while in 2050 this share decreases to 17 %, where the majority of the emissions origin from the production of the BEVs. This equals a reduction in annual direct emissions of 56 Mt CO_2-eq. Comparing the direct emissions from cars in the UK in 1990 to the potential annual direct emissions in 2050, given that they reach the level found in this thesis, equals an emission saving of 66.4 Mt CO_2-eq.

Generally, all life cycle emission parameters and carbon intensities of the electricity mixes are modelled to decrease year by year. This is however also the case in the ICEV baseline, and the parameters describing the life cycle emissions from the ICEVs are the same in both cases. One can therefore argue that the main driver for the emission reduction is the introduction of BEVs. The constraint on the additions of BEVs can be analyzed from the marginal value of the equation. Here, the marginal value represent the additional emission reduction over the whole optimization period if one more BEV was allowed added to the fleet in the first year. In the main scenario, emissions could have been reduced with an additional 2.1 mega ton CO_2-eq if one more BEV was added in the first year of the optimization period.

4.2 Additional scenarios

The additional scenarios were included to analyze the sensitivity of the optimal solution to key parameters. Six scenarios were made to achieve this. Here, the results from the scenarios will be analyzed in terms of how the optimal stock composition and annual emissions are changing.

4.2.1 Stock composition

The stock composition from the additional scenarios will be compared to the stock composition in the main scenario. The optimal stock composition only changed in three of the scenarios, which were the DA, BE-S and ST scenarios. This can be seen in Figure 4.6a-c, where the colored lines represent the values from these scenarios and the dotted lines represent the main scenario which is here used as a reference. The darker lines represent the ICEVs and the lighter lines represent the BEVs.

Comparing the DA and BE-S scenario, as seen in Figure 4.6a and c, one can see that the stock composition is affected more when the introduction is delayed. The shifts in these scenarios are likely to be linked to the constraint on the introduction rate of BEVs, which was changed in both cases. Relative to the main scenario the BEV introduction in the DA scenario was assumed to be 10 % slower, while it was assumed to be 8 % faster in the BE-S scenario. In the DA scenario the shift from a stock based on ICEVs to BEVs happen 5 years later than in the main scenario. The fleet will not reach a fully electric state due to the slower BEV introduction rate and still contains 5 % ICEVs in 2050. The contrary is seen in the BE-S scenario, where the shift happen 1 year earlier than in the main scenario. Due to the faster introduction rate in the BE-S scenario the fleet is 100 % electric from 2047. When the constraint applied limits the model in terms of number of BEVs introduced this will have implications on the whole optimization period, since the constraint is based on the size of the BEV stock in the previous year. A smaller number of BEVs added in year t means that a smaller number of BEVs can be added in year t+1, which can be seen in Figure 4.6a to limit the fleet of being 100 % electrified.

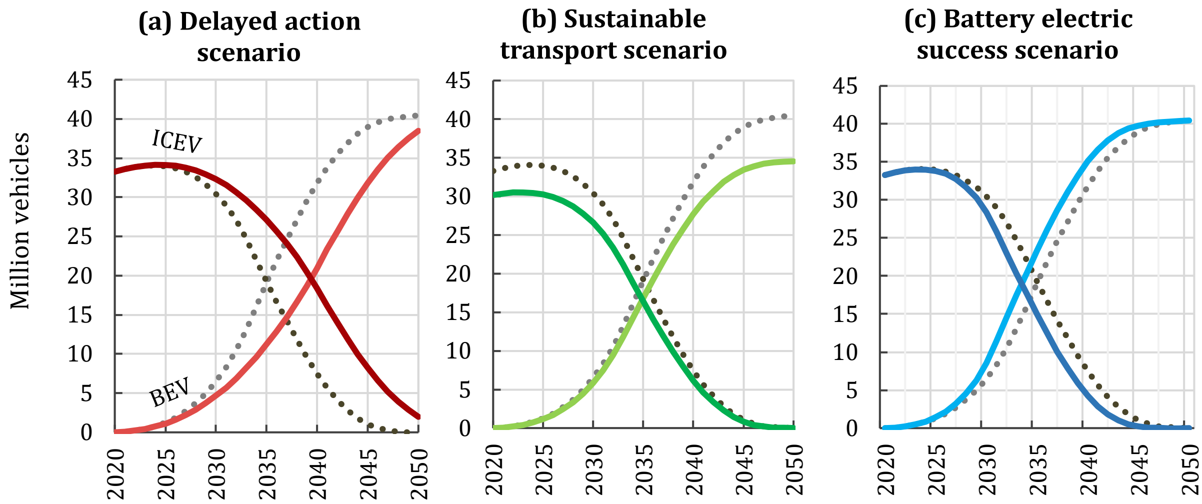

Figure 4.6a-c – Optimal stock composition in the delayed action, sustainable transport and battery electric success scenarios, all compared to the main scenario shown as the dotted line. The darker colored lines represent the ICEVs and the lighter lines represent the BEVs.

In the ST scenario, seen in Figure 4.6b, the stock composition switch is happening in the same year as in the main scenario. However, the stock is different than in the main scenario due to the different stock sizes. In the LW, PL and EL scenarios, the stock composition followed the same slopes as in the main scenario. In these scenarios the constraint of BEVs added was kept equal to the main scenario, and the change in the other parameter values did not affect the introduction rate of the BEVs, thus neither the optimal fleet composition. This shows that the stock dynamics are quite dependent on this constraint, especially when the life cycle emissions related to the BEVs are lower than for the ICEVs.

4.2.2 Vehicle stock emissions

Even though the stock composition only changed in three of the scenarios, the annual emission curves and total emissions were different in all cases. The total fleet emissions in the optimization period and the curves of the annual emissions, both shown relative to the ICEV baseline, can be seen in Figure 4.7 for the different scenarios. Figure 4.7a-f shows the annual emissions in year 2020 to 2050, while Figure 4.7g shows the cumulative emissions from the whole period for each scenario. The scenarios can here be seen as different measures to take, or pathways to follow, to reduce the emissions from the transport sector. Figure 4.7g shows it is clear that all the scenarios provide a reduction in the total emissions relative to the baseline.

