School of Built Environment

Uncertainty in GB electricity grid carbon intensity and its implications for carbon accounting and reporting.

by

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Abstract

The electricity sector is one of the largest sources of greenhouse gas emissions and the study of electricity grid carbon intensity has a key role in meeting the Climate Change targets. Evaluation of grid carbon intensity, typically measured in gCO_2eq/kWh, is fundamental to footprint calculation. The UK government (DEFRA) provides guidelines and annual grid carbon intensity figures for companies to report their emissions, but the use of a single annual value for grid carbon intensity introduces several key uncertainties into carbon assessment. This study examines the uncertainties that arise from using single annual values for carbon accounting and reporting purposes. Half-hourly UK grid carbon intensity values have been calculated and analysed for the years 2009-2017. Additionally, a power system (UC / ED) model of the GB power grid has been built. This model is being used to explore the sensitivities of grid carbon intensity to variable renewable energy and capacity assumptions. Grid carbon intensity is shown to widely vary not only inter-annually and intra-annually but also from one hour of generation to the next. Hence, the use of a single annual average figure raises doubts over the accuracy of the estimations. Finally, high resolution grid carbon intensity is being used to inform demand side management schemes and identify potential carbon benefits on the domestic and business level.

DECLARATION

I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

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Vasiliki Papaioannou

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To my brother, the eternal fan of science.

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Abbreviations

AEF .... Average emissions factor

BEIS .... (Department for) Business, Energy and Industrial Strategy

CC .... Climate change

CCGT .... Closed cycle gas turbine

CE .... Consumer Evolution

CHP .... Combined heat and power (plant)

CPLEX .... IBM ILOG CPLEX Mathematical programming software

CR .... Community Renewables

DECC .... Department of Energy and Climate Change

DEFRA .... Department for Environment, Food and Rural Affairs

ED .... Economic Dispatch

EV .... Electric Vehicle

FES .... Future Energy Scenarios

GB .... Great Britain

GHG .... Greenhouse gas emissions

LR-MEF ...... Long-run marginal emissions factor

MEF .... Marginal emissions factor

MERRA .... Modern-Era Retrospective Analysis for Research and Applications

MDF .... Marginal displacement factor

NG .... National Grid

OCGT .... Open cycle gas turbine

UC .... Unit Commitment

SP .... Steady Progression

TD .... Two Degrees

*The terms **"electricity carbon intensity"**, **"carbon intensity"** and **"grid carbon intensity"** are used interchangeably across this study and represent emissions from the grid. The term **"carbon factor"** is used to describe the emissions arising from a specific power plant.*

Finally, it is noted that in this study, all results pertaining grid carbon intensity and power plant carbon factors measured in $gCO_2eq./kWh$ are reported in g/kWh for brevity reasons. In a similar manner, "carbon" emissions represent greenhouse gas emissions (including CO_2, CH_4 and N_2O).

Chapter 1

Introduction

Decarbonising the electricity grid plays a pivotal role in most Climate Change mitigation scenarios (Vijay *et al.*, 2017) as the electricity and heat sector are together the largest emitting activities globally (Bosch *et al.*, 2017). National targets are also in place, committed to reduce carbon dioxide emissions in an attempt to limit Climate Change in the UK. The fifth carbon budget of Climate Change Committee (CCC, 2015) advises that the emissions generated by the power sector should be reduced by 75% of their 2015 levels by 2030s and 95% by 2050s. Hence, it is important to monitor the electricity grid carbon emissions.

In the business world, sustainability has started becoming a fundamental strategic goal as Climate Change mitigation gets embedded in the corporate decision making; Large-scale companies, driven by legislative measures, have become increasingly conscious of carbon reporting, which is seen as a marker for good management and corporate ethics. Those that perform well are demonstrating their good environmental management and sustainability, their ability to manage risk, drive efficiencies, and offer the best value to clients (Groening *et al.*, 2014), (Groening *et al.*, 2016). The insights gained from accurate carbon accounting can be used as a baseline for strategy control to identify potential for carbon savings.

The British government provides guidelines and grid intensity values for carbon accounting and reporting purposes (DEFRA, 2016a). Here, grid carbon intensity refers to greenhouse gas emissions for each kilowatt-hour of electricity generated and is typically measured in CO_2 eq. g/kWh. DEFRA updates these values annually as grid carbon intensity is heavily dependent on the relative prices of coal and natural gas as well as fluctuations in peak demand and renewables (DEFRA, 2016b). However, the grid operation varies dramatically from hour to hour because of the just in time nature of electricity production (Staffell, 2017).

Therefore, the **problem statement** can be summarised as follows:

Single annual figures of grid carbon intensity neither capture the uncertainty nor represent the highly dynamic behaviour of the GB electricity grid, thus raise doubts over their accuracy when used in carbon accounting and reporting schemes.

To investigate this uncertainty, the present study aspires to look further than just the annual average figures and examine the dynamic behaviour of grid carbon intensity in higher resolution. Furthermore, this study aims to make recommendations on how this dynamic behaviour can be factored into control strategies and demand management schemes that aim to achieve a carbon benefit. To address the above, the methodology that was followed consists of three parts:

- (i) historic data analysis
- (ii) power system modelling
- (iii) case studies

The time sequence among the three begins with data analysis being carried out first, followed by the model and then the case studies. The analysis part provided carbon intensity datasets for the years 2009 to 2017. These datasets were then used to assess the accuracy of a power system model that was designed for the purposes of this study. It is noted that a first small-scale version of the MILP model was jointly designed with fellow PhD researchers at the TSBE centre (Max Zangs and Alice Gunn). The updated version of the model that was used throughout this study consisted of a higher number of units, used different input parameters and optimised a different cost function. This model was run in order to produce annual grid carbon intensity datasets under a variety of future, and current feasible scenarios. Finally, both historic and simulated grid carbon intensity datasets were utilised in the case studies.

Analysis of historic, real data provides useful insights on the varying nature of grid intensity and identifies periodicity, intra-daily, seasonal and annual trends. Furthermore, the power system model that reflects and simulates the GB electricity grid, examines how grid carbon intensity would change under different weather and installed capacity assumptions. Finally, the aim of the case studies is to make recommendations on how carbon intensity datasets in high resolution can be utilised to inform charging strategies for electric vehicles and control strategies of combined heat and power generation plants.

1.1 Project aim and objectives

The aim of the project is **to assess the different sources of uncertainty in historic, current and projected GB grid carbon intensity and make recommendations on factoring its dynamic nature into real life applications**, while the objectives of the project can be described as follows:

- **Objective 1**: Explore historic grid carbon intensity variability and quantify the numeric uncertainty arising from different power system carbon factor assumptions;
- **Objective 2**: Apply power system model(s) to establish grid carbon intensity uncertainty under varying renewable resource inputs and future power station capacity projections;
- **Objective 3**: Investigate how time-varying carbon intensity influences carbon assessment in real-life case studies.
- **Objective 4**: Draw on findings derived from real-life case studies in order to establish implications of the dynamic behaviour of grid carbon intensity;

1.2 Thesis and contribution to knowledge

While past studies have looked into the behaviour of grid intensity over the last years, the historic analysis presented here is a comprehensive study for GB grid carbon intensity in high resolution, examining a broad time-frame of nine years and achieving higher resolution than previous studies. Furthermore, by utilising National Grid's capacity projections and re-analysis meteorological data in a power system model, this study is believed to be the first to produce annual carbon intensity datasets in high resolution under a range of weather and installed capacity assumptions. There is currently no robust methodology on how to use time-varying grid carbon intensity in real-life applications. A novel carbon-optimal strategy is designed for the charging of an electric vehicle and recommendations are made for the control strategy of a combined heat and power plant in University of Reading.

It is expected that this work will be relevant to anyone with an interest in the electricity grid carbon emissions such as power system operators, policy-makers, planners and even members of the public that are sensitive to the grid decarbonisation. Furthermore, the case studies can inform the relevant interested parties, any electric vehicles manufacturing or leasing company and the Energy team of University of Reading. This work should help to improve the understanding of the grid carbon intensity's dynamic nature, its sensitivities to weather and power system assumptions, and the potential to utilise this nature in real life applications to achieve carbon benefits.

1.3 Thesis outline

The structure of the present study consists of six chapters and is as follows

Chapter 2 reviews the academic literature in order to set the work of this study in context by presenting an overview of the various types of grid carbon intensity, carbon reporting procedures, relevant energy polices, future challenges for the grid and power system modelling.

Chapter 3 introduces the methodology for calculation of grid carbon intensity and then tests the results against the relevant figures provided by the government. Furthermore, different power plant carbon factors are used to establish the uncertainty ranges in half-hourly grid carbon intensity. Historic data analysis for generation data is then carried out for years 2009 to 2017.

Chapter 4 details the design of the GB power system model and examines how various renewable inputs and installed capacity assumptions affect the grid carbon intensity figures.

Chapter 5 introduces the electric vehicles and CHP case studies where annual datasets of grid carbon intensity are utilised to inform control strategies and achieve a carbon benefit.

Chapter 6 brings together everything presented in the previous chapters, presents a summary of the findings of this research and finally draws general conclusions about the uncertainty in grid carbon intensity.

1.4 Published work

Parts of the work presented in this thesis have also been published/presented as follows,

- School of Construction management and Engineering postgraduate conference, University of Reading, 2016, “Electricity carbon intensity of the UK grid for years 2009-2015.”, (poster presentation)
- NPL postgraduate conference, London 2016,“Electricity carbon intensity of the UK grid for years 2009-2015.”, (poster presentation) (second prize)
- School of Construction management and Engineering postgraduate conference, University of Reading,“UK grid dynamic carbon intensity for years 2009-2016.”, 2017 (oral presentation)
- TSBE postgraduate conference, University of Reading, “Time-varying carbon intensity of the UK grid for years 2009-2016.”, 2017 (poster presentation)
- WHOLESEM conference, London, “Time-varying carbon intensity of the UK grid for years 2009-2016.”, 2017 (poster presentation) , (http://www.wholesem.ac.uk/events/annual-conference/annual-conf-2017/Vasiliki_Papaioannou_wholeSEM_Poster.pdf)
- Energy 7 (International energy symposium) conference, Manchester, “Time-varying carbon intensity of the UK grid for years 2009-2016.”, 2017 (oral presentation)
- ESCC conference, Mykonos, “Variability in the UK grid carbon intensity and how it can inform controlled charging strategies of EVs.” 2017 (oral presentation)
- Energy, Elsevier *Variability in the UK grid carbon intensity and how it can inform controlled charging strategies of EVs, Vicky Papaioannou, Anthony Simpson, Phil Coker, Ben Potter, Valerie Livina* (submitted journal paper)

Chapter 2

Literature Review

2.1 Electricity grid carbon intensity

With Climate Change mitigation measures in place, the study of carbon emissions arising from the electricity grid has lately been an area of academic focus. Electricity grid carbon intensity is a metric commonly used to quantify carbon dioxide emissions that arise from an amount of electricity that was generated or transmitted. An overview of the different types of electricity carbon intensity was given by (Hitchin & Pout, 2002). These include system average, marginal, and grid carbon intensity of plant built/avoided. Furthermore, more recent studies (Khan, 2018), (Khan *et al.*, 2018) have recognised the highly dynamic behaviour of grid carbon intensity and another type named “temporal” or “time-varying” was recognised. It is noted that the latter is the key focus of the present study.

Annual carbon intensity is not only used in carbon reporting schemes but also commonly found in published research about the emissions from the grid (Ang & Su, 2016), (Ang & Goh, 2016), (Goh *et al.*, 2018). Ang & Su (2016) presents a study covering a time period from 1990 to 2013 for 124 countries. In this case, the metric “aggregate carbon intensity” is defined as the energy related carbon emissions divided by the produced electricity. The aggregate carbon intensity for the United Kingdom for year 2013 is measured to 438g/kWh thus 5% and 8% lower than the DEFRA’s and this study’s annual average figures.

The simplest and most widely used type of electricity carbon intensity is the system average. This is calculated by dividing the total carbon emissions (usually over a year) by the total amount of electricity that was generated/transmitted/delivered. However, the annual average metric is not appropriate in all cases as the relationship between carbon intensity and electricity demand is far more complex. When a demand change occurs not all power stations are equally affected. While the operation of the base load plants usually remains unchanged, the change is typically met by a load-following plant (marginal). In the United Kingdom this plant was typically coal-fired back in 2002 as explained by Hitchin & Pout (2002). In more recent studies, Thomson *et al.* (2017) analysed the marginal generation for years 2009 to 2014 and indicated that while for years 2009 and 2010 coal dominated the mix, closed cycle gas turbines were mostly the marginal plants in years 2011 and 2012. Finally, gas, renewables and interconnected electricity were included in the marginal mix for the period 2012 to 2014. Finally, based on this study's findings, in recent years (2015 to 2017) the dominant plant in the British marginal mix is usually gas-fired (see section 3.5). Marginal generation and the relevant intensity are discussed in greater detail in the following section.

2.1.1 Marginal electricity carbon intensity

All grid connected power stations in GB notify their dispatch profile to the System Operator, National Grid on a half hourly basis. These notifications include their output and availability and can be revised up to a period of 1 hour prior to each half hour period (a Settlement Period), this period is termed 'gate closure'. After 'gate closure' National Grid, balances supply and demand by varying power stations and large demand units output in the Balancing Mechanism. BEIS (2016b) defines the marginal plant as "the power generating unit dispatched in each settlement period with the highest SRMC (Short Run Marginal Cost)" or "the power generating unit whose output in the relevant settlement period followed system demand" or "the power generating unit which post gate closure in each settlement period paid the highest amount on £/MWH basis to purchase power off the system and hence reduce its output or had the highest accepted cost to increase generation."

The importance of the accurate and active incorporation of the demand-side interventions into the carbon emissions calculation and the policy making is emphasised by Hawkes (2010). While marginal emissions play a role in the carbon reduction strategy certain weaknesses have been identified by (Hawkes, 2010) in the existing calculation methodologies. A certain fixed carbon reduction that "will occur" as a result of an intervention is assumed, while there is no guarantee this will actually be achieved. Furthermore, the impact of an intervention is often assessed against the carbon content of either grid-average electricity or a speculative marginal emissions rate. However, a change in demand does not affect all elements of the electricity system proportionally and as such the use of a system-average emissions factor could be misleading, as could a poorly chosen marginal rate. In reality, specific generators respond to system demand changes, and it is the carbon intensity of these generators that dictates the actual carbon reduction brought about.

In simpler terms, a small demand change would not affect equally all of the online plants since the plant that will respond to this change is the plant that turned on last, usually the most expensive (named the marginal plant). Thus, marginal emissions refer to the emissions afforded by the plant that adjusted its generation output to deal with a small demand intervention. Marginal emissions have gained increased interest in academic works of the past years with a few studies claiming that system-average emissions fail to reflect the operation of the grid "in the margin" (Siler-Evans *et al.*, 2012), (Hawkes, 2010), (Thomson *et al.*, 2017).

Hawkes (2010) calculated the reduction of carbon emissions caused by a demand side intervention (marginal carbon emissions rates) for the UK performing regression analysis on half-hourly data covering the period 2002 to 2009. The marginal factors (MEF) was estimated as 690 g/kWh $\pm 10\%$, a figure higher than the system average for the same period (510 g/kWh). Technology specific MEFs for heat pumps and micro-CHP plants were also calculated but the discrepancies to the average MEF were found to be small. Therefore, an average MEF is deemed adequate to assess all demand side interventions, regardless of whether they generate or consume electricity. Uncertainty in the future MEFs was recognised to arise from underlying economics, carbon prices, increased renewable penetration, aggregated demand from the electrification of vehicles and heating and new technologies in the generation mix. The same author also introduced a model for calculating long-run carbon marginal emissions (Hawkes, 2014). The results estimated the GB LR-MEF (Long-run marginal emissions factor) to vary from 260 to 530 g/kWh for the next decade, but is expected to reduce to nearly zero in 2030s while the grid decarbonises.

Siler-Evans *et al.* (2012), carried out a regional assessment of the marginal emissions factors for the USA based on the work by Hawkes (2010). Regression analysis was performed on hourly generation and emissions data covering the period from 2006 to 2011 in order to compare marginal and average avoided emissions. Marginal factors were shown to be either higher or lower than the average ones, depending on the location and the timing of the intervention.

Another GB specific study by (Thomson *et al.*, 2017), assessed the marginal greenhouse gas emissions displacement of wind power, described as the marginal displacement factor (MDF). In this case, it is shown that wind power affects the system similarly to a demand-reduction intervention since the marginal plant has to curb its output in order for the grid to accommodate the "must-take" wind generation. The analysis was carried out for the period 2009 - 2014 and the results revealed high discrepancies in the estimated MDFs. Notably, for years 2009 to 2010 when CCGT was being operated in preference to coal, the MDF was found to be high. Between 2011 and 2012 when coal dominated the grid while CCGT provided a greater proportion of the marginal mix the MDF decreased. Finally, for years 2012 to 2014 the factor reduced too, as coal generation decreased and renewables and low-carbon interconnected electricity met the balance.