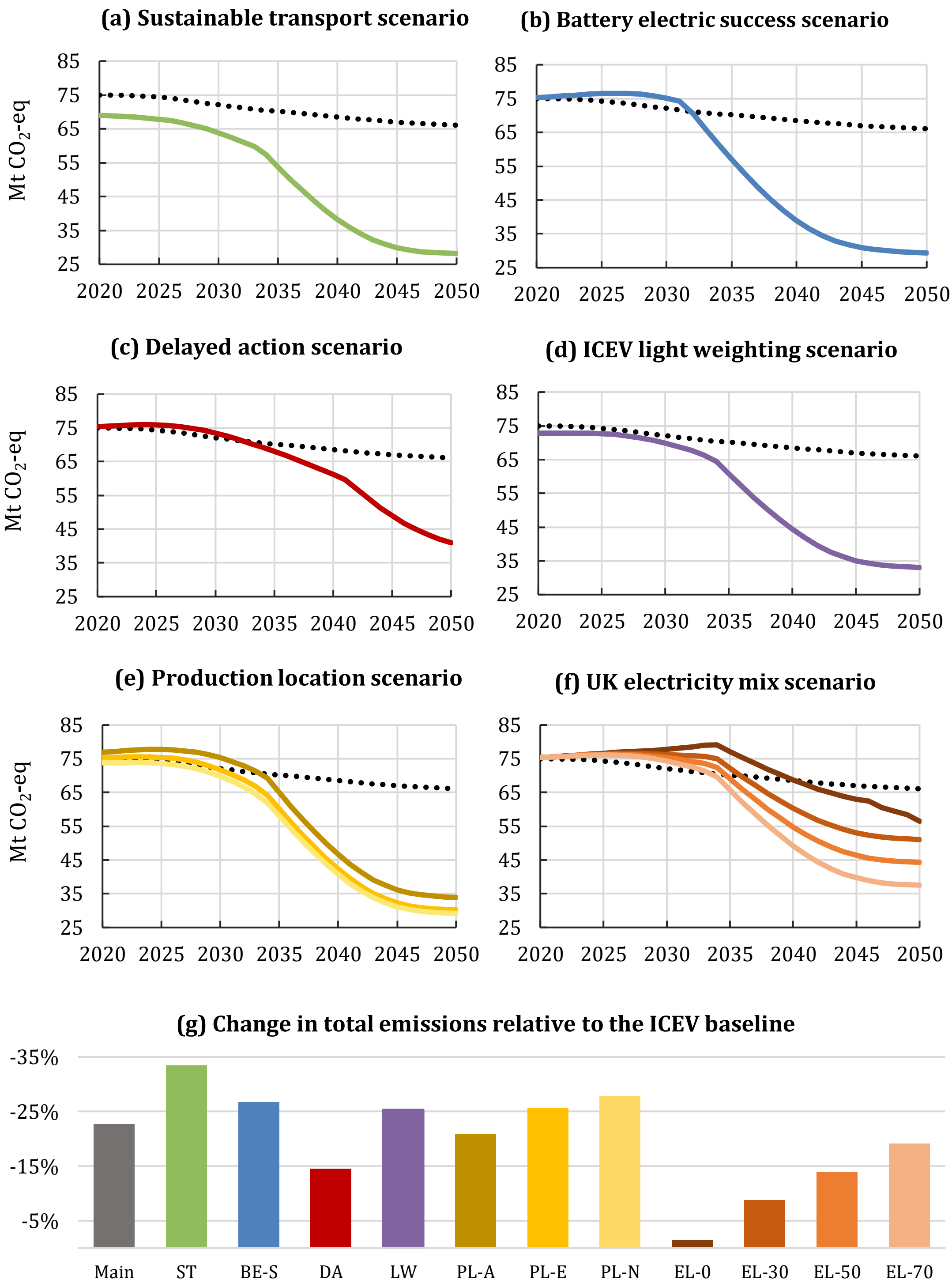

Figure 4.7a-g – Panel a to f show the annual emissions from all scenarios compared to the baseline case with only ICEVs (dotted line), where the emissions are shown in mega tons of CO_2-equivalents. Panel g shows the total emissions in the whole period for each scenario relative to the ICEV baseline case, where the change is given in percent.

The scenario providing the largest emission reduction, with 33 % lower total emissions, is the ST scenario shown in Figure 4.7a. In this scenario the vehicle stock was assumed to have a slower growth than in the rest of the scenarios, which is one of the drivers of emission reduction, since less cars on the road equals less emissions. Note that the additional emissions that would come from the increased use of public transport services is not included in this scenario. Including these emissions would have made the climate change mitigation potential lower than what was shown in Figure 4.7g.

Reducing the weight of the ICEVs, seen in Figure 4.7d, also proved to have a good emission reduction potential, even though the vehicle fleet composition did not change compared to the main scenario and the ICEV production emissions were assumed to increase. The emission intensity of ICEV operation was, however, also assumed to decrease. Given that the operation is contributing to more than 80 % of the total life cycle emission for the ICEV, it will have a good effect in terms of reduced emissions to improve the fuel efficiency of the conventional vehicles. In Figure 4.7g one can also see that the reduced emissions from the LW scenario is in line with the reduction seen from the BE-S scenario.

The BE-S and DA scenario, shown in Figure 4.7b and c, include two different trajectories of how the BEV introduction could look like. The annual emission curves are quite similar the first 10 years of the optimization period. After this point the emissions in the BE-S scenario see a steeper decline, resulting in lower annual emissions in 2050 than in the DA scenario. Regarding total emissions, one can see that the BE-S scenario offers a 6 % higher emission reduction than the DA scenario. Comparing the two scenarios to the main scenario one can see that the relative difference are 2 % and 4 %, for the BE-S and DA scenarios, respectively. Recall from Figure 4.6 that the switch points in these scenarios were moved earlier and later relative to the main scenario. This can then be used as an indication of the importance of the timing of the introduction of BEVs in order to minimize the total emissions. The more the introduction is delayed, the lower is the benefit from the fleet electrification within the given period.

In the PL scenarios the vehicles and battery pack were assumed to be produced in different countries or regions that have different electricity mixes. From the results in Figure 4.7e one can see that the regions with the electricity with the highest carbon intensity naturally also have the highest annual emissions. The same holds for the total emissions seen for PL-A, PL-E and PL-N in Figure 4.7g. An interesting observation here is the small difference between the case where the production was set to Europe and the case for Norway. The Norwegian electricity was modelled with a substantially lower carbon intensity than the European electricity, and it was expected that this would be more visible on the annual and total emissions. When changing the production location, other attributes of the production phase may also change. This is for instance the case for the battery production, where dry rooms are used during cell manufacture (Ellingsen et al., 2018). If the production is occurring in a region with a humid climate this may contribute to increasing the energy use, and vice versa for a dry climate. These factors are however not taken into account in the scenarios presented here.

In the EL scenarios, different trajectories for the development of the UK electricity mix was tested to see how this affected the stock composition and emissions. None of the cases in this scenario affected the stock composition. It is however evident that the total emission reduction potential decreases if there are no or little improvement in the carbon intensity of the electricity. Looking at all the cases in the EL scenario shown in Figure 4.7f, one can also see that the timing of decarbonizing the electricity plays an important role regarding how fast and how much the annual emissions from the passenger car fleet can be reduced. Comparing the EL-0 and EL-70 case from Figure 4.7g, where the carbon intensity relative to today's level was assumed to have a 0 % and 70 % improvement, one can see that there is a difference in emissions reduction potential of 13 %. Compared to the ICEV baseline one can also see that the introduction of BEVs provides a 2 % reduction in the total emissions if the electricity mix is not getting cleaner. Even though this is a small reduction, it is a reduction, and one can see the BEVs still are a better alternative than ICEVs if the electricity mix has not reached a low-carbon state.

5 Discussion

The optimal timing of vehicle fleet electrification in the UK was researched. This implied finding the combination of conventional diesel vehicles (ICEVs) and battery-electric vehicles (BEVs) in the fleet, while minimizing the total vehicle fleet emissions in the period 2020 to 2050. This was done through an optimization model, where the input parameters were based on data from LCA literature or government statistics. The dynamic behavior of the passenger car fleet was considered in the model, including vehicle fleet size, vehicle use and fleet turnover time. Also, future technological improvements in vehicle technologies and decarbonization pathways of the UK electricity were included.

Through the thesis, it was shown that it would be optimal introducing BEVs as soon and fast as possible to reduce the total vehicle fleet emissions. Seen from an environmental perspective, this implies that the fleet electrification not is constrained by the carbon intensity of the electricity. This was found to be the case even though the UK is still dependent on fossil energy sources such as natural gas and coal (IEA, 2018a). The electricity can, therefore, be deemed clean enough for the BEV to provide lower greenhouse gas emissions when compared to a diesel vehicle.

5.1 Assumptions and limitations

The optimization model was dependent on exogenous data. It was, therefore, emphasized benchmarking the parameter values in the current decade to literature and statistics from the same period. One of the main limitations of this thesis are the assumptions made linked to the future parameter values. Projecting the future states in terms of the carbon intensity of electricity mixes, life cycle emissions of ICEVs and BEVs and how the uptake of BEVs will look like is not feasible. One can, therefore, argue that the uncertainty of the parameter values is increasing along the modeling timeline. Nevertheless, where available, the assumptions were based on trends from statistical data and future goals or projections from governments, which are seen as credible sources for possible future outcomes. Misestimating the parameter values could have affected the optimal timing of BEV deployment. This mainly regards the parameters linked to the life cycle emissions of the vehicles, since these are used in the optimization model to choose the vehicle with the lowest climate change impact.

5.1.1 Life cycle emissions

The emission intensities of the vehicle life cycle phases are based on results from literature and car manufacturers. The study by Ellingsen et al. (2016) was used as a basis to model the emissions for both the ICEV and BEV. Ellingsen et al. (2016) state that the results in the study were well aligned with industry reports from, for instance, Volkswagen and Daimler. However, using exogenous LCA data in the optimization model give room for some uncertainties. Basing the data on a self-performed LCA study would have simplified the split of the production emissions concerning what is electricity related and what is non-electricity related. Besides, it could generally have made the estimation of the vehicle related parameters more accurate and tailored to the two drivetrain technologies assessed in this thesis.

The electricity requirements for producing the vehicles were based on averages from car manufacturers, which only accounts for the electricity used in the respective factories (BMW Group, 2018; Daimler AG, 2017; Nissan Motor Corporation, 2014, 2018b). Even though manufacturer data can be considered a credible source, only accounting for the electricity at the factory leads to an underestimation of the total electricity consumption in the whole production chain. The total electricity consumption, when accounting for upstream activities linked to raw material extraction and production, is most likely higher than what is used in this study. However, the sum of the constant emission term and electricity emission parameters in this thesis were benchmarked against the results from Ellingsen et al. (2016), and adjusted to be in line with the study. Modeling the production emissions as two parameters might, therefore, not lead to great uncertainty in the current decade. However, since one part is dependent on the carbon intensity of the electricity, this might lead to the parameter value being underestimated in the future, when the carbon intensity is low.

The operation phases were modeled based on the assumption that the energy and fuel consumption were static, hence not dependent on driving pattern, road gradients, and local conditions. Driving patterns with frequent starts and stops, representative for urban driving, will require more energy than driving on a highway at constant speed (Rangaraju et al., 2015; Sims et al., 2014). Steep road gradients also require more power from the motor, hence lead to a higher energy or fuel consumption. This implies that the operational parameters in this thesis represent a simplified version of reality. This simplification was, however, necessary to make sure the vehicle technologies were comparable on an equal basis in the optimization model.

The energy consumption of the BEV and the emission intensity of the ICEV were based on the study by Edwards et al. (2014). The study is accounting for the total well-to-wheel emissions and energy or fuel consumption in a European context. In the calculations, Edwards et al. (2014) used a passenger vehicle from the C-segment, which represents a medium sized car. This is consistent with the vehicle size modeled in this thesis. When comparing this emission intensity and energy consumption to what is applied in other studies, or measured by manufacturers, it was found that the values from Edwards et al. (2014) were lower.

Medium sized BEVs are often modeled with a 24 kWh battery , while in this thesis, a 42 kWh battery capacity was assumed. It should be noted that Edwards et al. (2014) based their calculations on a 24 kWh battery pack when assessing the energy consumption of the BEV, which may have led to the energy consumption parameter being underestimated in this thesis. Therefore, the model's dependency on this parameter was checked by changing the upper asymptotic value of the respective logistic function. This showed that the value could be increased by 100 % without affecting the optimal fleet composition. Higher energy consumption would, however, affect the total greenhouse gas emissions, and increase the total fleet emissions.