Finally, the author in (Khan, 2018), (Khan *et al.*, 2018), acknowledged marginal emissions and identified the marginal plant to be hydro and oil in the electricity systems of New Zealand and Bangladesh respectively. However, the overall study was carried out using system average emissions in high resolution.

The carbon intensity of a typical, marginal plant is appropriate for assessing the instantaneous effect of small changes in the electricity demand that happen within a short timeframe but fails to reflect more substantial and longer term mechanisms (Hitchin & Pout, 2002). However, marginal emissions is an appropriate metric to calculate carbon savings (Siler-Evans *et al.*, 2012).

2.1.2 Carbon intensity of plant built or avoided

A change in electricity demand can affect the total carbon emissions by two different mechanisms, directly and indirectly (Hitchin & Pout, 2002). The direct impact regards the additional load that causes one or more of the load plants to operate for longer or shorter hours, or/and adjust their power output. This applies to small demand changes and, as explained in the above section, is referred as marginal generation.

The indirect impact that is typically caused by significant and persistent demand changes reflects changes in investment decisions (costs, operating patterns). Such a change can also influence the timing of the construction/type of the new plant. In the case of a substantial demand reduction, this may amount to a decision about the retirement of an existing plant. The emissions caused by such changes are given by the carbon intensity of plant built/avoided as defined by (Hitchin & Pout, 2002).

2.1.3 Temporal or time-varying electricity carbon intensity

One very recent study by (Khan *et al.*, 2018) looked into the impact of time-varying on GHG emissions assessment in New Zealand. Assuming that the metric of annual average masks the variability of carbon intensity caused by different fuel mixes (Khan *et al.*, 2018) argued that a more nuanced approach that takes into account time variability should be followed. This could achieve better management of current generation infrastructure in order to minimise GHG emissions and provide insight on how to incorporate this variability into future generation plans. Analysis of one year of data (2015) showed a daily variation of $\pm 10\%$ and a seasonal variation of $\pm 40\%$.

While New Zealand's electricity sector has almost 80% renewable generation, the same author (Khan, 2018) also applied the time-varying carbon intensity approach on the fossil fuel oriented electricity system of Bangladesh. A time-varying carbon pricing scheme has been also introduced in this study as a potential aid to policymakers. A linear relationship between carbon intensity and demand was noticed in this study, which was not the case for the renewable dominated New Zealand grid. Further findings regard potential demand side management measures during peak-time as an act to reduce GHG emissions and the need for improvement of the efficiencies of the power plants which were found to be lower than the standard average. Although the carbon-pricing scheme may not be appropriate or applicable in the near future to the developing electricity system of Bangladesh the author (Khan, 2018) suggests that it could be used as a tool for future policy making.

A different study carried out for the United Kingdom looked into grid carbon intensity as part of the progress and impacts of decarbonising British electricity. According to Staffell (2017), "the carbon intensity of electricity is an important metric, widely used for assessing the impacts of electric vehicles, electric heating, microgeneration and demand reduction on national emissions". The grid carbon intensity of British electricity peaked at 508 g/kWh in 2012, and has since fallen 30% until 2015. December, 2015 was found to have the lowest ever carbon intensity (150 g/kWh) as a result of warm temperatures and high wind output (Staffell, 2017).

Electricity grid carbon intensity, as explained above, typically measured in CO_2 eq. g/kWh, seeks to quantify the amount of carbon dioxide emissions allocated to each unit of electricity, generated, transmitted or consumed. The formula for the grid carbon intensity calculation is given in eq. (2.1). This formula is consistent with the methodology followed by the National Grid's API forecast (N.G, 2017), other members of the scientific community (Staffell, 2017), (Lau *et al.*, 2015) and the Grid Carbon application (Rogers & Parson, 2017).

$$CI(t) = \frac{\sum_{n=1}^{N} c_n \cdot E_n(t)}{\sum_{n=1}^{N} E_n(t)} \tag{2.1}$$

where n is the fuel type index, N is the total number of fuels, c_n is the carbon factor for fuel n and E_n is the generated energy corresponding to fuel n at given time t.

As seen in the equation the individual power plant c_n carbon factors have a great impact on the calculation of grid emissions. Here, the term carbon factor is used to describe the total amount of greenhouse gases that is emitted per kWh by a specific electricity generating plant. Significant discrepancies were discovered in the carbon factors of the same power plant type across the literature. These discrepancies are caused by the different efficiency, age, whether life cycle assessment and which stages of LCA were considered when the emissions were calculated. A review of literature sources is carried out in detail in section 2.2.1.

2.2 Life cycle assessment of carbon emissions for different generating plants

Life cycle assessment (LCA) is a technique for assessing and evaluating the environmental consequences and impacts of products and services across all life stages (from cradle to grave) (Asdrubali *et al.*, 2015), (Varun *et al.*, 2009). According to (ISO4040, 2006) LCA is carried out by iterating four different phases, goal and scope definition, LCA inventory, life cycle environmetal impact assessment and interpretation. Regarding, energy LCA, there are several well established methodologies. Some of the most used are: IPCC method which calculates the total CO_2 emissions, the CED method which evaluates the total energy that has been used and the Ecoindator that assesses eleven different impact areas (Asdrubali *et al.*, 2015). As all electricity generating technologies emit some carbon emissions at some point in their life cycle, LCA is a recognised tool to assess the overall sustainability of different electricity sources.

The life cycle of an electricity generation plant includes typically the construction, the operational and the decommissioning phases. Fossil-fuel based power technologies are more dependable and flexible than nuclear reactors and intermittent renewables plus they are vital for the second-by-second balancing of supply and demand (Green & Staffell, 2016). However, they emit substantially more greenhouse gases during their operation (Green & Staffell, 2016). Lave and Freeburg (Lave & Freeburg, 1973) highlighted that coal power plants were responsible for more emissions not only from direct combustion but also from mining and transport.

It has been argued that carbon emissions from renewable energy systems are not nil, opposed to popular belief, (Varun *et al.*, 2009). The low carbon electricity generation technologies such as wind, solar and nuclear do not cause direct emissions during their operational phase but they are still responsible for some emissions during the other phases of their life such as construction, maintenance and decommissioning. However, all renewable technologies have significantly lower LCA emissions compared to the fossil ones (Varun *et al.*, 2009), (Weisser, 2007).

In the majority of the existing studies, carbon factors consider only the emissions caused directly at the point of electricity generation, such as when coal is burnt in a coal-fired power station. To provide a more accurate picture of the emissions caused by generation technologies, all stages of their life cycles must be considered; These include their construction and maintenance; the extraction, processing and transport of their fuels (if applicable); and their ultimate decommissioning and disposal. Inconsistencies are being noticed when looking at the values of carbon factors for different electricity generating technologies in different countries (Hondo, 2005), (Odeh & Cockerill, 2008), (Lau *et al.*, 2014a), (Staffell, 2017). The reasons behind this as explained by (Baldwin, 2006) are differences between individual plants (some older and/or less efficient), different technologies(e.g. run-of-river vs. reservoir storage), different life-cycle assessment input (boundary definition) parameters and different studies (date).

2.2.1 International carbon factor review of different generating plants

To understand the noticed inconsistencies, a review of international literature was carried out which points to a wide range of carbon factor values for different plant types (Turconi *et al.*, 2013), (Hondo, 2005), (Odeh & Cockerill, 2008), (Varun *et al.*, 2009), (Staffell, 2017), (Rogers & Parson, 2017), (Lau *et al.*, 2014a), (Lau *et al.*, 2014b). This review considers international studies alongside UK references and notes reasons underlying some marked differences.

Turconi *et al.* (2013) conducted a wide review of 167 inernational case studies regarding the life cycle assessment of different types of electricity generating plants. The carbon emissions were then assessed against three life cycle stages that include: fuel provision from the extraction of fuel to the gate of the plant, plant operation and maintenance including residue disposal and infrastructure that includes commissioning and decommissioning of the plant. Significant variations were found, even for the same individual electricity generating technology. The identified discrepancies were shown to originate from the energy recovery efficiency and the fuel gas cleaning system for fossil fuel based plants and from the electricity mix used during both the manufacturing and the installation phase for nuclear and renewable generation plants.

Hondo (2005) carried out life cycle assessment of carbon emissions for nine types of electricity generating technologies in Japan. This study considered emissions during the construction and operation phases for all technologies but nuclear where decommissioning was also assessed. The results indicated that the vast majority of LCA emissions of wind and solar electricity generation plants is associated with the construction phase. For fossil fuel technologies the majority of emissions are direct and occur during the operational phase from the combustion of the fuel.

Varun *et al.* (2009) looked into ten international case studies to evaluate the LCA emissions for different types of electricity generating technologies and considered the construction, operation and decommissioning phases. Fossil fuel plants were compared with renewable energy technologies and the results were clearly in favour of the second. However, solar PV technologies were shown to be responsible for a significant amount of emissions. It is noted that this study assigned the highest carbon factor to solar PV in table 2.2.

Odeh & Cockerill (2008) examined life cycle emissions from UK coal power plants. This study considered the emissions from the construction, operation and decommissioning phases and specified that the operational phase includes the upstream (mining and transport) and the downstream processes (waste disposal and recovery of land). Consistently with previous studies, the results indicated that the majority of direct emissions is due to fuel combustion during the operational phase. Furthermore, it was shown that methane leakage during the mining phase is responsible for the majority of indirect emissions.

Finally, the authors in (Staffell, 2017) and (Rogers & Parson, 2017) consider only operational emissions in their work while the author in (Lau *et al.*, 2014a) and (Lau *et al.*, 2014b) considers life cycle emissions without providing details about the stages considered.

Examining separately each power station type and their corresponding carbon factors, high discrepancies are observed for renewable power systems. The carbon factors for wind turbines display a range of 38 g/kWh according to Turconi *et al.* (2013). Since the greatest proportion of carbon emissions are produced during the manufacturing process the total figure is heavily dependent on the grid carbon intensity for different countries. Onshore and offshore turbines have similar carbon emissions, since the higher efficiencies of offshore plants compensate for their heavier manufacturing process (Arvesen & Hertwich, 2012). An even higher range up to 114 g/kWh is estimated by Varun *et al.* (2009). The lowest limit of the range at 9.9 g/kWh is calculated for onshore wind in Denmark while the highest one (123.7 g/kWh) is observed in a Japanese case study (Varun *et al.*, 2009). The findings of Turconi *et al.* (2013) agree with Varun *et al.* (2009), the discrepancy noticed in emissions of onshore and offshore wind energy is only 2 g/kWh while the largest carbon contribution originates from material manufacturing.

For solar energy technologies, Hondo (2005) calculates the emissions of Japanese rooftop type polycrystalline silicone solar pV of 3KV to 26 g/KWh while the calculated ranges for the international studies by Varun *et al.* (2009) and Turconi *et al.* (2013) are 200 and 177 g/kWh respectively. The carbon emissions assigned to solar technologies indicate this high variability due to different grid carbon intensity of the country during manufacturing (Turconi *et al.*, 2013), solar panel typology (Fthenakis & Chul, 2007) and climate conditions during installation.

In the work by (Turconi *et al.*, 2013) emission factors for nuclear power are shown to vary greatly, with differences of up to one order of magnitude (3 to 35 g/kWh). For this type of generation, the lowest range of 32 g/kWh is observed across the whole body of reviewed literature. All studies agree on the majority of carbon emissions coming from the uranium extraction (Turconi *et al.*, 2013) and enrichment (Hondo, 2005) processes. Although nuclear carbon factors are lower than coal and gas based technologies, the disposal of radioactive materials has the potential to cause higher damage to the surroundings (Varun *et al.*, 2009).

Hydropower technologies such as reservoir dam schemes and run-of-river plants are assigned carbon factor ranges of 203 g/kWh (Varun *et al.*, 2009) to 338 (Turconi *et al.*, 2013). These variations are explained by the used technology type, different local climate conditions, reservoir size, water depth, type and amount of flooded vegetation and soil type (Weisser, 2007), (Gagnon & van de Vate, 1997), (Dones *et al.*, 2004). Hydropower plants in tropical climates produce more emissions, i.e 340 g/kWh in Brazil as opposed to 0.3 to 35 g/kWh in Finland (Turconi *et al.*, 2013). This is due to high quantities of biomass mostly in the forest cover and warm conditions with decomposition process at continuous work for twelve months per annum (Varun *et al.*, 2009, pp 1071).

For coal-based power system types a more modest variation of 15 g/kWh Staffell (2017) is noticed for plants located in the United Kingdom. In this case, this is due to the net efficiency discrepancy that measures up to $\pm 0.5\%$. As with other fuels, studies that review international plants yield wider ranges of 390 g/kWh (Turconi *et al.*, 2013) while the remaining studies assign single values that vary from 910 to 989.7 g/kWh (Odeh *et al.*, 2008), (Hondo, 2005). For coal-based technologies, the majority of carbon emissions is produced during the operation phase, hence the variability is caused by different types of technology, process efficiency and age of plant.

Finally, for gas based electricity generating technologies that include both open and closed cycle gas turbines, the carbon factor ranges are shown to vary from 88 for Japan (Hondo, 2005) to 620 g/kWh for international case studies (Turconi *et al.*, 2013). It is also noticed that discrepancies of 0.4% and 0.7% in the net efficiencies cause variation of 10 and 6 g/kWh in the relevant carbon factors for open cycle gas turbine and closed cycle gas turbine plants respectively (Staffell, 2017).

The carbon factors assigned to coal, oil, gas (including CCGT and OCGT technologies), nuclear, hydro, solar and wind plants are presented in tables 2.1 and 2.2. High discrepancies have been noticed in all types of generating plants. For renewable technologies, climate conditions, material manufacturing, source and location of electricity used and type of technology all impact the LCA carbon emissions. For conventional coal and gas plants, the majority of emissions is being produced during the operational phase, hence type of technology, efficiency and age of the plant are the factors that create the variability. The uncertainty that is caused in the grid carbon intensity calculation by different carbon factor assumptions needs to be recognised and investigated. It is realised that the ranges of carbon factors in the international case studies of the literature include climate conditions and grid intensity which are very dissimilar to the United Kingdom. Thus, for the purposes of this study, the carbon factors from two UK specific studies (Lau *et al.*, 2014a) and (Staffell, 2017) were selected in order to quantify the impact on annual and half-hourly grid carbon intensity values (section 3.6).

	Author(s)	*Country of study*	*LCA*	*Value (g/kWh)*
Wind				
	(Turconi *et al.*, 2013)	167 international case studies	fuel provision, plant operation, infrastructure	3–41
	(Hondo, 2005)	Japan	construction, operation,	29
	(Varun *et al.*, 2009)	10 international case studies	construction, operation, decommissioning	9.7-123.7
	(Staffell, 2017)	UK	operation only	0
	(Rogers & Parson, 2017)	UK	operation only	0
	(Lau *et al.*, 2014a)	UK	not specified	96
	(Lau *et al.*, 2014b)	UK	not specified	20-94
Hydro				
	(Turconi *et al.*, 2013)	167 international case studies	fuel provision, plant operation, infrastructure	2–340
	(Hondo, 2005)	Japan	construction, operation,	11
	(Varun *et al.*, 2009)	10 international case studies	construction, operation, decommissioning	3.7-237
	(Staffell, 2017)	UK	operation only	0
	(Rogers & Parson, 2017)	UK	operation only	0
	(Lau *et al.*, 2014a)	UK	not specified	13
	(Lau *et al.*, 2014b)	UK	not specified	2–13
Solar				
	(Turconi *et al.*, 2013)	167 international case studies	fuel provision, plant operation, infrastructure	13-190
	(Hondo, 2005)	Japan	construction, operation,	26
	(Varun *et al.*, 2009)	10 international case studies	construction, operation, decommissioning	53.4-250
	(Staffell, 2017)	UK	operation only	0
	(Rogers & Parson, 2017)	UK	operation only	0

Table 2.1: Carbon factors for renewable power systems.

	Author(s)	*Country of study*	*LCA specification*	*Value (g/kWh)*
Coal	(Turconi *et al.*, 2013)	167 international case studies	fuel provision, plant operation, infrastructure	660-1050
	(Hondo, 2005)	Japan	construction, operation	975.2
	(Varun *et al.*, 2009)	10 international case studies	construction, operation, decommissioning	975.3
	(Staffell, 2017)	UK	operation only	922-952
	(Rogers & Parson, 2017)	UK	operation only	910
	(Odeh & Cockerill, 2008)	UK	construction, operation [1], decommissioning	989.7
	(Lau *et al.*, 2014a)	UK	not specified	990
	(Lau *et al.*, 2014b)	UK	not specified	788-899
Gas				
	(Turconi *et al.*, 2013)	167 international case studies	fuel provision, plant operation, infrastructure	380-1000
	(Hondo, 2005)	Japan	construction, operation	518-606
	(Varun *et al.*, 2009)	10 international case studies	construction, operation, decommissioning	607.6
	(Staffell, 2017)	UK	operation only	388-661
	(Rogers & Parson, 2017)	UK	operation only	360-480
	(Lau *et al.*, 2014a)	UK	not specified	488
	(Lau *et al.*, 2014b)	UK	not specified	367-586
Oil				
	(Turconi *et al.*, 2013)	167 international case studies	fuel provision, plant operation, infrastructure	530-900
	(Hondo, 2005)	Japan	construction, operation	742
	(Varun *et al.*, 2009)	10 international case studies	construction, operation, decommissioning	742.3
	(Staffell, 2017)	UK	operation only	813-1057
	(Rogers & Parson, 2017)	UK	operation only	610
	(Lau *et al.*, 2014a)	UK	not specified	700
	(Lau *et al.*, 2014b)	UK	not specified	600-699
Nuc.				
	(Turconi *et al.*, 2013)	167 international case studies	fuel provision, plant operation, infrastructure	3–35
	(Hondo, 2005)	Japan	construction, operation, decommissioning	24
	(Varun *et al.*, 2009)	10 international case studies	construction, operation, decommissioning	24.2
	(Staffell, 2017)	UK	operation only	0
	(Rogers & Parson, 2017)	UK	operation only	0
	(Lau *et al.*, 2014a)	UK	not specified	26
	(Lau *et al.*, 2014b)	UK	not specified	20-26

Table 2.2: Carbon factors for conventional power systems.