One factor that was not considered in this thesis is the limited lifetime of lithium-ion batteries. The lifetime depends on the number of charging cycles (Ellingsen et al., 2018), and the battery might need to be replaced during the vehicle lifetime. In this thesis, it was assumed that the batteries will last the whole vehicle life. Including the battery pack replacement could have changed the optimal fleet composition, since it would increase the total life cycle emission of the BEVs. It was, however, chosen to leave this out of the model since the lifetime of the vehicles, in terms of kilometers driven, changes depending on the production year. Assuming the vehicles reach the age of 14 years, which is the average passenger car lifetime in the UK (SMMT, 2018a), leads to a maximum kilometer lifetime in the model of 201 000 km, while the minimum lifetime would be 162 000 km. Nissan and Volkswagen offer a battery warranty of 8 years or 160 000 km, which can indicate how long the battery can be expected to last (Nissan Motor Corporation, 2018a; Volkswagen AG, 2019). To test the importance of omitting the battery replacement, the model was run with two battery packs in the BEV production phase for the main scenario. This did not change the optimal fleet composition but led to a 12 % increase in the total greenhouse gas emissions over the whole period.

5.1.2 Carbon intensity of the electricity

The parameters for the carbon intensity of the electricity in the UK, Europe, Norway, and Asian countries, were based on the study by Itten et al. (2014). The study assessed the carbon intensity of electricity produced and consumed in different countries based on data from 2008. This study was chosen since all countries relevant to this thesis were included. Also, it was seen as beneficial that the carbon intensities are based on the same modeling framework and method. Itten et al. (2014) present the carbon intensity for electricity at different voltage levels, where the electricity at high voltage has a lower carbon intensity than electricity at low voltage, which is due to transmission losses in the grid. All electricity used in this thesis were assumed to be consumed at low voltage.

From the carbon intensities stated by Itten et al. (2014) it was found that the carbon intensity of the electricity at low voltage was 4 to 6 % higher than for the electricity at medium voltage for Europe and the Asian countries. For Norway the low voltage electricity had an 18 % higher carbon intensity. It should be noted that the absolute difference in the Norwegian carbon intensity at various voltages is significantly smaller than for the other countries, and the high percentage difference is caused by the values being low.

From the cases in the production location scenario, it was clear that the change in the carbon intensity affected the total climate change mitigation potential from the fleet electrification. The use of a different voltage level in the parameter modeling could therefore have led to a change in the emission reduction potentials.

The BEV can be charged from a regular wall outlet of 120 to 240 volts, depending on country. Fast chargers and superchargers are also available, providing charging up to 500 volts (Collin et al., 2019; Tesla Motors, 2019). The assumption regarding BEVs being charged at low voltage electricity is, therefore, seen as reasonable. In automotive industry, the manufacturing plant may take in electricity at higher voltage from the grid. The electricity used in the machines, however, is likely to be at a lower voltage, transformed via internal transformers in the factory (EATON, 2011; Moeller GmbH, n.d.). The overall assumption regarding use low voltage electricity in all parameters applied to the model is, therefore, seen as reasonable.

5.1.3 Vehicle fleet characteristics

The parameters linked to the UK vehicle fleet characteristics were mainly based on statistical data from the government and are therefore deemed certain. This comprises the historical and current size of the passenger car fleet, annual driving distance, and vehicle age distribution. Since the statistical data was only available for the UK over a timeframe of four years, it was assumed that the data for GB, with some adjustments, were representative for the UK vehicle fleet. This is not something that is seen to affect the optimal fleet composition substantially. In the sustainable transport scenario, where both the vehicle fleet size and annual operating distance were changed, one could see that the transition from ICEVs to BEVs was the same as in the main scenario. The fleet size and operating distance will, however, affect the total greenhouse gas emissions from the fleet, and potentially wrong estimates would be visible here.

The average vehicle age was set to 14 years based on statistics (DfT, 2018f), and the maximum age was set to 20 years. The assumed vehicle lifetime is linked to the vehicle fleet turnover rate through the share of vehicles scrapped at given ages. The trend in statistics showed that the vehicles in the current decade were used longer compared to the previous decade. Increasing the average vehicle age in the model would lead to a slower fleet turnover, and potentially delay the BEV introduction. On the contrary, a lower vehicle age would accelerate the fleet turnover, and hence be beneficial since newer and more energy efficient vehicles are introduced at a faster rate. This would though probably lead to a higher share of the total emissions coming from the vehicle production phase since more vehicles are added to the fleet to meet the total vehicle demand.

5.1.4 BEV introduction rate

The environmental superiority of the BEV found in this thesis is consistent with findings from literature, where multiple researchers state that the BEV would be the preferable option over a fossil fueled car if charged with low-carbon electricity (Casals et al., 2016; Ellingsen et al., 2016; Hawkins et al., 2013). Ellingsen et al. (2016) found that the BEV had a 20 to 27 % lower impact than the ICEV when comparing equally sized cars. Hawkins et al. (2013) found that the BEV had a 10 to 14 % higher emission reduction potential, depending on the battery chemistry. In this thesis, it was found that the impact from a BEV was 12 and 28 % lower than for an ICEV, for the cars produced in 2010 and 2020, respectively. This is in the range of what was found in the literature. One can here see that the gap between the BEV and ICEV in the year 2020, which is when the BEVs are being introduced in the UK, is rather big. This indicates that even though some of the parameters might be slightly off, it would most likely not affect the ranking of the vehicle technologies in terms of total environmental burden. It would, however, have been visible on the total emission from the vehicle fleet.

Existing studies often include the economic aspect of vehicle acquisition, operation, and maintenance, when assessing future optimal fleet compositions. BEVs usually have a higher purchasing cost than ICEVs (BEIS, 2018), which could affect the uptake rate of BEVs. When taking into account the economic dimension, it is often found that the ICEV will be the preferred option, unless fiscal incentives are implemented to bridge the financial gap between the two drivetrain technologies (Figliozzi et al., 2012; Kwon et al., 2013; Lemme et al., 2019). The results from this thesis are therefore highly BEV positive compared to other studies due to the focus on the environmental dimension only.

If the costs were taken into account in this thesis, the optimal timing of BEV introduction would likely be later than what is found, due to the BEV currently being more costly to obtain. This is, however, outside the scope of this thesis, where the focus has been on minimizing the total emissions from the fleet. The costs could though be included as a factor to model the constraint on the maximum annual BEV uptake, and in this way provide some additional detail to the model. It is expected that the BEV and ICEV will reach cost parity in the mid-2020s (CCC, 2019), which may accelerate the BEV sales. Until this point is reached, there is a need for financial incentives. Aside from costs, BEV uptake is also dependent on other factors such as consumer preferences, for instance how the consumers perceive electric vehicles compared to conventional vehicles with regard to range and availability of charging points.

Some studies also include other drivetrain technologies than what is included in this thesis. Comparing the fleet transition from the main scenario to the BLUE Map trajectory by the IEA (2011), it is clear that the results from this thesis show a faster transition to electric vehicles. Alternative drivetrains, meaning hybrid, plug-in hybrid, electric and fuel cell vehicles, are predicted to constitute 80 % of the light-duty vehicle sales in 2050 according to the IEA. Whereas in this thesis, the electric market share was found to 100 % in 2050. It should though be mentioned that the scenario modeled by the IEA includes global car sales, which may lead to differences because of differences in development level among the various countries. Some of the same patterns can, however, be seen in the study by Fridstrøm et al. (2016), which only consider the Norwegian vehicle fleet. The study modelled the fleet transition in a low-carbon scenario, considering fiscal policy measures, and the fleet is predicted to contain 25 % BEVs in 2050. This is a much lower share than what is found to be environmentally optimal in this thesis, and it is especially surprising considering the current high market share of BEVs in Norway.

It can then be argued that the fleet electrification pathways proposed or estimated by other authors are not optimal from an environmental perspective. More effort should, therefore, be put into increasing the introduction rate of BEVs, since this is one way to reduce the greenhouse gas emissions from the transport sector, given a low-carbon electricity mix. From the comparison to other trajectories based on current policies, one can also argue that established policies are too weak to facilitate the required BEV uptake.

5.2 Implications

Since climate change is a complex problem, successfully mitigating this is also very complex. The drivers for climate change are numerous, and the drivers should be seen together in an interlinked system, and not as individual black boxes. This thesis exemplifies how the decarbonization of the transport sector is dependent on the decarbonization of the power sector, both locally and in the manufacturing countries.

5.2.1 Emission goals and mitigation potential

Through the Climate Change Act, the UK has committed to reducing the annual emissions by 80 % relative to 1990 levels. Emission reduction goals are usually set on a national scale as a given percentage relative to the emissions level in a previous year. However, there are usually not set specific targets on a sectoral basis, nor defined what pathway that should be pursued. It can then be debated whether this is the best way to promote climate change mitigation or not. Essentially, this could mean that the UK can continue polluting for many years, as long as the final emission level is reached in the end. This can, due to the lack of initial mitigation efforts, lead to the cumulative emission burden over the period being high, contributing to further greenhouse gas accumulation in the atmosphere.

From the comparison of the ICEV and BEV life cycle emissions in Figure 4.1, it was found that the BEVs had a lower climate change impact, regardless of production year. This indicates that the electricity mix in the UK is currently clean enough for BEVs to have an emission reduction potential if implemented on a large scale. Reaching the emission level as found in the main scenario in this thesis, would mean the direct annual emissions from the passenger cars in the UK will be reduced by 92 %, relative to 2017 levels (Jones et al., 2019). This is, however, given that the carbon intensity of the electricity mix in the UK will see a significant reduction towards 2050.

In the scenario that included the least positive trajectory of the carbon intensity, the total annual emissions would be reduced by 42 %, also relative to 2017 levels. This reflects the importance of focusing on low-carbon technologies in the power sector in parallel with the introduction of BEVs. The government have set goals to decarbonize the electricity system, intending to increase the share of renewable energy sources substantially, as well as implementing carbon capture and storage technologies on existing fossil-fueled plants (DECC, 2011). The UK is currently deemed one of the global leaders in decarbonization, both in terms of actual reduced emissions and ambitions set in their carbon budget plan (IEA, 2019a). The power sector has been the most significant contributor to the national emission reduction in the past years (BEIS, 2019), where the reduction mainly is a result of the switch from coal to natural gas, as well as the implementation of renewables. If the UK's goal of decarbonizing the power sector is achieved, there is a higher chance that the decarbonization of the transport sector will be successful.

As pointed out by Hill et al. (2019), the UK's emission reduction target only considers direct emissions. This is insufficient when assessing BEVs due to the production phase constituting a significant share of the total embodied emissions. This was seen in Figure 4.5, where the majority of the annual emissions in 2050 came from the production of BEVs. Only considering direct emissions, or emissions embodied in the electricity used, will lead to an underestimation of the total environmental burden caused by the BEVs. The use of LCA is therefore important when assessing different vehicle technologies. The method provides some additional insight regarding the environmental performance of the technologies compared to only considering direct emissions during vehicle operation, which is often the case (IEA, 2019c). Considering the total life cycle emissions in emission targets should, therefore, be encouraged. This could also put additional pressure on manufacturers to improve and streamline their production processes.

This also relates to the need for understanding where the emissions occur on a spatial scale. The direct emissions linked to the operation of the vehicles will take place in the UK. However, it is not certain that the production of the battery pack and the rest of the vehicle will happen within the UK. In the main scenario in this thesis, the production of the battery was assumed to happen in Asia, meaning the emission burden of this activity is assigned to countries in this region, and therefore most likely not accounted for in the UK emission target. This is also true for the emissions linked to the vehicle production, which in this thesis was assumed to occur in Europe. It may be especially problematic when manufacture is happening in the less developed countries, since these may have less strict regulations considering the environmental aspect of the production phase.

In addition to emissions of greenhouse gases, other impact categories and potential trade-offs of fleet electrification should also be assessed. Trade-offs might be the increased demand for raw materials such as cobalt, nickel or lithium (CCC, 2019), or increased levels of terrestrial acidification, freshwater or marine eutrophication and human toxicity related to the production of the lithium-ion battery (Hawkins et al., 2013). These factors were not explored in detail in this thesis, nor included in the optimization model, but are relevant in terms of decision making to capture the full picture of the benefits and drawbacks of an electrified fleet, as well as for mapping out potential material scarcity concerns.

5.2.2 Consumer behavior and policies

The optimal solution from an environmental perspective is to introduce as many BEVs as possible, and preferably switch all car sales from ICEV to BEV in the beginning of the optimization period. This is, however, not seen as a realistic path since policies and infrastructure facilitating this transition are currently not in place (CCC, 2019). The question is then how the government can facilitate the required changes to promote BEVs. Today, the uptake of electric vehicles is still largely dependent on policy measures (IEA, 2018c), meaning that even stronger incentives from the UK government could contribute to increasing the BEV market share.