[1] including upstream and downstream processes

2.3 A timeline of carbon policy in Great Britain and its impact on grid carbon intensity

Energy policy area is among the most important drivers that have the potential to drastically curb carbon emissions and change the electricity grid and the fuel mix (Cairney *et al.*, 2019). Must-follow legislative measures can successfully drive down greenhouse gas emissions especially on the business level. Key processes that influence the energy regime at the carbon-related policy level as explained by (Foxon *et al.*, 2010) include: "public awareness of climate change and willingness to accept and undertake changes in response, government commitments to meet national and international targets for emission reductions and the promotion of low carbon energy sources, ideological commitments to liberalized energy markets, concerns over security of primary energy supplies, external factors leading to high and/or volatile oil and gas prices, related concerns over energy affordability and fuel poverty, factors which could lead to physical disruption of external supplies (war, terrorism, foreign governments limiting supply), changes in the international economic and financial situation, such as those associated with the current credit crunch". Below, an overview of the UK low-carbon energy policy is being described as presented in the briefing paper on Energy Policy by the House of Commons in 2016 (White & Hough, 2016):

Climate Change Act was introduced in 2008 and set a statutory target for the UK to achieve an 80% reduction in greenhouse gases by 2050 against a 1990 baseline, by setting five yearly carbon budgets.

The UK Carbon Plan in 2011 set the required measures to meet the first three carbon budgets. The 4th carbon budget was agreed in 2011 with a target of a reduction of emissions of 52% compared to 1990 levels while the 5th carbon budget was planned by June 2016.The Climate Change Committee, the statutory body set up to monitor and advice on progress towards the 2050 climate targets, has submitted its recommendation to the Government that the budget should be set at 57% for the fifth budget.

The UK is also legally bound to achieve a renewable energy target of 15% by 2020, as part of the European Union's overall target of 20% renewables by that date.

In addition, the Paris Climate Change conference was held in December 2015 following up the Kyoto Protocol. According to this, an aim was set for emissions to peak "as soon as possible" and for emissions from human activity and absorption by carbon sinks to balance some time in the second half of the century (White & Hough, 2016), (UKCCC, 2016).

Electricity market reform was initiated in 2010, implemented in the Energy Act of 2013 and set targets such as decarbonisation of electricity generation and cost reduction of electricity for the consumers (White & Hough, 2016).

The Carbon Plan, published in 2011 is a government wide action that brings together the strategies to curb greenhouse gas emissions and deliver climate change targets. Regarding the electricity sector, the three key parts of the portfolio are renewable power, nuclear power, and coal and gas-fired power stations fitted with carbon capture and storage (DECC, 2011a). By 2050, emissions from the power sector need to be close to zero. With the imminent electrification of heating and transport, average electricity demand may rise by between 30% and 60%. As a result, the grid might require as much as the current capacity to deal with peak demand (DECC, 2011a). "Electricity is likely to be produced from three main low carbon sources: renewable energy, particularly onshore and offshore wind farms; a new generation of nuclear power stations; and gas and coal-fired power stations fitted with CCS technology. Fossil fuels without CCS will only be usedas back-up electricity capacity at times of very high demand. The grid will need to be larger, stronger and smarter to reflect the quantity, geography and intermittency of power generation and be able to cope with the supply and demand fluctuations" (DECC, 2011b).

Alternative measures such as the Climate Change Levy (CCL) and Climate Change Agreements (CCAs) are also in place in the United Kingdom. The CCL, introduced in 2001, aims to reduce energy consumption on the non-domestic level by by taxing the supply of specified energy products such as electricity, gas and coal for use as fuels (DECC, 2014b). Carbon taxes are generally considered to have a positive environmental impact although concerns have been raised about the resulting increased utility costs (Mclaughlin *et al.*, 2019). CCAs are voluntary agreements giving a variety sectors a discount on the Climate Change Levy in exchange for signing up to energy efficiency or carbon reduction targets (DECC, 2014b).

Revewing the timeline of the UK energy policies and its impact on carbon emissions, the decarbonisation progress in the power sector in 2016 is considered to be "good" (White & Hough, 2016) as the total penetration of renewables in the grid has been steadily increasing since 2009 (DECC, 2015) while the UK contains complex constantly evolving mechanisms to promote energy efficiency with various authorities being involved in the development, implementation and monitoring processes (Malinauskaite *et al.*, 2019). Nevertheless, criticism has been made on energy efficiency policies on the domestic level regarding their limited scope, the consumer cost and the way of implementation (Hinson *et al.*, 2018). Finally, the Climate Change Committee did warn that achieving the successively stringent targets will become increasingly challenging (White & Hough, 2016).

2.4 Grid carbon intensity in a UK carbon reporting framework

Carbon accounting and reporting procedures are inherently dependent on the relevant policies already in place. Baboukardos (2017) highlights the benefits of mandatory carbon reporting while (Tauringana & Chithambo, 2015, p. 425) argue that "non-mandatory guidance could increase disclosure as much as do mandatory requirements". Carbon accounting has the potential not only to monitor the overall decarbonisation progress on a country level, but also to develop and inform Climate Change mitigation policy (Barrett *et al.*, 2013). The main carbon reporting schemes in the UK are ESOS, CRC (to be replace by SECR in the near future) and the regulatory requirement for company reporting of greenhouse gas (GHG) emissions using DEFRA factors, which is the scheme of greatest relevance to the present study. A brief outline of the schemes is given below.

ESOS is a mandatory energy assessment scheme for organisations in the UK. Organisations that qualify for ESOS must carry out ESOS assessments every 4 years. These assessments are audits of the energy used by their buildings, industrial processes and transport to identify cost-effective energy saving measures (DECC, 2014a). The type of organisations that needs to report to ESOS is any UK company that either employs 250 or more people, or has an annual turnover in excess of 50 million euro (£38,937,777), and an annual balance sheet total in excess of 43 million euro (£33,486,489).

The CRC energy efficiency scheme (Carbon Reduction Commitment) was announced in 2007 and introduced in 2010. Under the scheme, organisations that consumed over 6,000 megawatt-hours (MWh) of electricity through settled half-hourly meters during the year are required to monitor their energy use, report their energy supplies and buy allowances for every tonne of carbon they emit (DECC, 2016). The Government proposes that the Streamlined Energy and Carbon Reporting (SECR) scheme will be applied from April 2019 to replace the expiring CRC phase (DECC, 2017b). The proposed means for reporting is company accounts in line with other existing initiatives such as ESOS and mandatory greenhouse gas (GHG) reporting.The new SECR reporting framework will apply to all quoted companies and apply to large UK incorporated unquoted companies; those with at least 250 employees, or annual turnover greater than £36m, and an annual balance sheet total greater than £18m. (Two or more of the criteria apply to a company within a financial year) (DECC, 2017b). The said companies would have to disclose Scope 1&2 emissions according to the GHG methodology (Scope 3 will remain voluntary) and publish an intensity metric in their annual reports, report on global energy use and provide a narrative commentary on energy efficiency action taken in the financial year (DECC, 2017b).

In April 2013, the UK government introduced a regulatory requirement for company reporting of greenhouse gas (GHG) emissions in their Director's Annual Report and Accounts (DECC, 2013a). This has undergone parliamentary clearance and came into force in October 2013. Companies that are now required to report their Scope 1 (direct) and Scope 2 (indirect) emissions. As defined by Section 385(2) of the 2006 Companies Act, this applies to companies that are: UK quoted, UK incorporated and whose equity share capital is officially listed on the main market of the London Stock Exchange or in a European Economic Area or is admitted to dealing on either the New York Stock Exchange or NASDAQ (DECC, 2013a). The three scopes of identifying and categorising emissions are as follows (DECC, 2013a, p. 48):

- *Scope 1* (Direct emissions): Activities owned or controlled by the organisation that release emissions straight into the atmosphere. They are direct emissions. Examples of scope 1 emissions include emissions from combustion in owned or controlled boilers, furnaces, vehicles; emissions from chemical production in owned or controlled process equipment.
- *Scope 2* (Energy indirect): Emissions being released into the atmosphere associated with the consumption of purchased electricity, heat, steam and cooling. These are indirect emissions that are a consequence of the organisation's activities but which occur at sources the company does not own or control.
- *Scope 3* (Other indirect): Emissions that are a consequence of the company's actions, which occur at sources which the company does not own or control and which are not classed as scope 2 emissions. Examples of scope 3 emissions are business travel by means not owned or controlled by the organisation, waste disposal, or purchased materials or fuels.

To account for their electricity related emissions businesses are provided with a single number of gird carbon intensity that is updated annually and represents the last calendar year. Limited literature has been identified that reviews and critiques the robustness of the GHG reporting scheme. While Haslam *et al.* (2014) questions the malleability associated with the three scope classification and the soft boundaries of ownership of the reporting entity, Bebbington *et al.* (2019) argues for an additional "Scope 4" future emissions. Since fossil fuel reserves are finite and known, there is scope to convert such data to likely future electricity grid emissions. In such a case, interested parties and stakeholders could "make their own judgements regarding risks associated with unburnt carbon in the context of known carbon budgets" (Bebbington *et al.*, 2019, p. 16). Although the argument for accounting for future greenhouse emissions is certainly valid, another one could be made about the time-varying nature of the grid emissions.

Power system management is a highly dynamic progress that involves balancing supply and demand minute by minute. While dispatchable power plants have to adjust their outputs, must-take renewables further amplify the continual fuel mix changes. It has already been indicated that different plant types have carbon factors that range from zero (for a wind or solar plant if just the operational emissions are considered) to 1050 g/kwh (for a coal plant) (tables 2.1, 2.2). Different fuels are expected to have a significant effect on the figure that reflects the total grid emissions at any given time so it can be argued that a single annual value does not fully represent the grid operation. Tranberg *et al.* (2019) introduced a method of real time consumption-based carbon accounting for the European electricity systems. This method traces the power flows from production to consumption and significant differences were measured for the respective carbon intensities. These differences are attributed to the variant fossil fuel share of interconnected imported electricity. This power flow method could also be applied on country level if data is available in high spatial resolution or to simulate electrification of vehicles and heating. Finally, it has the potential to lay the foundation for time-varying electricity taxes (Tranberg *et al.*, 2019, 4).

2.5 Future grid carbon intensity uncertainty

Driven by national and international Climate Change policies, the UK electricity sector is undergoing a significant transition. Aging power plants are expected to retire and affect the capacity margins (Sithole *et al.*, 2020), new heating technologies (Lindberg *et al.*, 2019) and the electrification of vehicles will likely cause increased demand but at the same time have the potential to provide storage solutions and ancillary services to the system. Furthermore, although high renewable grid penetration will aid the system defossilisation, it is anticipated to challenge the supply security and the system flexibility (Child *et al.*, 2019). All these factors constitute substantive sources of uncertainty for the future of the electricity grid emissions.

In an attempt to explore this uncertainty National Grid has outlined different credible pathways for the future of energy for the next 30 years and beyond. An overview of those scenarios, Consumer Evolution, Community Renewables, System Progression and Two Degrees for 2030 are given in tables 2.3 and 2.4 (N.G, 2018a, p. 3). Among the four scenarios, only two of them, Community Renewables and Two Degrees achieve the 2050 decarbonisation target. Given the different conditions pertaining demand, transport, heat and electricity supply carbon intensity is projected to develop differently (figure 2.1). These values have been simulated with BID3, a generation dispatch model that optimises total system cost and outputs total generation in hourly resolution (N.G, 2018a). Dispatch models are discussed in greater detail in later sections of this study. Then, carbon intensity is calculated according to the following formula (N.G, 2018a, p. 15):

$$Carbon \quad intensity(g/kWh) = \frac{Carbon \quad emissions \quad from \quad generation(g)}{Electricity \quad generation \quad output(kWh)}$$

According to BID3 projections grid carbon intensity decreases to 74, 48, 117 and 136 g/kWh under 2030 Community Renewables, Two Degrees, Steady Progression and Consumer Evolution scenarios respectively. Furthermore it falls to 32, 20, 52 and 72 g/kWh under the 2050 scenario assumptions (N.G, 2018a, p. 97). Once more, it is noticed that future emissions are “flattened” and described in total annual values. The challenges of modelling a possible future grid are acknowledged but the need to further examine the system behaviour in a higher resolution remains. A dispatch model similar to the one used by National Grid could be used to produce time-series of grid carbon intensity in hourly or half-hourly resolution under the Future Energy Scenario installed capacity assumptions (see section 4.6).

Exploring the potential transition pathways sheds light on the uncertainty of the system capacity development. However, another substantive source of both current and future uncertainty of electricity emissions is the variability of renewables.

	Consumer Evolution	*Community Renewables*
electricity demand	Moderate-high demand: high for (EVs) and moderate efficiency gains	Highest demand: high for EVs, high for heating, good efficiency gains
transport	Most cars are EVs by 2040; some gas used in commercial vehicles	Most cars are EVs by 2033; great use of gas in commercial vehicles
heat	Gas boilers dominate; moderate levels of thermal efficiency	Heat pumps dominate; high levels of thermal efficiency
electricity supply	Small scale renewables and gas; small modular reactors from 2030s	Highest solar and onshore wind

Table 2.3: Consumer Evolution and Community Renewables scenarios (based on (N.G, 2018a, p. 3)).

	Steady Progression	*Two degrees*
electricity demand	Moderate-high demand: high for EVs and moderate efficiency gains	Lowest demand: high for EVs, low for heating and good efficiency gains
transport	Most cars are EVs by 2040; some gas used in commercial vehicles	Most cars are EVs by 2033; high level of gas used for commercial vehicles
heat	Gas boilers dominate; moderate levels of thermal efficiency	Hydrogen from steam methane reforming from 2030s, and some district heat; high levels of thermal efficiency
electricity supply	Offshore wind, nuclear and gas; CCUS[2] gas generation from late 2030s	Offshore wind, nuclear, largescale storage and interconnectors CCUS gas generation from 2030

Table 2.4: Steady Progression and Two Degrees scenarios (based on (N.G, 2018a, p. 3)).

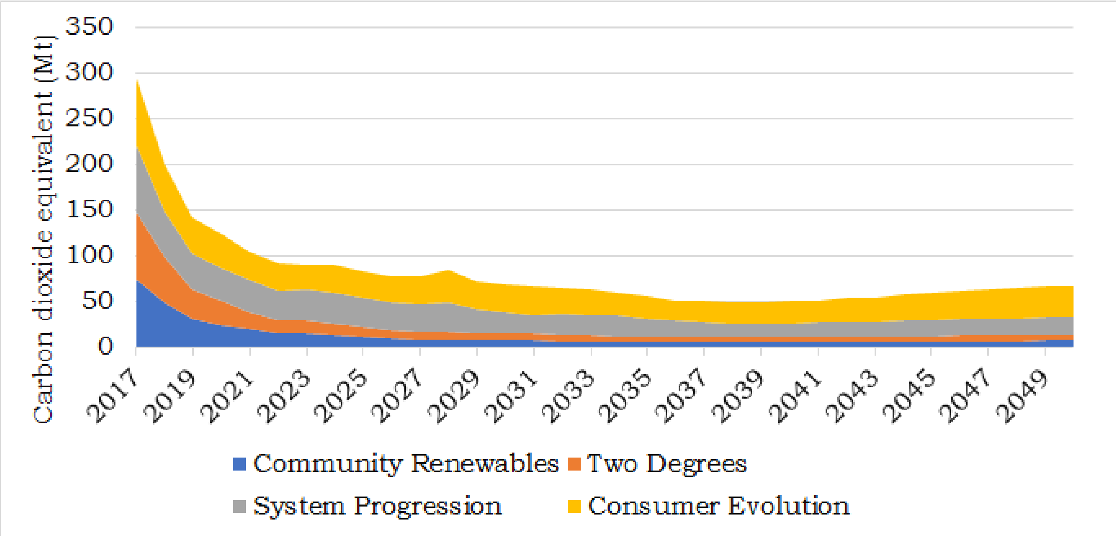

Figure 2.1: Carbon intensity ($CO_2eq.$ Mt) for Future Energy Scenarios (based on data workbook from N.G (2018a)).