Even though it was found that the deployment of BEVs starts in 2020, and the goal of a 50 % electric market share by 2030 is met in the main scenario, ICEVs will still dominate the fleet until 2035. This is consistent with what is found by Fridstrøm (2017), which identifies a lag between the time new vehicle technology is introduced until they constitute a substantial share of the total fleet. This demonstrates the importance of addressing the fleet dynamics and understanding the drivers behind the in- and outflow of vehicles. This was seen in the battery electric-success and delayed action scenarios, where the change in BEV introduction rate shifted the timing of BEV fleet domination. One could see in the delayed action scenario, where the BEV introduction was slower than in the main scenario, that the fleet did not end up as fully electrified in 2050. In the battery-electric success scenario, however, the whole fleet was electrified before 2050. Due to the dynamics of the vehicle fleet, the BEVs will have a limited mitigation potential in the short-term, but on the contrary be beneficial in the longer term when they start dominating the vehicle fleet. This reflects the need for facilitating a high BEV uptake as soon as possible through targeted policies to avoid a further lag in the emission reduction benefits the BEVs can provide.

In the UK, the lack of infrastructure in terms of charging stations is seen as one of the barriers to mass introduction of BEVs. Therefore, affordable home chargers and access to publicly available chargers play an important role in how the consumers perceive the BEV. The availability of fast chargers also needs to be addressed, since this is important to decrease the charging time and make BEVs competitive with the ICEVs. Consumers state that the accessibility to frequent charging points, as well as fast chargers, are especially important for long-distance trips (OLEV, 2015). Thus, there is also a need for understanding how the consumers use their vehicles, and the driving distance or type of trips the BEVs are used for might be different compared to the ICEV (OLEV, 2015). This barrier is linked to the range anxiety expressed by potential BEV owners (OLEV, 2015), and the consumers can perceive the range as a problem because they might need to plan their trips to a larger extent. Thus, a wide-reaching charging network is essential to mitigate the range-anxiety (BEIS, 2018).

Another barrier to BEV uptake is the higher acquisition cost when compared to an ICEV (BEIS, 2018). The initial cost is stated by consumers as the most important characterisitc when buying a new vehicle (OLEV, 2015). Looking to Norway, which is currently the country with the highest market share of electric vehicles (IEA, 2018c), financial incentives such as tax exemptions and no fares through toll roads have helped boost the BEV sales. Some financial incentives targeting low-emission vehicles are currently in place in the UK (UK Government, 2019). However, considering the low share of BEVs in the fleet of 0.15 %, one could argue that more ambitious policies are needed to encourage a higher BEV uptake by the consumers. This could be, for instance, increasing the current grant on low-emission vehicles.

On the contrary, financial incentives such as subsidies and tax exemptions are costly and may place a heavy burden on national budgets (Fearnley et al., 2015). Nevertheless, financial incentives target the whole population regardless of local conditions, and can have a larger effect on the BEV uptake than local measures. The lack of climate change mitigation measures may induce high costs for societies in the future, due to damages caused by, for instance, sea-level rise, more frequent extreme weather events and wildfires (UNFCC, 2014). Besides, the more the action of mitigating climate change is delayed, the less are we able to limit the damage, while the costs of doing so will increase. Since financial issues and budgeting often are emphasized by governments, it could be relevant to assess the budget implications of financial policies together with the potentially saved costs of emission mitigation from the fleet electrification.

The second most important characteristic for consumers when buying a vehicle are the fuel costs (OLEV, 2015). Due to the price difference of electricity and conventional fuels, the BEV is cheaper to operate (IEA, 2018c). This would then lead to reducing the costs for the consumers in the long term. If financial incentives for vehicle acquisition are in place, the benefit of low-cost operation could be used to further promote the BEVs. It should, though, be addressed that the lower operation costs could lead to a rebound effect (Sims et al., 2014). This implies that the BEV owners, due to the saved costs, drive more and longer distances than they usually would. Even though operating the BEVs is less emission intensive compared to the ICEV, this could lead to additional emissions.

Fearnley et al. (2015) also point out access to bus lanes as a successful measure that was highly valued by the current and potential BEV owners in Norway. This is an almost free incentive that may make the BEV more attractive to consumers. This could be successful especially in regions where traffic in rush hour is high. However, it implies that the number of BEVs in the bus lane must not exceed the lane capacity, which then would delay public transport. Besides, this incentive will only have local effects in areas where bus lanes exist, which mostly are in urban or suburban areas.

In this subsection, some successful incentives applied in Norway were given as examples of how the uptake of BEV generally can be promoted to consumers. It should, however, be noted that policies deemed successful in one country might not have the same effect in another. This calls for assessments on a national scale to tailor policies and incentives to the local conditions. Also, the effectiveness of policies should be researched and evaluated to assure they have the desired effect.

5.3 Further work

The optimization model used in this study has the potential of becoming more detailed, and there is room for improving some of the data and assumptions. Also, other aspects aside from greenhouse gas emissions could be included. Some suggestions for future work are described below.

- **Data improvement:** There is room to improve the data and assumptions in the model. This should though be focused on improving the parameter values in the current period since the gap between the total life cycle emissions of the BEV and ICEV is smaller here.
- **Economic dimension:** The economic dimension could be included in the model since this is one of the significant drivers for change. This could, for instance, be done through using a multi-objective optimization model or defining the objective function as a sum of weighted scores regarding the environmental and economic dimensions. The economic dimension could also be included by linking the economic parameters to the constraint on the uptake rate of BEVs, to reflect the consumers in the market. It could also be relevant to include other factors affecting the uptake, such as technology acceptance or the level of technology-specific infrastructure availability.
- **Additional drivetrain technologies:** Instead of only including BEVs and ICEVs, it could be relevant to also include plug-in hybrid electric vehicles (PHEVs) in the model. The PHEVs are seen as a technology that can play an essential role in the transition from an ICEV based to an electrified fleet (DfT, 2018c).
- **Additional countries:** The optimization model used in this thesis is applicable to other countries. It could be especially relevant to apply the model in countries where the carbon intensity of the electricity mix is high, hence timing of BEV introduction more critical from an environmental perspective.
- **Electricity grid impact:** Electrifying the vehicle fleet also has some consequences for the national electricity grid. This concerns, for instance, peak power demand and overall electricity supply. There might therefore be a need of updating the grid to meet the increased load and electricity consumption posed by the BEVs. This was not discussed in this thesis, but is important for governments to consider.

6 Conclusion

The optimal timing of vehicle fleet electrification in the UK was investigated in this thesis. This implied finding the combination of conventional diesel vehicles (ICEVs) and battery-electric vehicles (BEVs) in the fleet, subject to minimizing the total vehicle fleet emissions in the period 2020 to 2050. It was found that the deployment of BEVs in the UK is beneficial in terms of mitigating climate change, even though the electricity mix is not yet fully renewable. Since the life cycle emissions of BEVs is lower than for ICEVs, the optimal solution would be to deploy the BEVs as fast as possible.

In the short-term, meaning the next decade, it was found that the deployment of BEVs led to an increase in the annual fleet emissions, due to the higher embodied emissions in the production phase. In the remaining years towards 2050, the large scale BEV deployment will contribute to reducing the national emissions compared to a fleet consisting of only ICEVs. In 2050, the annual direct emissions from the fleet will be reduced by 92 %, relative to 2017 levels, given a BEV deployment rate as in the main scenario. From the scenario analysis, it was clear that the mitigation potential is reduced if the deployment of electric vehicles is delayed or the UK fails to decarbonize the power sector. Other benefits, aside from reduced emissions, could come from electrification of the vehicle fleet. This might be an improvement of local air quality due to less emissions of particles, which can affect human health, or less noise pollution.

Through the analysis of the results, it was shown that the constraint on the BEV uptake was the main factor affecting the rate of BEV introduction. The question is then how the UK government can facilitate the required rate of BEV uptake to obtain an environmentally optimal vehicle fleet. Various barriers linked to consumer behavior and vehicle costs were identified, where the lack of suited policies may further delay the fleet electrification. Incentives such as tax exemptions, no fares through toll roads and access to bus lanes have had good effect in some countries. Also, providing the necessary infrastructure is important for BEVs to be competitive to ICEVs. This implies that the UK government must establish a wide-reaching and publicly accessible charging network, to mitigate the range anxiety expressed by potential BEV owners.

In sum there is a potential for climate change mitigation through the electrification of the UK's passenger car fleet. To achieve this, it is crucial that the UK continue decarbonizing the power sector and facilitate the BEV uptake through implementing policies and incentives. This calls for national scale assessments to tailor policies and incentives to local condition, as well as understanding consumer behavior and potential barriers for large scale BEV uptake.

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A Statistical data: Vehicles in the UK

Table A.1 – Statistical data showing the number of passenger cars* and the total vehicle movements in the UK from 1997 to 2017. Annual driving distance is calculated from these columns. 1: DfT (2018f), 2: DfT (2018d), 3: ONS (2018).

	Passenger vehicles[1] [thousand cars]	**Total vehicle movements[2] [billion vkm]**	**Annual driving distance [vkm/year]**	**Population[3] [million]**	**Cars per 1000 capita**
1997	23 832	365.8	16 022	58.3	409
1998	24 293	370.6	15 910	58.5	415
1999	24 975	377.4	15 741	58.7	426
2000	25 406	376.0	15 406	58.9	431
2001	26 126	381.2	15 172	59.3	442
2002	26 782	390.6	15 150	59.4	451
2003	27 240	390.0	14 863	59.6	457
2004	28 028	394.2	14 585	60.0	468
2005	28 520	392.7	14 269	60.4	472
2006	28 609	397.4	14 394	60.8	470
2007	29 000	397.9	14 211	61.3	473
2008	29 161	395.0	14 027	61.8	472
2009	29 247	394.0	13 949	62.3	470
2010	29 421	385.9	13 578	62.8	469
2011	29 467	387.4	13 609	63.3	466
2012	29 723	386.7	13 463	63.7	467
2013	30 141	386.2	13 253	64.1	470
2014	30 612	394.2	13 312	64.6	474
2015	31 250	398.6	13 177	65.1	480
2016	31 850	405.0	13 128	65.6	485
2017	32 200	409.4	13 122	66.0	488
Average change	1.6 %	0.6 %	-1.0 %	0.6 %	0.9 %

* Refers to the fact that data on the vehicle fleet size only was available for UK from 2014 to 201,7, and the size is therefore estimated with basis in the size of the vehicle fleet in GB.

B Logistic function variables and corresponding values

Table B.1 – Values used for the different parameters for the logistic functions in the main scenario.

Parameter	Variable	Value	Unit	Based on
Vehicle fleet size in the UK	A	25.4	10^6 veh	DfT (2018f)
	B	41.2	10^6 veh	DfT (2018f); (DfT, 2018f); ONS (2018)
	r	0.10		
	τ	2020		
Annual driving distance per vehicle	A	15 700	km/veh	DfT (2018d)
	B	11 300	km/veh	DfT (2018d); DfT (2018a)
	r	0.10		
	τ	2015		
Carbon intensity of electricity in the UK	A	690	gCO_2-eq/kWh	Itten et al. (2014)
	B	110	gCO_2-eq/kWh	Hammond, Howard & O'Grady (2013)
	r	0.20		
	τ	2025		
Carbon intensity of electricity in Europe	A	550	gCO_2-eq/kWh	Itten et al. (2014)
	B	110	gCO_2-eq/kWh	European Commission (2018)
	r	0.15		
	τ	2025		
Carbon intensity of electricity in Asia	A	870	gCO_2-eq/kWh	Itten et al. (2014)
	B	370	gCO_2-eq/kWh	CNREC (2018); MOTIE (2017); METI (2015)
	r	0.15		
	T	2030		
Carbon intensity of low-carbon electricity	A	50	gCO_2-eq/kWh	Itten et al. (2014)
	B	30	gCO_2-eq/kWh	Ecoinvent Centre (2010)
	r	0.10		
	T	2035		
Electricity requirement for ICEV production	A	2000	kWh/veh	Volkswagen AG (2018); (Nissan Motor Corporation, 2014, 2018b); BMW Group (2018); Daimler AG (2017).
	B	900	kWh/veh	
	r	0.10		
	τ	2025		
Constant emission term for ICEV production	A	4000	$kgCO_2$-eq/veh	Ellingsen et al. (2016)
	B	3400	$kgCO_2$-eq/veh	Ellingsen (2016); Bauer et al. (2015)
	r	0.10		
	τ	2025		
Emission intensity of ICEV operation	A	0.16	kgCO2-eq/km	Edwards et al. (2014)
	B	0.11	kgCO2-eq/km	Edwards et al. (2014)
	r	0.10		
	τ	2020		
Emission intensity for ICEV EOL	A	550	$kgCO_2$-eq/veh	Ellingsen et al. (2016)
	B	350	$kgCO_2$-eq/veh	Ellingsen et al. (2016); Own Assumption
	r	0.10		
	τ	2025		
Electricity requirement for BEV production	A	2000	kWh/veh	Ellingsen et al. (2016)
	B	900	kWh/veh	Own assumption
	r	0.15		
	τ	2030		
Constant emission term for BEV production	A	5800	$kgCO_2$-eq/veh	Ellingsen et al. (2016)
	B	4670	$kgCO_2$-eq/veh	Own assumption
	r	0.15		
	τ	2030		