2.5.1 Renewable variability and the arising uncertainty

As the United Kingdom is legally bound to reduce their greenhouse emissions grid decarbonisation is already in process. Among other schemes such as the feed in tariff, emissions performance standard and the carbon price floor an attempt to meet the national energy demands with cleaner generation technologies is already in place. The majority of renewables are likely to come from wind and solar as other types of non-fossil energy solutions such as hydro and bioenergy are constrained by limited resource and higher costs (Joos & Staffell, 2018). Although concerns were initially raised whether renewables may not be available at sufficient quantities at competitive prices or even not acceptable on social or political grounds (Weisser, 2007), generation by fuel type data from Elexon show that wind generation has been successfully increasing since 2009 in the United Kingdom at a rapid rate (see chapter 3). However, as further decarbonisation goals become increasingly demanding, the way forward and the transition from a fossil fuel based grid to a near zero-carbon is not trivial.

Seasonality, variability, limited predictability (Galvan *et al.*, 2006), (Eltigani & Masri, 2015) and intermittency are the key characteristics that may hinder the introduction of carbon-free energy sources into the grid (Connolly *et al.*, 2010). Perry *et al.* (2008) questions whether the non-reliable and intermittent nature of renewables will challenge the stability of the supply mix while (Sharifzadeh *et al.*, 2017, 385) argues that their application will enhance the energy security by diversification of the supply. Coker *et al.* (2013) have looked into the assessment of the variability of renewables; where variability is considered as a combination of different characteristics instead of a single parameter. To smooth the effects of this variability, energy supplied from the combination of wind, solar and tidal instead of a single renewable source was shown to have a more symmetrical distribution and lower spread (Coker *et al.*, 2013). Furthermore, "complementarity and substitutability of technologies" (Fais *et al.*, 2016, 164) and flexibility are the key enablers for successful renewable integration. Renewable resources such as wind and solar provide unprecedented opportunities for defossilisation of the power system and it is possible to integrate them into the existing grid infrastructure and overcome the uncertainties in both supply and demand sides, provided that such uncertainties inform the design of the grid while operational decisions are optimized in real-time (Indra al Irsyad & Halog, 2019). Once more, the existing literature highlights the need to take into account the "time" element of system operation to examine the impact of renewable variability. Carbon emissions that arise from the electricity generation are expected to reduce while zero-carbon energy sources dominate the mix. Similar to the capacity projections of Future Energy Scenarios, renewable sources are highly variable. Hence, a dispatch model could be used to simulate different wind and solar outputs and investigate the behaviour of grid emissions from one hour to the next.

In this light, exploring the uncertainty regarding the system operation Staffell & Pfenninger (2018) assessed the impact of increasing weather output under projected demand and capacity assumptions. The most important qualitative finding of this study was that the net zero demand and thus zero grid carbon intensity may occur as early as 2021 and become a regular occurrence by 2030 (under the Two Degrees capacity assumptions) due to the increasing wind and solar output. This finding, further supported by the results of chapter 4, indicates that the amount of wind and solar in the mix will be adequate so that no dispatchable plants would have to turn on in order to meet demand. Although the infrastructure for such a grid operation, that runs solely on renewables, is yet to be realised (Indra al Irsyad & Halog, 2019), the theoretical foundations are already in place.

2.5.2 Electrification of vehicles

Amidst global efforts to mitigate climate change there is widespread attention to decarbonising electricity grids and increasing electrification of transport. This implies a growing coupling between power system operation and reduction of carbon emissions from transport, with accompanying concerns whether power systems have the capability to meet the resulting load increase. Notwithstanding such concerns there is also some optimism that flexible charging of electric vehicles could provide flexibility that actually supports grid operation.

However, projected demand changes are expected due to electric vehicles. While the national electricity demand profile follows a regular and predicable pattern, it is projected to change in the future mostly due to de-industrialisation and new demand side technologies (electric vehicles and heat pumps) (Boßmann & Staffell, 2015). While previous studies assumed that the future demand profile would equally expand across the day, Boßmann & Staffell (2015) showed that the impact of heat and transport electrification is more pronounced during peak hours. Projections estimated that an additional 30 GW of capacity would be required by 2050 in the UK to meet peak demand. Regarding the demand side management on the electrification of transport, smart charging strategies are strongly recommended for net load smoothing and efficient integration of renewables.

A number of countries have now announced phase-out dates for new diesel/petrol cars (2025 - Norway, 2030 - Ireland, Netherlands and Slovenia and an India aspiration, 2032 - Scotland, 2040 UK and France) with many polluted cities setting more aggressive targets including Oxford, Paris, Athens and Madrid (IEA, 2018). National Grid's EV Project Director is encouraging the UK to pull forward the UK Government 2040 target (for the banning of the internal combustion engine only car) to 2030 target (HOC, 2018).

There are many documented comparisons of diesel/petrol vs. electric cars, however each has a different set of assumptions that can significantly impact the outcome. These include: scope of study; carbon intensity of the electricity system; size and fuel efficiency of cars assessed; nature of driving; life-time mileage assumptions; availability of manufacturing bills of materials and methods. The carbon intensity of the grid is the greatest of these factors – as it contributes to all of the in-life emissions of electric vehicles, as well as a significant proportion of vehicle manufacturing emissions.

In 2010 it was estimated that in China, life-cycle emissions of EVs were actually 6.7% greater than internal combustion vehicles (ICE), due to the heavy weighting towards coal powered generation of the electricity system. This is projected to change to 10.4% lower than ICE by 2020 and will continue to improve as the Chinese grid decarbonises (Wu *et al.*, 2018). From a European standpoint the numbers look much more favourable for electric vehicles. Vrije Universiteit Brussel (Van Mierlo *et al.*, 2017) developed a tool based on multiple life-cycle studies and estimated that the life-cycle emissions for a fully electric vehicle are currently around a third of a comparable diesel vehicle – assuming an electricity system carbon intensity of around 250g/kWh, similar to the UK 2017 carbon intensity (see figure 3.8). Around two-thirds of the EV emissions come from the fuel, and due to the annual improvements in global electricity carbon intensities, the emissions per mile will drop for EVs throughout their life. This estimate was backed up in the IEA Global EV Outlook report (IEA, 2017) which presents a "well to wheels" comparison, suggesting emissions for fully electric cars are less than 50% of diesel cars in Europe, and this should be replicated across the world as global policies to reduce carbon emissions continue to be implemented.

Electrification of vehicles effectively links the environmental performance of vehicles to the environmental performance of the electricity grid. Clear, timely and accurate estimation of carbon emissions to vehicles is needed to ensure effective progress. By utilising grid intensity values in high resolution, different emissions scenarios can be calculated depending on the charging profiles for different times of the day while carbon savings can be calculated in projected grid conditions.

2.5.3 Future heating solutions and their potential carbon savings in the immediate and long-term future

Since space heating in the United Kingdom is predominantly provided by fossil fuels, without policy intervention the risk of a gas lock-in that hinders the policy goal of decarbonisation is real (Eyre & Baruah, 2015). Cogeneration plants and heat pumps are found amongst the most discussed heating technologies of the current and future UK electricity grid. While cogeneration uses a fuel with a set carbon factor in the case of this study, heat pumps use electricity provided by the grid. Thus, their resulting carbon emissions are directly related to the value of grid carbon intensity at time-of-use.

Cogeneration is considered a more efficient form of power generation due to the limited transmission losses and greater fuel efficiency. Combined Heat & Power (CHP) converts a single fuel into both electricity and heat in a single process. In the case that this fuel is gas, CHP has the significant potential to reduce carbon emissions and to improve energy efficiency only in the immediate and near future grid conditions (Kelly *et al.*, 2014).

In the early years of the CHP introduction in the UK heating landscape, criticism has been made that the liberalised electricity market effectively discriminates against small-scale CHP plants as opposed to the Danish system of feed-in tariffs that would facilitate the absorption of high levels of renewables (Toke & Fragaki, 2008). Since then, substantial progress has been noted on the policy level and the British government published guidance on combined heat and power in 2013 in an attempt to promote this low carbon technology and advocate its potential benefits that include energy bills savings, carbon emissions savings, reduced transmission and distribution losses and increased energy supply security (DECC, 2013b). These measures that aim to incentivise the installation of CHP include among others (DECC, 2018b, p. 200):

- "exemption from the Climate Change Levy (CCL) of all fuel inputs to, and electricity outputs from, Good Quality CHP;
- exemption from Carbon Price Support (CPS) on fuel to CHP consumed for the

generation of heat;

- exemption from Carbon Price Support (CPS) on fuel to CHP consumed for the generation of Good Quality CHP electricity which is consumed on site
- Eligibility to Enhanced Capital Allowances for Good Quality CHP plant and machinery
- Business Rates exemption for CHP power generation plant and machinery;
- Reduction of VAT (from 20 to 5 per cent) on domestic micro-CHP installations;
- Extension of the eligibility for Renewable Obligation Certificates (ROCs) to energy from waste plants that utilise CHP";

Regarding the potential carbon savings, the figures from the latest DUKES report (DECC, 2018b) compare CHP with the UK fossil fuel basket carbon intensity and the UK total basket carbon intensity, which includes low carbon sources such as nuclear and renewable generation. According to the report, the carbon emission savings from CHP in 2017 as compared to the National Grid basket were 10.70 Mt CO_2, which equates to 1.83 Mt CO_2 per 1,000 MWe installed capacity. Against the total basket, CHP savings reached 4.91 Mt CO_2 which equates to 0.84 Mt CO_2 per 1,000 MWe installed capacity.

Heat pumps are a promising and relatively new heating/cooling technology that provides high efficiencies compared with fossil fuel combustion. "The underlying principle of their operation is the reverse of a heat engine: using mechanical work to move heat against its natural gradient from a cold location to a hotter one, e.g. from outdoors into the home" (Staffell *et al.*, 2012, p. 9293). They are classified as air source and ground source where the heat is derived from the surrounding air or the ground respectively.

The operational carbon emissions allocated to a heat pump are directly linked to the carbon intensity of the electricity to power it. Research has indicated that the potential carbon savings on domestic level range from 50% when displacing oil, solid fuel or electric heating to 10% when displacing low-carbon gas boilers (Staffell *et al.*, 2012).

In summation, gas CHP plants when displacing grid electricity are expected to provide a carbon benefit only as long as their total emissions are lower than the grid carbon intensity at time-of-use while heat pumps provide obvious benefits in a future decarbonised electricity system. While previous studies (Kelly *et al.*, 2014) have highlighted the fact that CHP benefits are certain only in the immediate and near term there is need to quantify these benefits under the current and feasible future grid conditions and against the respective grid carbon intensity time-series.

2.6 Simulating the carbon intensity of the Great Britain electricity grid

2.6.1 The GB electricity system

The literature review has shown the need to understand high resolution temporal variability in grid carbon intensity behaviour. It has also shown that dispatch models offer the means to do this. High resolution generation output values can be used in order to explore the uncertainty associated with grid carbon emissions under different installed capacity and renewable input scenarios and assess the benefits of gas operated CHP and electric vehicles in current and future grid conditions. To design such a model the requires an understanding of the GB electricity system operation.

An electric power system is usually comprised of four main elements: power generation, power transmission, power distribution and power consumption (Mohsenian-Rad, 2012). Great Britain has a liberalised electricity market and on the generation side, electricity is being produced from coal, gas, oil and nuclear power plants, hydroelectric plants and wind farms. Their basic operational principles are summarised in table 2.5.

Suppliers (such as British Gas, Eon, SSE, EDF, Npower and Scottish Power) purchase electricity in the wholesale market and then sell it to the customers. Bilateral contracts are traded between suppliers, generators, traders and consumers in half-hourly blocks up to one hour before real-time (gate closure).

Type of generating unit	*Operational principle*
CCGT	Combined cycle plants use exhaust gases in high temperature to generate steam in heat recovery steam generators that is used to drive a steam turbine generator. Their operational advantage is their high efficiency.
OCGT	In the simple cycle inlet air is compressed and then mixed and burned with fuel oil or gas in a combustion chamber.
NUCLEAR	Light-water nuclear units use either pressurised water or boiling water reactors with enriched uranium which is fabricated into fuel assemblies before use.
HYDRO	Hydroelectric units have input-output characteristics similar to the steam turbine ones and work transforming the kinetic energy of moving water to electric.
PUMPED STORAGE	Pumped hydroelectricity storage stores energy in the form of water in an upper reservoir, pumped from another reservoir at a lower elevation. During periods of high electricity demand, power is generated by releasing the stored water through turbines in the same manner as a conventional hydropower station. During periods of low demand (when electricity is also lower cost) the upper reservoir is recharged by using lower-cost electricity from the grid to pump the water back to the upper reservoir.
WIND	Wind generators use the torque exerted by the wind to rotate the turbine blades and generate electrical power. The minimum wind speed required to get the blades to rotate and generate power is called cut-in speed while the maximum wind speed, above which there is risk of damage to the rotor, is called cut-out speed.
SOLAR	Solar power plants are divided in photovoltaic and concentrated power generation. While photovoltaic sources capture and covert indirect sunlight into direct current concentrated plans use mirrors or lenses to concentrate large amounts of solar thermal energy onto a small area.

Table 2.5: Generation unit types (Wood *et al.*, 2013).

While the distribution network is owned and operated by a a number of companies (Electricity North West, ESB Networks, Northern Ireland Electricity Networks, Northern Power grid, SP Energy Networks, Scottish & Southern Electricity Networks, UK Power Networks, Western Power Distribution) National Grid owns and manages the national transmission network. National Grid is also responsible for implementing the balancing mechanism (BM) in order to balance demand and supply at half-hourly intervals. Balancing is performed in half-hourly blocks and comprises of a variety of technologies and services (ancillary services). These include (DRAX, 2018):

- Frequency response: where flexible (usually thermal) generations adjust their outputs in order for the high voltage network frequency to be maintained at

$50Hz \pm 1\%$;

- Reactive power and voltage management: which has to be at $400kV$;
- System inertia: Inertia of a spinning plant is effectively stored energy and can be used to smooth sudden changes in frequency;
- Reserve power is delivered via spinning reserve (2 minutes response time, mostly thermal, hydro plants and pumped storage), short-term operating reserve (STOR) (20 minutes response time, delivered by plants with high marginal cost that cannot survive on the market such as diesel engines and aeroderivative turbines) and demand turn-up where excess generation is addressed by commercial or industrial users increasing their consumption or turning off their own generation;

However, the balancing will be required to adapt to the rapidly transforming electricity system. Since the 1990s dash for gas UK had moved to a mix of coal, gas and nuclear. While some nuclear plants were decommissioned in the 2000s the system was kept by gas, steady demand and the slow renewable penetration (Grubb & Newbery, 2018). The transition that is taking place expects the gas to change from the backbone of the current grid and adopt a flexible, supportive role in a renewable dominated electricity system (Facchini *et al.*, 2019).

In the future GB electricity grid, grid-scale batteries are expected not only to provide reserve but also aid the voltage control of the system by absorbing or releasing reactive power while smart PV inverters are expected to support the reactive power and voltage control mostly on the distribution network. Furthermore, current academic research explores the inertial response emulation that will enable wind turbines to offer faster frequency response (DRAX, 2018). Finally, thermal generators can also se configured to provide benefits to the system stability without contributing to the actual fuel mix. By running in synchronous compensation mode, they will be able to produce or consume reactive power.

2.6.2 Modelling the GB electricity system

Understanding the real-life operation of the electricity system to be simulated is only the first step of the process. While power system modelling functions digress from real-life operation the selection of the appropriate model/modelling approach should be carried out considering the research problem and the desired output. A wide range of GB power system models have been developed and are currently used under a variety of schemes. Hall & Buckley (2016) reviewed and classified 22 GB power system models under their underlying methodology. The classification includes econometric, macro-economic, economic equilibrium, optimisation, simulation, back-casting, multi-criteria and accounting models.

Optimisation models entail the use of mathematical optimisation to find a preferred mix of technologies, given certain constraints. An objective function to be minimised is defined and this function usually involves cost as it assumes that real world decisions are made only on the basis of least cost principle (Hall & Buckley, 2016).

Another dichotomy in model classification is explained by Pfenninger *et al.* (2014) where, while most power system models are used for planning purposes (capacity expansion models), the importance of high-resolution analysis of varying demand and renewable energy leads to an increased need for operational (or dispatch) models.The most widely used operational models are identified as WASP and PLEXOS (Pfenninger *et al.*, 2014).

The desired model output for the present research is a set of grid carbon intensity values in high resolution. In order to calculate this, generation by fuel type data similar to Elexon (2017) is needed. Reviewing the existing literature on the utilisation of optimisation/dispatch models it is realised that a model similar to PLEXOS would be suitable for the purposes of this study.