Electricity requirement for battery production	A	3700	kWh/batt	Ellingsen et al. (2018)
	B	2900	kWh/batt	Own assumption
	r	0.10		
	τ	2030		
Constant emission term for battery production	A	2000	kgCO_2-eq/batt	Ellingsen et al. (2016)
	B	1700	kgCO_2-eq/batt	Own assumption
	r	0.10		
	τ	2030		
Energy consumption BEV operation	A	0.15	kWh/km	Edwards et al. (2014)
	B	0.11	kWh/km	Edwards et al. (2014)
	r	0.15		
	τ	2030		
Emission intensity for BEV EOL	A	750	kgCO_2-eq/veh	Ellingsen et al. (2016)
	B	400	kgCO_2-eq/veh	Ellingsen et al. (2016)
	r	0.10		
	τ	2030		

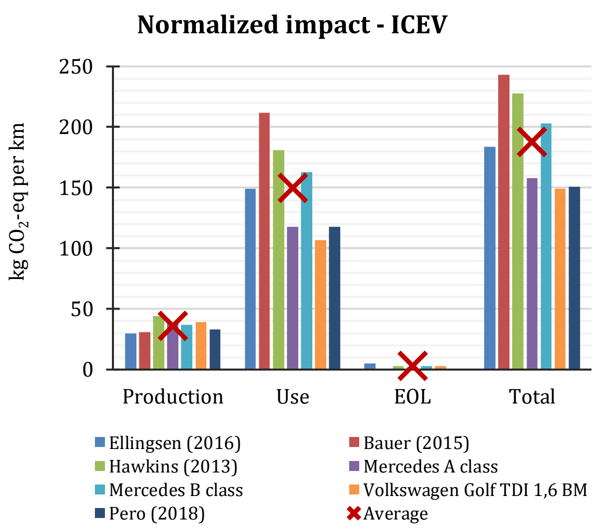
C Overview of LCA literature and BEV models

Table C.1 – Life cycle assessment results for ICEVs from literature, given in kg CO_2-eqivalents

Production	Use	EOL	Weight	Lifetime	Vehicle type	Source
5400	26900	300	1500	180 000	Medium car (C segment)	Ellingsen et al. (2016)
7390	52320	n.a.	1550	240 000	Medium car	Bauer et al. (2015)
6600	27150	450	1350	150 000	Small car	Hawkins et al. (2013)
4950	25650	n.a.	1357	150 000	n.a.	Pero et al. (2018)
9450	30900	n.a.	n.a.	150 000	n.a.	Bicer et al. (2018)
6100	23400	300	1370	160 000	Mercedes-Benz A 180 D	Daimler AG (2018)
5900	26100	500	1400	160 000	Mercedes-Benz B 180 CDI	Daimler AG (2011)
5800	16155	450	1318	150 000	Golf VI TDI BlueMotion	Volkswagen AG (2010)

Table C.2 – Life cycle assessment results for BEVs from literature, given in kg CO_2-eqivalents.

Production	Use	EOL	Weight	Lifetime	Comment	Source
9600	15900	700	1500	180000	Medium car (24,4 kWh)	Ellingsen et al. (2016)
11900	11900	700	1759	180000	Large car (42,1 kWh)	Ellingsen et al. (2016)
12275	36000	n.a.	1900	240000	Large car (50 kWh)	Bauer et al. (2015)
13200	15450	465	1400	150000	Small car (24 kWh)	Hawkins et al. (2013)
9000	10350	n.a.	1595	150000	Medium car (n.a)	Pero et al. (2018)
7350	16650	n.a.	n.a.	150000	n.a.	Bicer et al. (2018)
11100	8250	150	1567	150000	VW e-Golf (24,2 kWh)	Volkswagen AG (2012)



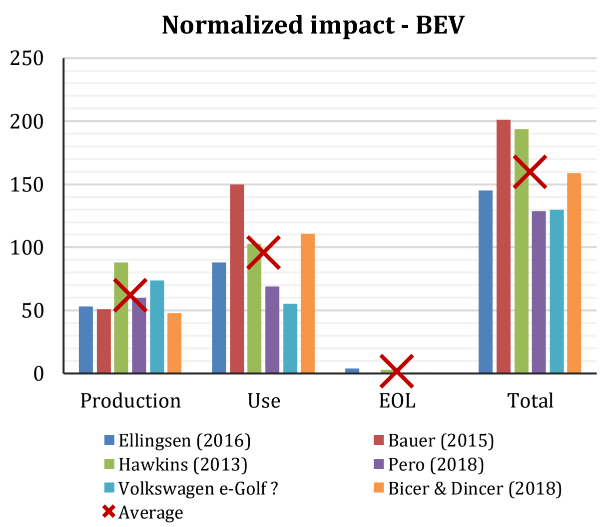


Table C.3 – Overview of battery-electric models on the market, year launched and battery capacity.

Manufacturer	**Model**	**Launched**	**Battery [kWh]**
Mitsubishi	iMiev	2010	16
Nissan	Leaf	2011	24
Tesla Motors	Model S	2012	60/90
Ford	Focus Electric	2013	23
BMW	i3	2014	22
Volkswagen	e-Golf	2014	24,2
Kia	Soul Electric	2014	27
Renault	Zoe	2014	22
Tesla Motors	Model X	2015	60/90
Mercedes	B-Class Electric drive	2015	28/32
BMW	i3	2016	33
Opel	Ampera E	2016	60
Hyundai	Ioniq	2016	28
Kia	Soul Electric	2017	30
Tesla Motors	Model 3	2017	50/62/75
Nissan	Leaf	2018	40