In academic research, PLEXOS is widely used to explore how renewable variability will affect any component of the electricity system. In specific, Edmunds *et al.* (2015) examines the changes in thermal plant operation schedules with varying renewable input while Johnson *et al.* (2019) investigates the system inertia with high renewable penetration and Cleary *et al.* (2020) estimates the electricity prices and carbon emissions of large scale wind exports from Ireland to Great Britain. Furthermore, PLEXOS is also used to appraise the future primary energy consumption in the Italian thermoelectric sector (Bianco *et al.*, 2015), investigate the benefits of heat electrification in a wind dominated Irish electricity market (Vorushylo *et al.*, 2018), study cost-optimal and zero-carbon European electricity system operation in 2050 (Zuijlen *et al.*, 2019) and evaluate the value of GB-France interconnectors in 2030 generation mix scenarios (Pean *et al.*, 2016).

All of the aforementioned studies share the common feature of using a dispatch model, in this case PLEXOS, to simulate capacity scenarios and renewable inputs and estimate electricity prices, generation mix and carbon emissions of potential future electricity system conditions. In simpler terms, dispatch models are widely used by the academic community to answer to questions similar to the ones set by this study. However, while the literature review indicated that PLEXOS is a fitting model to simulate installed capacity scenarios and various renewable inputs, the design of a new dispatch power system model was ultimately decided since it offers increased flexibility and better visibility of the input-output flow. In order to achieve this, the basic functions of dispatch models were studied and appropriate modelling techniques were selected.

The two basic functions/problems of a dispatch model are economic dispatch (ED) and unit commitment (UC). Both ED and UC are short-term cost-optimising functions and are described in detail below. Economic dispatch regards the optimum power outpout allocation among the units at minimum cost (Wood *et al.*, 2013). In mathematical terms, Economic Dispatch is an optimisation problem with constraints:

$$C_t = \sum_{i=1}^{N} C_i(P_i) \tag{2.2}$$

$$\sum_{i=1}^{N} P_i = P_{demand} \tag{2.3}$$

$$P_{i,min} \leq P_i \leq P_{i,max} \tag{2.4}$$

where C_t is the total cost of the system that needs to be optimised (equation 2.2)and p_i is the power output of i unit. The constraints of this optimisation problem are given by equations 2.3 and 2.4 and can be described as follows; The power output of a unit has to be within the operating limits of the unit and the sum of the outputs of all units has to meet the total demand of the system.

ED can be solved with the lamda iteration method, dynamic programming and genetic algorithms (Wood *et al.*, 2013) (Dogra *et al.*, 2014) (Kazarlis *et al.*, 1996). Unit commitment (UC) regards the turn-on and turn-off schedules of the available units at minimum cost fullfiling several operational constraints of the system. Such constraints are (Wood *et al.*, 2013): spinning reserve, min up time, min down time, crew constraints, start up cost, hydro, must-run constraints and fuel constraints.

UC has a similar formulation with ED (extensively covered in chapter 4). However, the main difference between ED and UC is that while the ED algorithm optimises the power output of N specific units, the UC algorithm has to "select" the number of units that are going to turn on. This sort of problem is called a "binary decision" and its simulation is more complex. UC solution methods include priority list, dynamic programming, Lagrange relaxation, integer programming, Benders decomposition and genetic algorithm (Carrión & Arroyo, 2006), (Fontes *et al.*, 2012), (Salam, 2007), (Senjyu *et al.*, 2003).

The mixed-integer linear programming (MILP) solution, used for the Unit Commitment, gained interest approximately a decade ago due to the drastic improvement in numerical solution times of commercial solvers (B. Hobbs, 2001). Furthermore, this method has been put in use by ISO's in several markets including the PJM energy market in United States (Streiffert *et al.*, 2005). Delarue and his team (Delarue & D'haeseleer, 2007) contrasted the heuristic approach of priority list and a mixed-integer solution for the UC problem and found out that the MILP method always reached a proven optimal solution although the computational times for the priority list method were significantly lower. Finally, the widely used large-scale dispatch model PLEXOS utilises a mixed-integer linear programming approach with detailed modules for various power plants, the transmission grid, and for market planning or capacity expansion (Pfenninger *et al.*, 2014). It is finally noted, that in this study the ED function has been simulated with the built in Matlab non-linear solver since there was no need for non-integer constraints. The priority list was used for the UC function in a benchmark model to set a baseline while the MILP approach was implemented in the core and final version of the model.

2.7 Summary

Grid carbon intensity has already been investigated by a variety of national and international studies. However, limited literature was identified that focuses on the time-varying behaviour of grid carbon intensity (Khan, 2018), (Khan *et al.*, 2018) and in most cases, emissions arising from the grid are described in a single annual either aggregate (Ang & Su, 2016) or average (Goh *et al.*, 2018), (Ang & Goh, 2016) figure. While the minute by minute operation of the electricity grid is overlooked, the subsequent emissions cannot be adequately and accurately represented in single values. A metric for quantifying grid emissions, marginal grid carbon intensity, introduced by Hawkes (2010) describes the effect of demand side interventions to the British electricity grid and is shown to digress up to 10% from the system average for years 2009 and 2010. While claims have been made by Hitchin & Pout (2002) that this metric is only appropriate to describe the short term but fails to capture the system operation in longer time spans, taking into account marginal emissions further advances our understanding of the system operation and highlights the dynamic behaviour of grid carbon emissions.

Analysing the grid carbon intensity formula used by (N.G, 2017), (Staffell, 2017), (Lau *et al.*, 2015) and (Rogers & Parson, 2017) it is noticed that the fuel mix hence the relevant carbon factors of the different fuels affect the total figure of grid emissions. An international literature review indicated high discrepancies in the carbon factors for different generating technologies. For renewable sources it is shown that the variation is caused by different topology and climate conditions, source of electricity and material manufacturing. For conventional generating plants, the net efficiency and the type of technology used in the operational process are the factors that cause the discrepancies. To investigate the uncertainty in intensity calculations by carbon factor assumptions, this study uses a range instead of a single number to quantify the impact on annual and half-hourly values.

The areas of carbon policy and carbon accounting and reporting are intrinsically related and have significant roles in achieving the national decarbonisation goals. Although the benefits of mandatory carbon reporting are evident (Baboukardos, 2017), (Tauringana & Chithambo, 2015) in the good progress of the British grid decarbonisation of latest years (White & Hough, 2016), criticism has been made on the UK DEFRA carbon reporting scheme. Malleability associated with the scope classification (Haslam *et al.*, 2014) and the lack of future emissions accounting (Bebbington *et al.*, 2019) introduce key uncertainties in the carbon reporting process. Noting that the annual average grid intensity values provided by DEFRA do not accurately represent the dynamic balancing of the system, recent studies (Tranberg *et al.*, 2019) highlight the importance of real time electricity carbon accounting and lay the foundation for time-varying electricity taxes.

Future projections regarding changing capacity margins (Sithole *et al.*, 2020), renewable penetration (Staffell & Pfenninger, 2018), electrification of vehicles and new heating technologies (Lindberg *et al.*, 2019) are expected to amplify the uncertainty pertaining the grid behaviour and its resulting emissions. Future Energy Scenarios by National Grid outline potential energy transition pathways for the UK grid and a dispatch model is being used to simulate potential future grid carbon intensity values. However, once more it is noticed that the depiction of feasible grid scenarios is flattened to annual values of emissions. Hence, it is realised that a suitable dispatch generation model such as the one used by National Grid could be designed to produce grid carbon intensity datasets in high resolution under different capacity and renewable input assumptions. Furthermore, those datasets could also be utilised to explore the efficiency of heating systems in a decarbonised future and inform controlled charging strategies for electric vehicles.

Dispatch power system models are extensively used to simulate, amongst others, operational schedules (Edmunds *et al.*, 2015), high renewable penetration (Johnson *et al.*, 2019), carbon emissions (Cleary *et al.*, 2020) and are ultimately considered an appropriate tool for the scope of this study. Researching the power system model functions and their potential algorithmic solution methods, the mixed integer linear programming (MILP) approach is selected for the Unit Commitment problem. The MILP method is not only used within the widely used PLEXOS model but is also found to always reach a proven optimal solution (Delarue & D'haeseleer, 2007) when compared to heuristic methods such as priority list.

Chapter 3

Historic data analysis of GB grid carbon intensity for years 2009 to 2017

3.1 Introduction

The present chapter addresses objective 1: *"Explore historic grid carbon intensity variability and quantify the numeric uncertainty arising from different power system carbon factor assumptions."*

The DEFRA approach for annual average figures of grid carbon intensity, where annual fuel consumption is known across all UK power stations cannot be used for time varying values, as power station fuel input is not available at this temporal resolution. To achieve half-hourly figures, the known output of GB power stations with an assumed carbon factor for each power station type are combined. While the annual average figures of grid carbon intensity are more straightforward to use in company reporting schemes and useful under certain circumstances, grid carbon intensity values in half-hourly resolution provide insights on the dynamic nature of the electricity grid and uncover patterns of behaviour.

Analysis of half-hourly grid carbon intensity data has been carried out for years 2009-2017 in order to identify half-hourly, daily, monthly and annual trends. Different plant carbon factors (due to different assumed efficiency and age of the plant) have also been used to assess uncertainty ranges and impact on the annual grid intensity values. The evolution of the GB fuel mix and the type of marginal plant have also been studied.

3.2 Method

In the present study, the methodology that has been followed in order to derive grid carbon intensity values in half-hourly resolution is widely used and consistent with the methodology followed by the National Grid's API forecast (N.G, 2017), other members of the scientific community (Staffell, 2017), (Lau *et al.*, 2015) and the Grid Carbon application (Rogers & Parson, 2017).

The figures for grid carbon intensity have been calculated using equation (2.1):

$$CI(t) = \frac{\sum_{n=1}^{N} c_n \cdot E_n(t)}{\sum_{n=1}^{N} E_n(t)}$$

where n is the fuel type index, N is the total number of fuels, c_n is the carbon factor for fuel n and E_n is the generated energy corresponding to fuel n at given time t. The range of E_n values was derived using half-hourly generation by fuel type data (available on Elexon (2017)).

Embedded solar and wind generation data from National Grid (NG, 2017) were also considered. Due to Elexon data gaps, linear interpolation was applied. In specific, the zero grid carbon intensity values were replaced by the average of the previous and next element: $CI(t) = \frac{CI(t-1)+CI(t+1)}{2}$.

From eq. (2.1) it is noticed that different carbon factor assumptions (c_n) are expected to have an impact on grid carbon intensity calculations. Hence, three GB specific studies (Staffell, 2017), (Rogers & Parson, 2017), (Lau *et al.*, 2014b) have been selected and table 3.1 presents the carbon factors of different power systems, as listed in these sources. It should be noted that although the work by (Lau *et al.*, 2014b) focused on the GB grid, the range of carbon factors in this study is derived from international literature (presented in tables 2.1 and 2.2). As explained in section 2.2.1 international carbon factors assume climate and topology conditions that are dissimilar to the United Kingdom. This explains the high discrepancies that are noticed in column C in table 3.1 as opposed to UK specific column A of the same table. It is also noted that carbon factors from (Staffell, 2017) and (Rogers & Parson, 2017) do not consider life cycle emissions and assess only the operational phase. Regarding the factors from (Lau *et al.*, 2014b), it is not specified whether life cycle assessment was considered. However, since non-zero carbon factors are assigned to nuclear and wind generation, it can be assumed that other phases apart from operation were considered.

Staffell (2017) also presents the respective efficiencies for different plant types (presented in table 3.2). It is noticed that discrepancies of 0.5%, 3.6%, 0.4% and 0.7% in the net efficiencies cause variation of 15, 122, 10 and 6 g/kWh in the relevant carbon factors for coal, oil, open cycle gas turbine and closed cycle gas turbine plants respectively. Finally the interconnected electricity carbon factors assume a fuel mix of 76% nuclear, 12% hydro, 6% fossil for France, 58% gas, 26% coal, 5% each of biomass, nuclear and wind for Netherlands and 50% gas, 26% coal and lignite, 20% wind for Ireland.

The majority of this analysis has been carried out using the carbon factors as listed in the work by (Staffell, 2017). These factors have also been used by the grid carbon intensity forecast of National Grid (N.G, 2017) and they have been selected for the purposes of this study as they are the most recent and GB specific. However, separate calculations have been carried out using the whole range of carbon factors from table 3.1 in section 3.6 in order to examine how they affect the figures of grid carbon intensity and establish uncertainty ranges.

(g/kWh)	(A) Staffell	(B) GridCarbon	(C) Lau
Coal	937 ± 15	910	788–899
Nuclear	0	0	20–26
Oil	935 ± 122	610	600–699
Wind	0	0	20–94
Hydro	0	0	2–13
Closed cycle gas turbine	394 ± 6	360	367–487
Open cycle gas turbine	651 ± 10	480	466–586
French imports	53 ± 14	90	–
Dutch imports	474 ± 25	550	–
Irish imports	458 ± 15	450	–

Table 3.1: Carbon factors for different plant types and interconnected electricity **(A)** (Staffell, 2017), **(B)** (Rogers & Parson, 2017), **(C)** (Lau *et al.*, 2014b)

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	Efficiency net %	Efficiency gross %
Coal	34.3 ± 0.5	36.1 ± 0.6
Oil	28.6 ± 3.6	32 ± 4.2
OCGT	28.3 ± 0.4	28.8 ±0.5
CCGT	46.7 ± 0.7	47.7 ± 0.8

Table 3.2: Efficiency figures for different plant types (Staffell, 2017).

3.3 Validation against DEFRA annual averages

The Department for Environment, Food & Rural Affairs (DEFRA) publishes annual electricity carbon values for company reporting reasons. As explained in the 2017 company reporting methodology information (DECC, 2018a), the figures of grid carbon intensity are calculated through a model that uses fuel and emissions data from the power stations and autogenerators sectors in the UK. In an attempt to replicate the DEFRA numbers personal communication was held with the Higher Scientific Officer of the Greenhouse Gas Inventory Team. However, the model and the input data are not available to the public as they contain commercially sensitive information.

Table 3.3 presents the percentage errors of this analysis' annual averages against the DEFRA values. It should also be noted that DEFRA publishes the factor (annual average of the UK grid carbon intensity) with a two-year delay, meaning that the 2014 DEFRA factor corresponds to 2012 data. For this reason, the comparison was performed accordingly and 2017 was omitted since the 2017 data will be published by DEFRA in

2019. The percentage error ranges from 0.5 to 3%. The noticed discrepancies can be explained if the different methodology and the omission of pumped storage from this study, is taken into account. It should also be noted, that the use of a fuel carbon factor assumes the same efficiency for all same fuel plants.

Year	**Present Analysis** (g/kWh)	**DEFRA (data year** (g/kWh)**)**	**Error** ($\%$)
2017	239.1		
2016	274.1	283.1	3.2
2015	360.6	351.6	-2.6
2014	419.9	412.1	-1.9
2013	475.0	462.2	-2.8
2012	505.4	494.3	-2.2
2011	448.8	445.5	-0.8
2010	457.9	460.0	0.5
2009	443.8	452.1	1.8

Table 3.3: Error percentage of grid carbon intensity annual averages against DEFRA values.

3.4 Fuel mix for years 2009 to 2017

Electricity grid carbon intensity at a certain time is directly dependent on the fuel mix that was used at this time (equation 2.1). Hence, before attempting to interpret the results of grid carbon intensity it is important to examine how the fuel mix has evolved over these years.

Figures 3.1, 3.2 and 3.3 present the half-hourly Elexon generation by fuel type while table 3.4 presents the total annual generation in GW and the standard deviation for each fuel type for years 2009 to 2017. In the space of nine years the GB fuel mix has drastically changed but the two most interesting features regard coal and wind generation. Coal is the most carbon intensive fuel in the GB fuel basket with a factor of 937 g/kWh (for the present analysis). DECC reports that the past nine years have seen the closure, capacity reduction,full/partial mothballing or conversion to biomass of several large coal power stations under the European Union Large Combustion Plant Directive, (LCPD, 2001/80/EC) (DECC, 2017a). In figures 3.1a and 3.3c coal generation (in yellow) has decreased from a max of 25 GW in 2009 to a max of less than 10 GW in 2017. The total annual generation by coal reached a maximum of 274408 GW in 2012 and since then it has decreased to barely over 41000 GW in 2017.

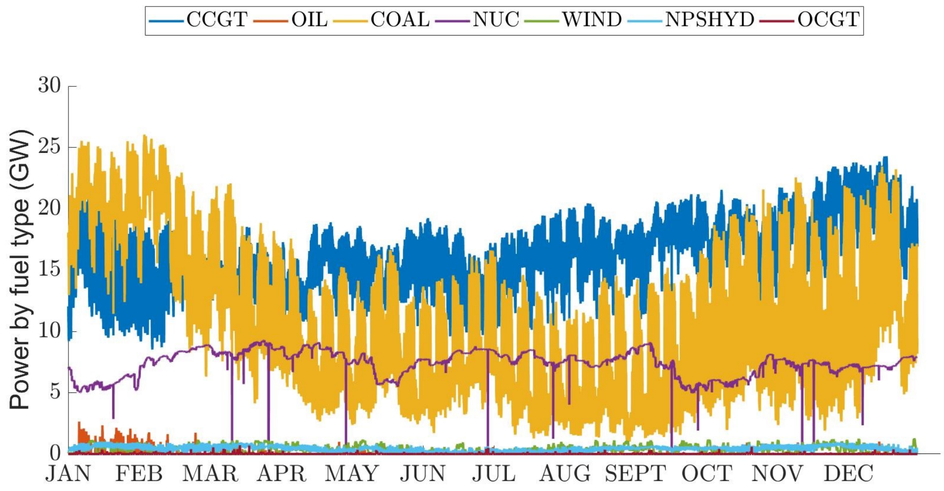
Wind generation is virtually non existent in the first two years, 2009 and 2010 and gradually increases during the period of 2011 to 2016. In 2017 it is noticed that the half-hourly wind generation reaches 10 GW. The highest standard deviation for wind generation was noticed in 2017 when it reached a value (2169) similar to the one pertaining coal generation (2629) (table 3.4).

These two significant changes of the fuel mix, the reduction of the most carbon intensive fuel and the increased zero-carbon wind generation, are expected to decrease grid carbon intensity figures for the relevant years.

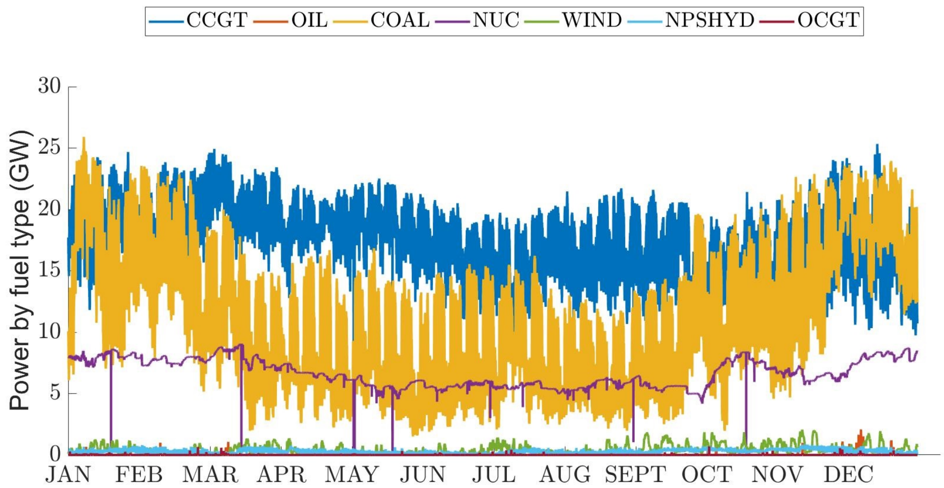
Finally, annual generation by closed cycle gas turbines has fluctuated from 160410 to 294275 GW throughout the years, but has steadily provided a higher baseload than coal in all years except for 2012 (table 3.4).

Fuel	2009		2010		2011	
	Total (GW)	Std	Total (GW)	Std	Total (GW)	Std
CCGT	294275	2963	313717	3120	253916	3533
Oil	935	218	185	86	23	25
Coal	198097	6196	205899	5681	206918	5366
Nuclear	129776	1039	116882	1124	129466	1130
Wind	6639	303	7366	399	19432	784
OCGT	7106	219	4273	167	7387	216
	2012		**2013**		**2014**	
	Total (GW)	**Std**	**Total (GW)**	**Std**	**Total (GW)**	**Std**
CCGT	166112	3821	160410	4722	173393	4596
Oil	40	38	15	24	11	15
Coal	274408	4198	251473	3336	193263	4051
Nuclear	131970	834	131869	969	119450	1038
Wind	25212	1053	37240	1394	42293	1661
OCGT	6549	221	5828	236	7849	274
	2015		**2016**		**2017**	
	Total (GW)	**Std**	**Total (GW)**	**Std**	**Total (GW)**	**Std**
CCGT	168686	4170	254482	4653	238503	5261
Oil	5	11	0	0	0	0
Coal	148903	3684	55985	2737	41223	2629
Nuclear	131357	613	133496	663	131084	623
Wind	46752	1642	42377	1579	64669	2169
OCGT	8189	258	6759	257	7921	286

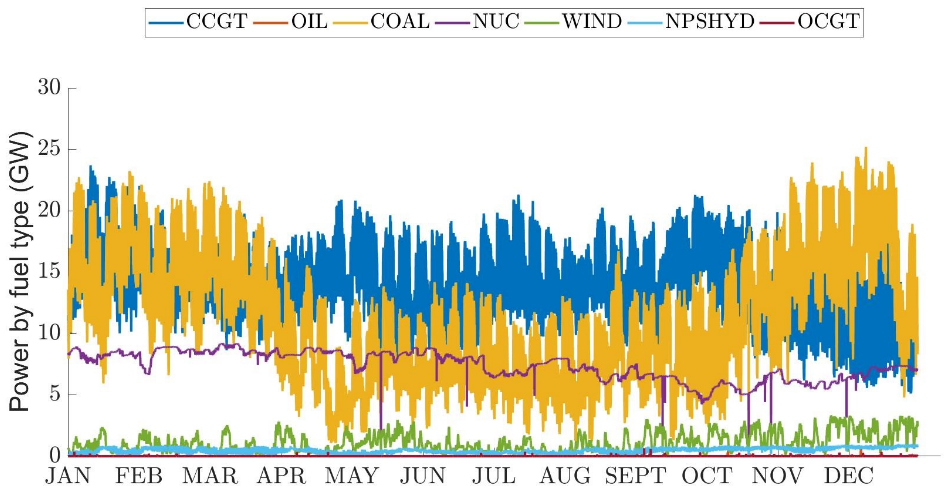
Table 3.4: Total annual generation (GW) and variation per fuel type.



(a) 2009

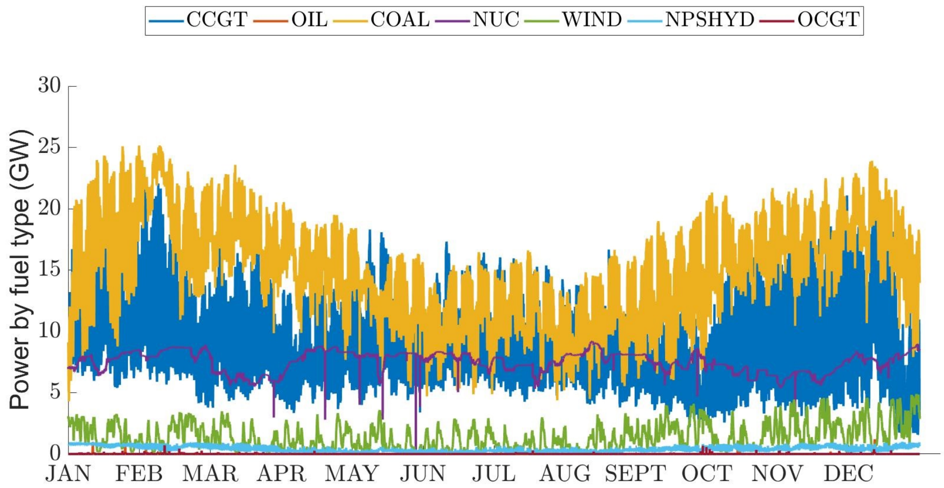


(b) 2010

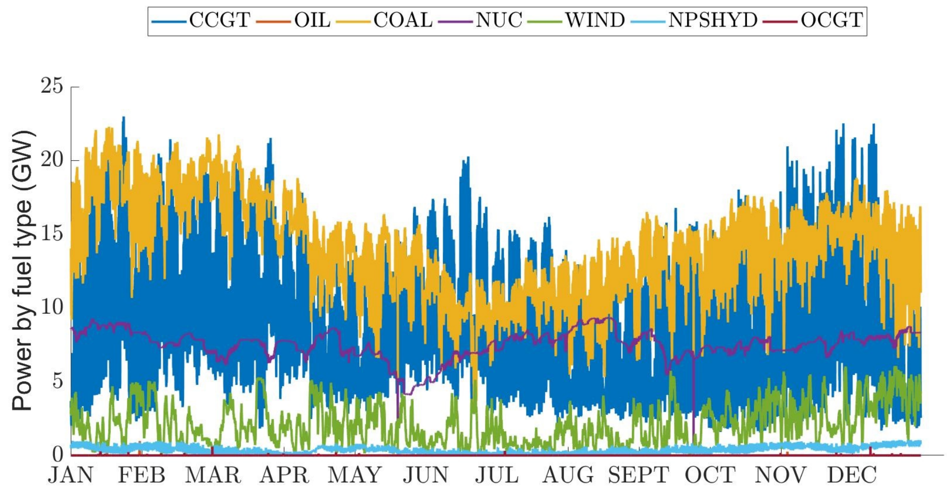


(c) 2011

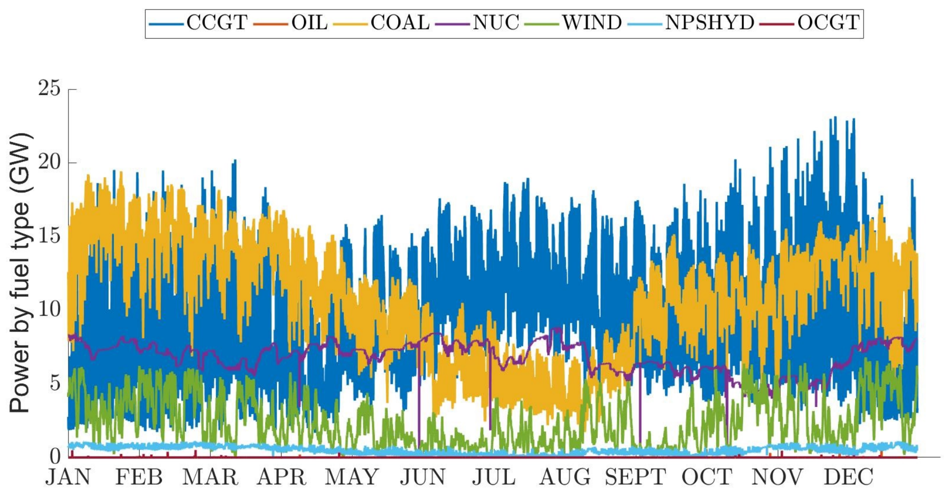
Figure 3.1: Generation by Elexon fuel type for years 2009-2010-2011 (GW)



(a) 2012

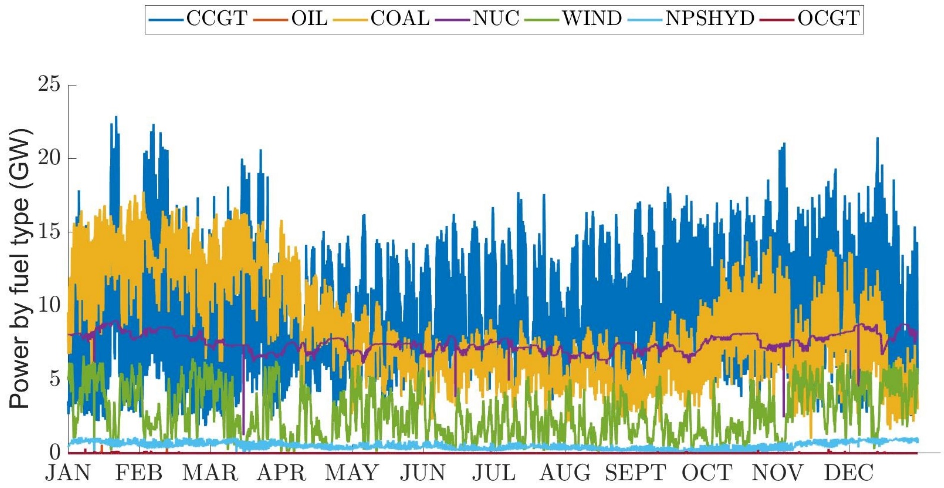


(b) 2013

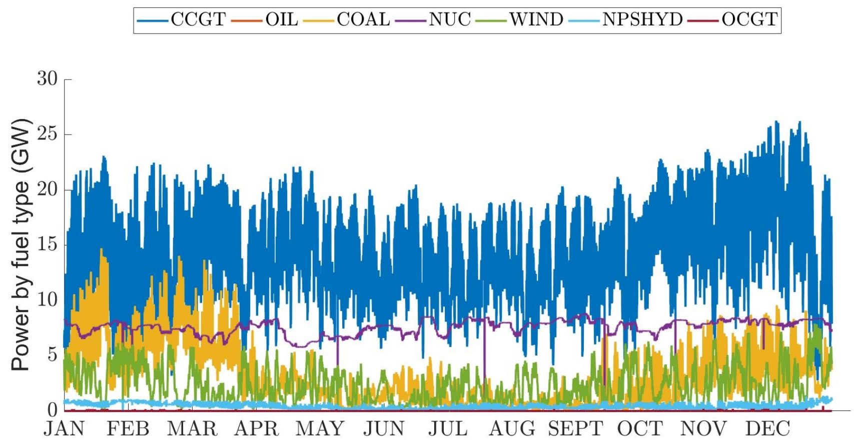


(c) 2014

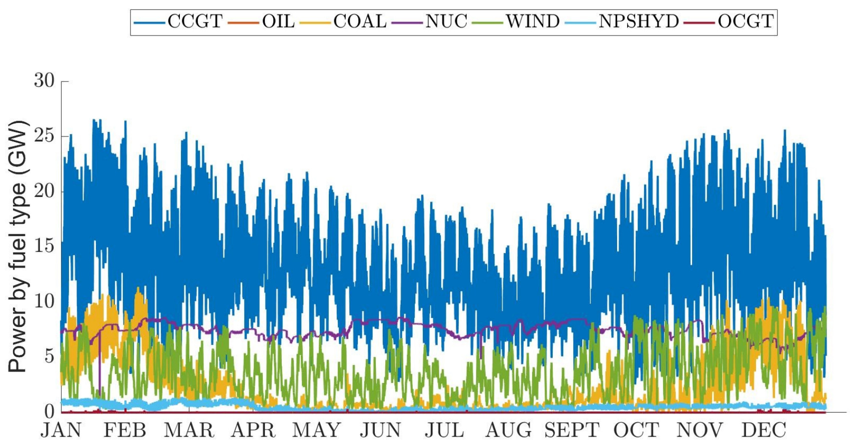
Figure 3.2: Generation by Elexon fuel type 2012-2013-2014 (GW)



(a) 2015



(b) 2016



(c) 2017

Figure 3.3: Generation by Elexon fuel type 2015-2016-2017 (GW)

3.5 Marginal generation

As discussed in section 2.1.1, a demand side intervention does not symmetrically affect all of the online plants at the time the said intervention occurs. The marginal plant(s) are the plants that will “load-follow” and adjust their output(s) (shrink in the case of a demand reduction or expand in the case of a demand increase). An investigation following the published methodology by (Khan, 2018) was conducted for different fuels that were used to generate electricity, to identify the marginal fuel(s) in the electricity system. The correlation coefficient has been calculated between the change in half-hourly generations from each type of fuel against half-hourly change in the total generation. Table 3.5 presents the results for the years 2009 to 2017.

To calculate the correlations, the Spearman correlation coefficient ρ has been used:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \tag{3.1}$$

where d is the pairwise distances of the ranks of the variables xi and yi and n is the number of samples. Spearman’s ρ is a rank-based version of Pearson’s correlation coefficient, which can be used for variables that are not normal-distributed, more volatile and have a non-linear relationship.

Strong to very strong positive correlation, ranging from 0.87 to 0.92, was found for CCGT plants in all cases. Moderate to strong correlation, ranging from 0.64 to 0.89, was found for coal.

Table 3.5 presents an overview of the marginal mix in each year of the analysis, in all cases except 2009 where the same correlation was found for the two fuels, CCGT is shown to be the dominant fuel in the marginal mix. However, the proportion of the two fuels that comprise the marginal mix is shown to fluctuate. CCGT is shown to have a stronger correlation (0.91 and 0.92), compared to coal (0.69 and 0.64) in years 2013 and 2017.

	CCGT	COAL
2017	0.92	0.64
2016	0.9	0.72
2015	0.91	0.82
2014	0.91	0.78
2013	0.91	0.69
2012	0.87	0.82
2011	0.9	0.88
2010	0.91	0.89
2009	0.89	0.89

Table 3.5: Correlation coefficient table for marginal generation.

3.6 Uncertainty from power station carbon factors assumptions on grid carbon intensity

3.6.1 Impact on annual average grid garbon intensity

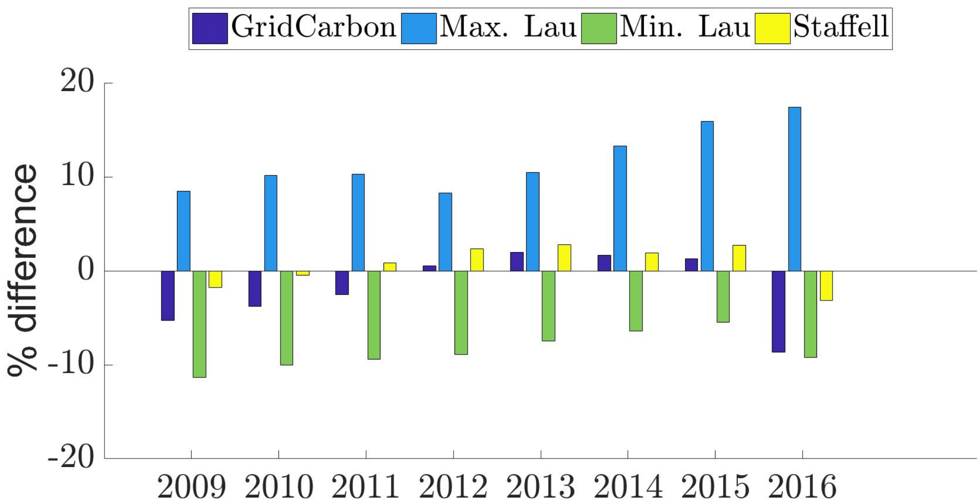


Figure 3.4: Percentage change of annual average of grid carbon intensity calculated with different carbon factors to DEFRA annual corresponding values.

Figure 3.4 shows the percentage of difference of annual average values of grid carbon intensity to DEFRA corresponding values using the variety of carbon factors from table 3.1. The average figures from (Staffell, 2017) and the maximum and minimum values from (Lau *et al.*, 2014b) have been used. The year 2017 is omitted from this comparison. As previously mentioned, DEFRA publishes the grid carbon intensity annual figures with a two year delay, meaning that 2017 data will be published in 2019. It is noted that interconnected electricity was considered only for the calculations carried out with the carbon factors by (Staffell, 2017) and pumped storage was omitted in all cases.

The annual average value of grid carbon intensity can vary by more than 10% depending on the carbon factor of different plant types. It is noticed that, as expected, the factors by (Staffell, 2017) yield the lowest errors ranging from 0.4% to 3.1%. Gridcarbon factors gave the second best results with errors ranging from 0.5% to 8%. Finally, the maximum from the carbon factors range in (Lau *et al.*, 2014b) caused the highest discrepancies that varied from 7% to almost 18%.

3.6.2 Impact on half-hourly grid garbon intensity

While, figure 3.4 showed the impact of different carbon factors on annual average grid carbon intensity values, this section aims to establish uncertainty ranges on half-hourly grid carbon intensity using different plant carbon factors. Two separate approaches have been implemented using the carbon factor ranges from table 3.1.

3.6.2.1 Uncertainty range using a uniform distribution of plant carbon factors

Drawing on the methodology as described in Lau *et al.* (2014b), for each plant type, a uniform distribution of a hundred points (instead of the Monte Carlo method as carried out in the original study) was generated within the ranges (g/kWh) shown below:

- Coal: 788-899
- Nuclear: 20-26
- Oil: 600-699
- Wind: 20-94
- CCGT: 367-487
- OCGT: 466-487

It is noted that, consistent with the original study by Lau *et al.* (2014b), interconnected electricity was omitted from the calculations. Using 2016 generation by fuel type data (Elexon, 2017), a hundred different grid carbon intensity values were calculated for each half-hour using the uniformly distributed plant carbon factors. The average figure alongside the standard deviation were also calculated for each half-hour. The uncertainty range is defined: $(CI_{mean} - std)$ - $(CI_{mean} + std)$ and is presented in the grey area in figure 3.5. Figure 3.5 shows that half-hourly uncertainty range is by average $\pm$ 25%.

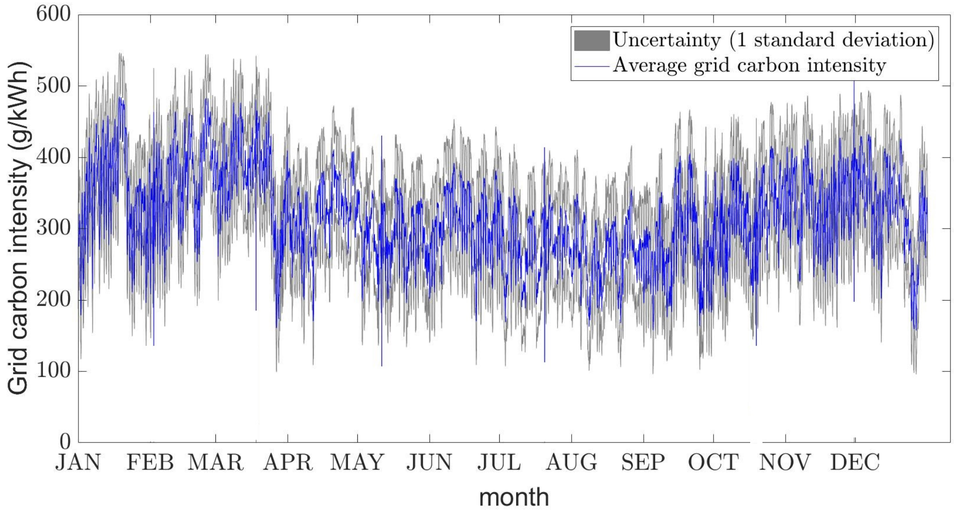


Figure 3.5: Average half-hourly grid carbon intensity and uncertainty range using different carbon factors (2016).

3.6.2.2 Uncertainty range using an upper and lower bound of plant carbon factors

In this case, the minimum, average and maximum values of the carbon factor ranges g/kWh as listed in (Staffell, 2017) have been used:

- Coal: 937 $\pm$ 15
- Oil: 935 $\pm$ 122
- CCGT: 394 $\pm$ 6
- OCGT: 651 $\pm$ 10
- French imports:53 $\pm$ 14
- Dutch imports: 474 $\pm$ 25
- Irish imports: 458 $\pm$ 15

In this case, using 2017 generation by fuel type data (Elexon, 2017) three values of grid carbon intensity were calculated for each half hour calculated with the minimum, average and maximum carbon factor for each fuel type. Figure 3.6 presents the % change compared to the grid carbon intensity calculated with the average values of carbon factors. In this case, the half-hourly change is noticed to be by average $\pm$ 2%.

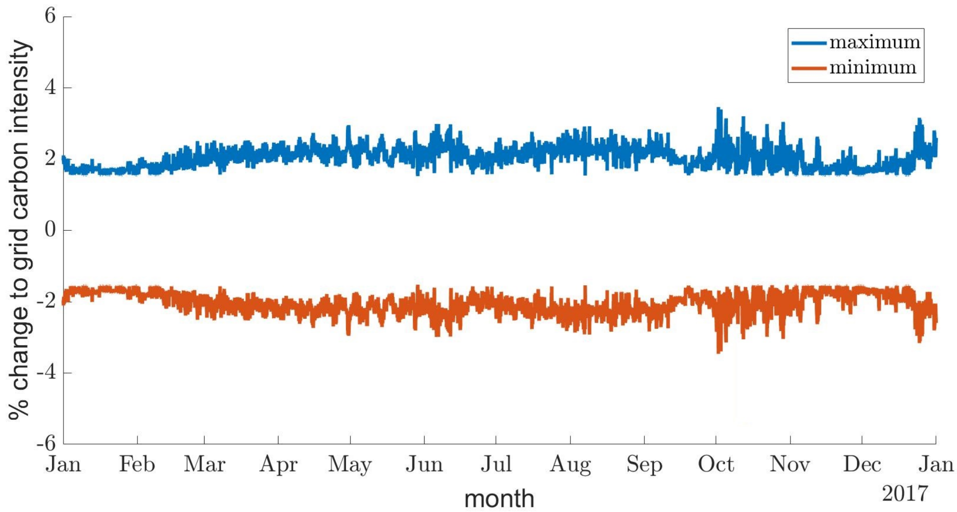


Figure 3.6: % change to half-hourly grid carbon intensity using different carbon factors (2017).

The results indicate that depending on the methodology and the range of factors, the discrepancies in the uncertainty ranges of half-hourly grid carbon intensity are high ranging from 2 to 25%.

3.7 GB grid carbon intensity for years 2009 to 2017

Figure 3.7 presents the frequency of half-hourly grid carbon intensity values for years 2009 to 2017. Carbon intensity was at its highest with a maximum of 647 g/kWh during 2012 where coal generation surpassed that of gas (also shown in figure 3.2a). Since then, grid carbon intensity has steadily declined by reaching a new low maximum of 445 g/kWh in the latest year of the data analysis. This drastic decrease of 202 g/kWh in the maximum values of grid carbon intensity can be explained by the significant energy generation and supply changes that have taken place in the recent years. Fossils fuels' supply has dropped from 83% in 2009 to 45% in 2015 and the increased renewable capacity reached a record of 25% in generation share (DECC, 2017a). However, Staffell (2017) highlights that the reasons behind such changes are more complex as the grid behaviour is affected by international events. An example as explained by Staffell (2017), regards the decrease in gas usage that happened in 2012; The Fukushima disaster

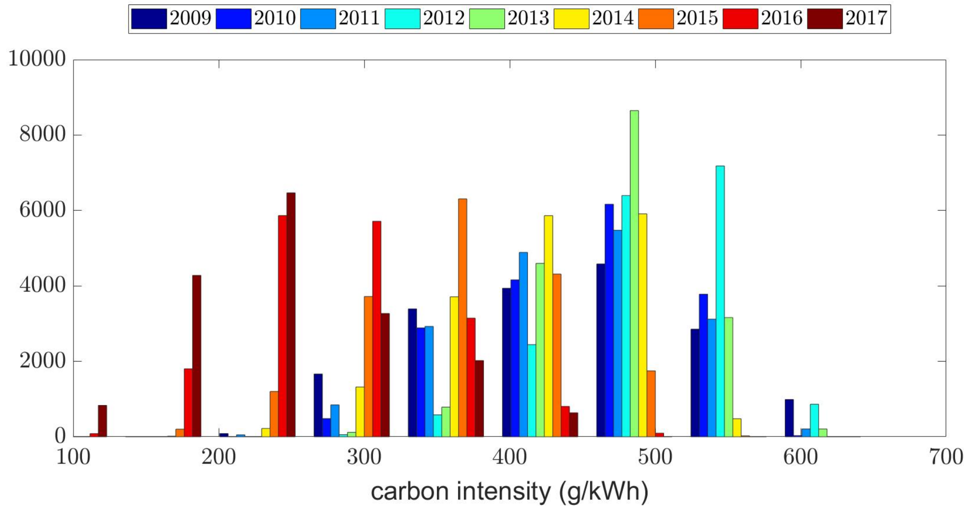


Figure 3.7: Half-hourly grid carbon intensity for years 2009 to 2017.

aftermath led Japan to import more gas at the same time when gas supplies were reduced due to the Arab Spring while American coal provided a cheap alternative. As a result, the fuel mix used in 2012, heavier in carbon due to the increased amounts of coal, drove the grid intensity figures higher than the previous three years. Figure 3.8 shows that the average grid carbon intensity does not follow a consistent intra-annual pattern although a drop can be noticed during warm months (June, July, August) in all cases. In figure 3.12 that presents the half-hourly grid carbon intensity for years 2009 to 2017, the colourmap ranges from 0 to 600 g/kWh where warm colours (yellow to red) represent half-hours of high grid carbon intensity greater than 400 g/kWh. Consintently with figure 3.8 it can be seen that in all cases half-hourly grid carbon intensity is generally higher in January and December and lower in the period July to September.

While there is great variability for each year in Figure 3.8, in Figure 3.9 daily mean grid carbon intensity follows a relatively consistent pattern. The minimum values of grid carbon intensity occur from 04:00 to 05:00 for all years. In all cases, grid carbon intensity starts increasing from 06:00 to reach its peak around 12.00, remains relatively high during the afternoon and the evening and begins to drop close to midnight. This pattern seems to be in accordance with a typical, daily energy use profile including the lunchtime energy peak, a smaller peak during the evening after the end of working hours and finally the drop during night hours. Moreover, in Figure 3.9 the variation from one half-hour to the

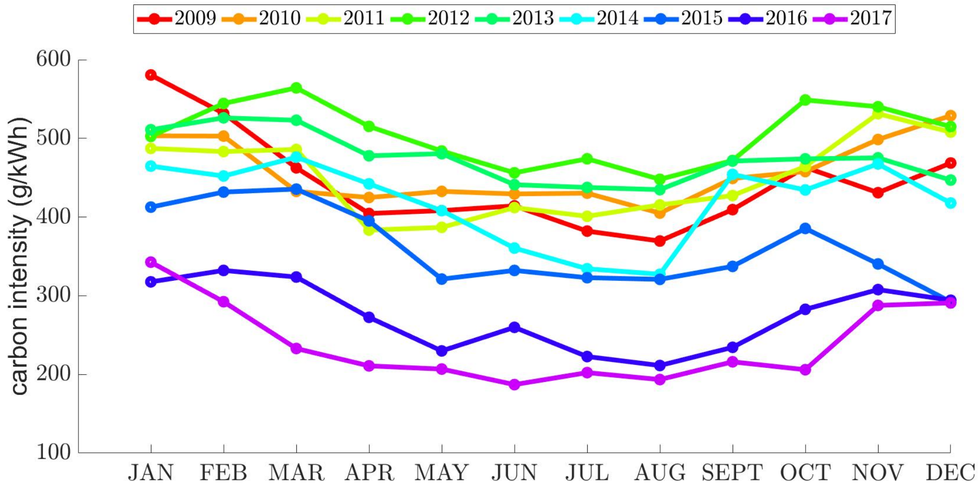


Figure 3.8: Monthly average grid carbon intensity for years 2009 to 2017.

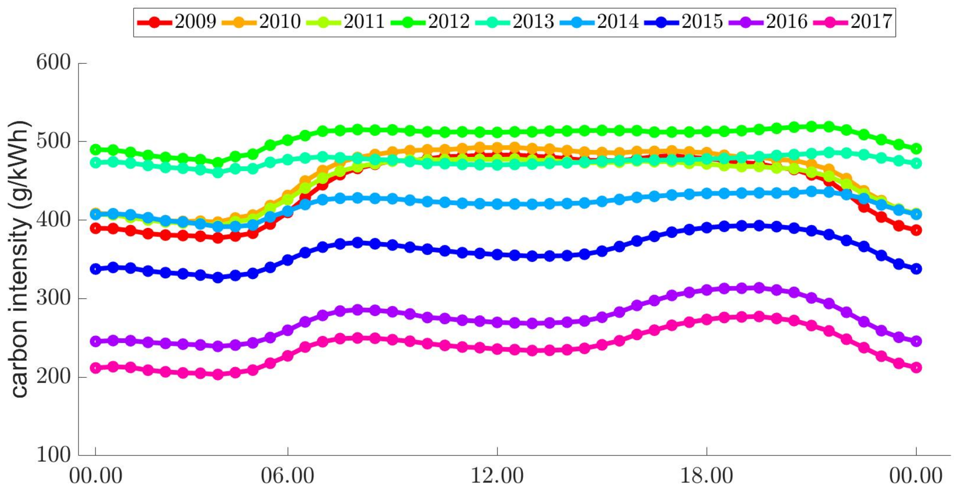
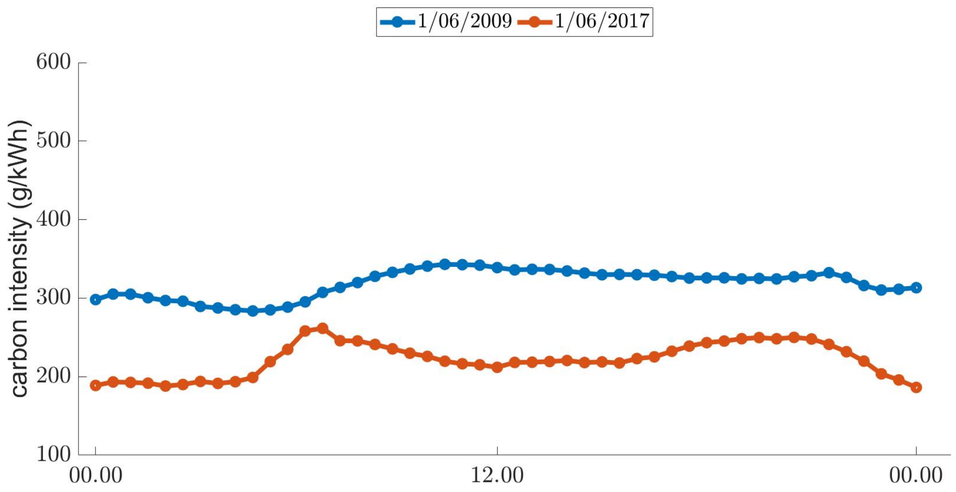


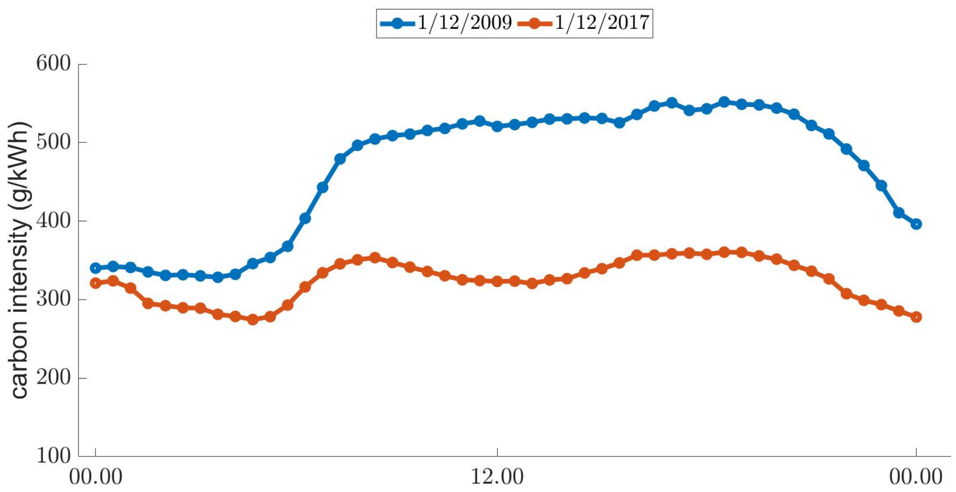
Figure 3.9: Half-hourly average grid carbon intensity within a day for years 2009 to 2017.

next is more evident. Examining the in-day variability of grid carbon intensity in high resolution, figure 3.12 agrees with the profile of figure 3.9 which is more evident in the first few years of the analysis (2009 to 2012) where the fuel mix was dominated by coal (seen in table 3.4).

Figure 3.10 shows the grid carbon intensity's half-hourly profiles for the first of June and December in 2009 and 2017 respectively while figure 3.11 presents the half-hourly generation by fuel type for the same days. These figure contrast summer and winter in the earliest (2009) and most recent year (2017) of this study in order to examine the behaviour of grid carbon intensity in a narrower timeframe.



(a) Half-hourly grid carbon intensity on the first of June 2009 and 2017.

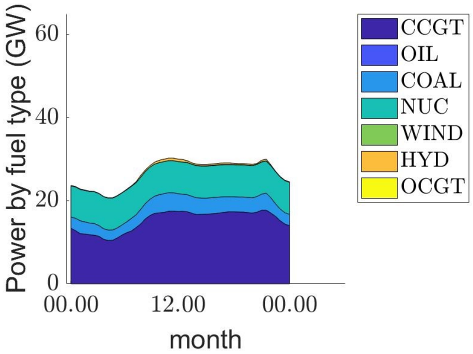


(b) Half-hourly grid carbon intensity on the first of December 2009 and 2017.

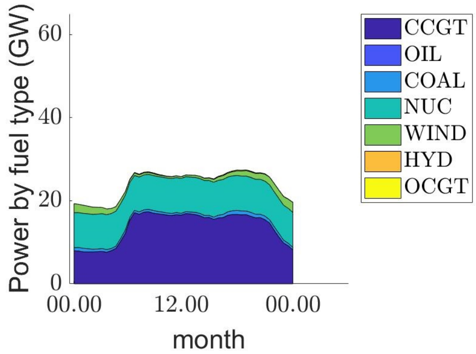
Figure 3.10: Half-hourly grid carbon intensity in a day in June and December, comparing 2009 and 2017.

As expected due to the lower demand, grid carbon intensity remained relatively low, compared to December for the same years, across the first day of June in both cases, varying up to 59 g/kWh in 2009 and 75 g/kWh in 2017 (figure 3.10a). Examining now the relevant generation profiles in figures 3.11a and 3.11b it is noticed that they are very similar. On both figures, a steady baseload of CCGT and nuclear are observed while the main difference is the elimination of coal and presence of wind in figure 3.11b which can explain the 100 g/kWh discrepancy in the respective grid intensity values.

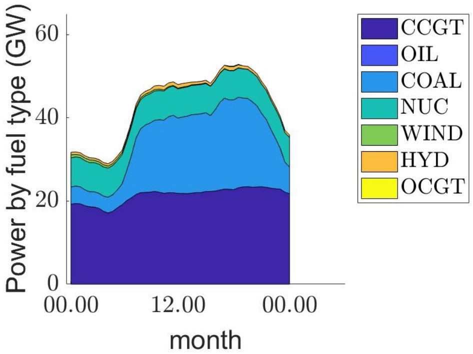
Although higher grid carbon intensity values are noticed in December for both years the



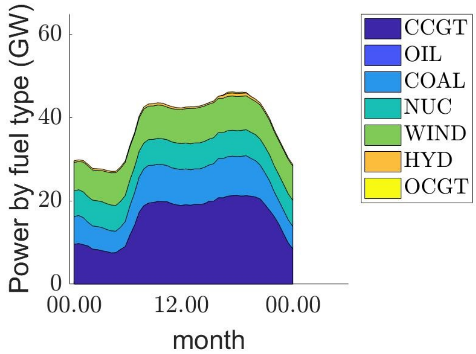
(a) Generation by fuel type on 1/06/2009.



(b) Generation by fuel type on 1/06/2017.



(c) Generation by fuel type on 1/12/2009.



(d) Generation by fuel type on 1/12/2017.

Figure 3.11: Half-hourly generation by fuel type in a day in June and December, comparing 2009 and 2017.

profiles in figure 3.10b are very different. While grid carbon intensity varied only by 85 g/kWh in December 2017, the highest intra-day variability is seen in December 2009. In this case the grid carbon intensity fluctuated up to 220 g/kWh within the same day. It is noted that DEFRA listed 443 g/kWh as the annual grid carbon intensity for year 2009 (table 3.3) whereas it is shown that the variability of grid carbon intensity can amount to 50% of its annual average figure during a single day.

Finally, contrasting the generation profiles across the two years (figures 3.11c and 3.11d), the progress of decarbonisation is evident. While both demand profiles are quite similar, the fuel mix that meets demand is not. In the case of December 2009, a baseload of CCGT is noticed but coal occupies the majority of the baseload whilst in the mix of December 2017, CCGT adopts a load following role. This limits the fluctuation and results in a flatter grid carbon intensity daily profile.

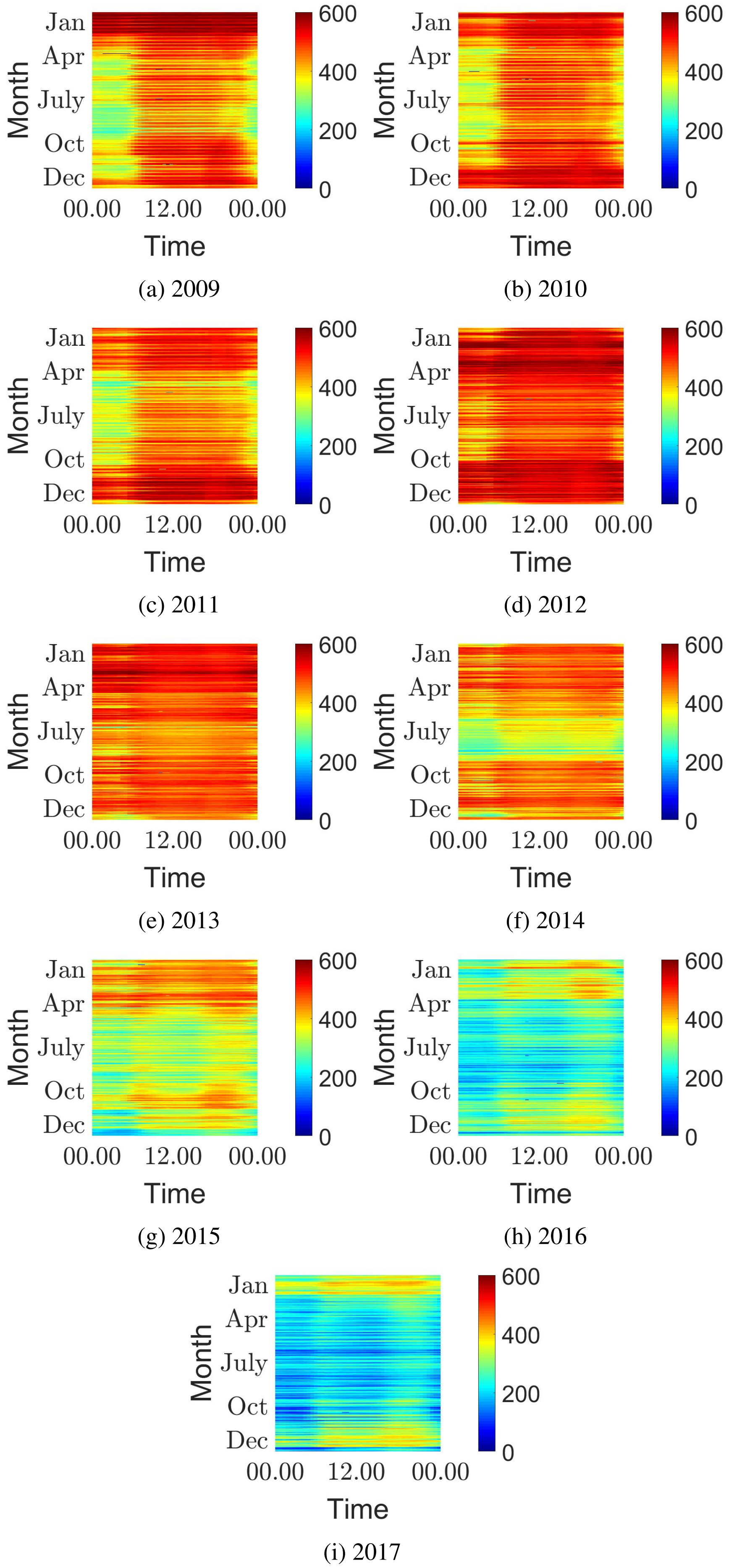


Figure 3.12: Half-hourly grid carbon intensity (g/kWh) for years 2009 to 2017.

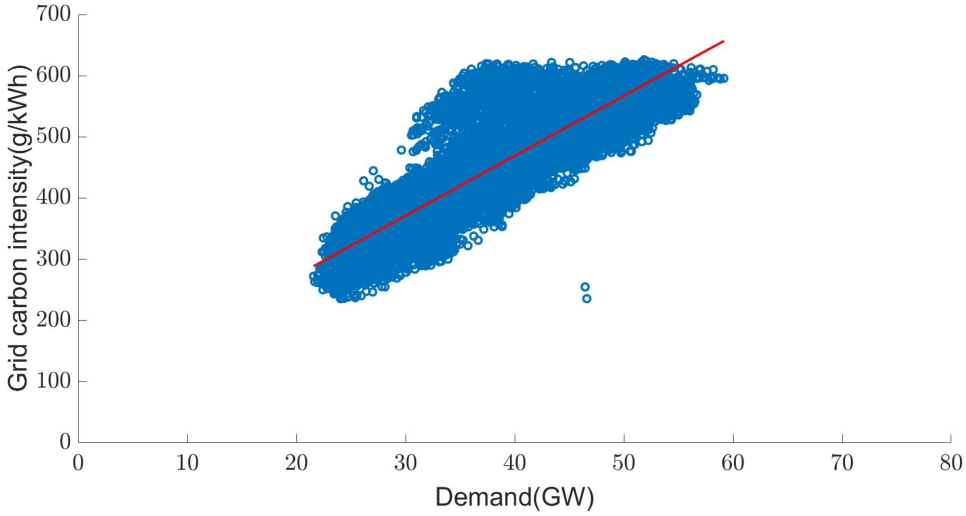
3.8 The relationship between grid carbon intensity and transmission system demand

To understand the relationship between transmission system demand and grid carbon intensity the Spearman correlation coefficient ρ (equation (3.1)) has been used and a linear fit was applied. Furthermore, the linear relationship between the independent variable x electricity demand and the dependent variable y grid carbon intensity was examined for all years in table 3.6. The linear relationship that is examined is $y = a \cdot x + b$ where x is electricity demand (independent variable), y is grid carbon intensity (dependent variable), a is the gradient and b is the intercept.

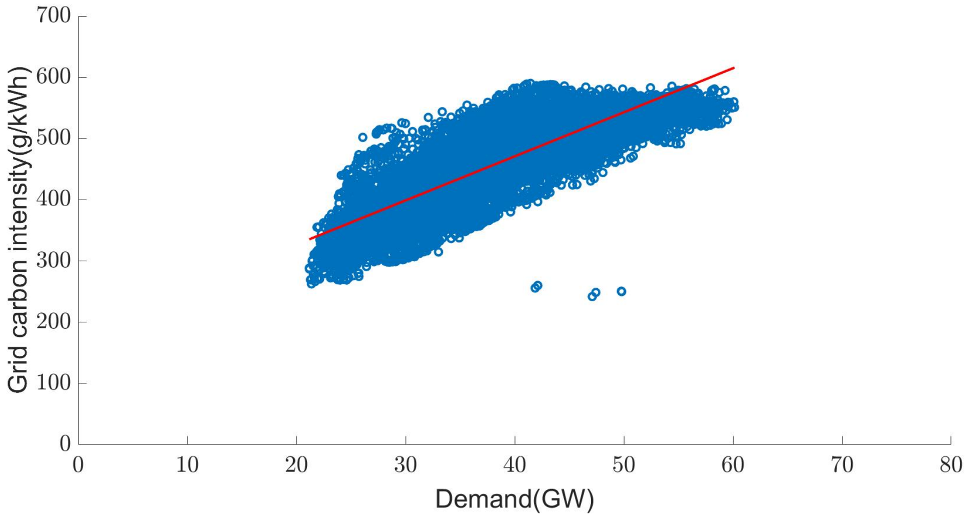
	a	b	ρ
2009	0.009	90	0.87
2010	0.006	216	0.85
2011	0.007	172	0.77
2012	0.003	390	0.52
2013	0.002	371	0.38
2014	0.0048	251	0.5
2015	0.0062	152	0.61
2016	0.007	20	0.78
2017	0.008	-27	0.78

Table 3.6: Parameters of linear relationship and Spearman correlation coefficient for electricity demand against grid carbon intensity for years 2009 to 2017.

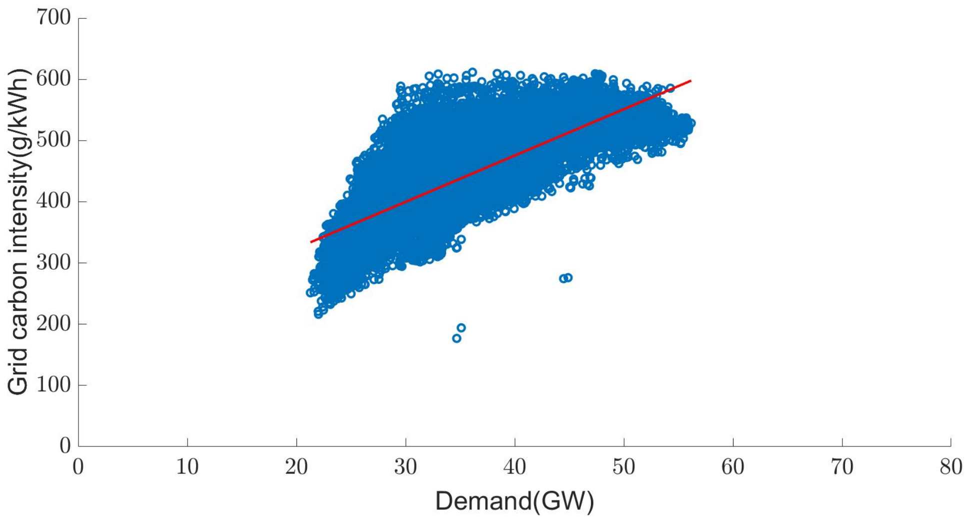
blueThe linear fit between grid carbon intensity and demand is more clear in years 2009 and 2016 (figures 3.13a and 3.15b) where the scatter plots indicate a positive linear relationship with some variation around it.



(a) 2009

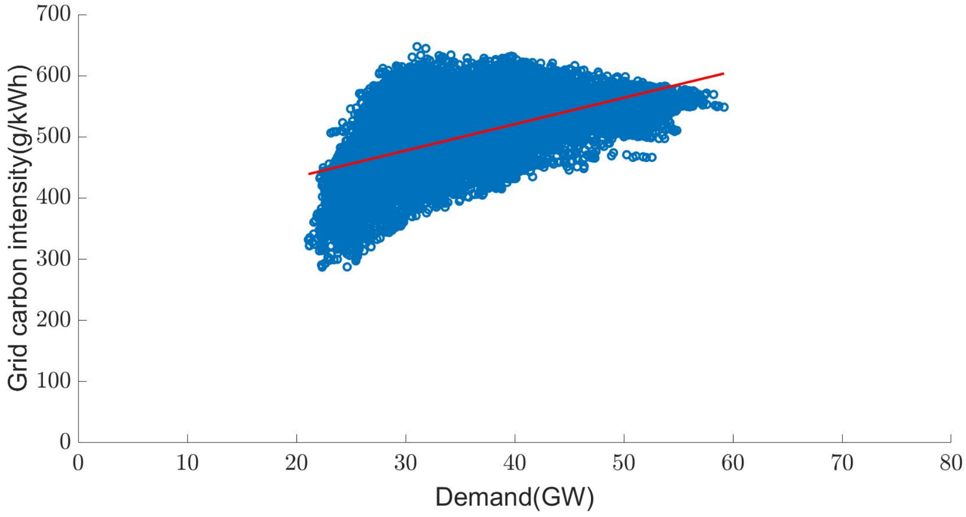


(b) 2010

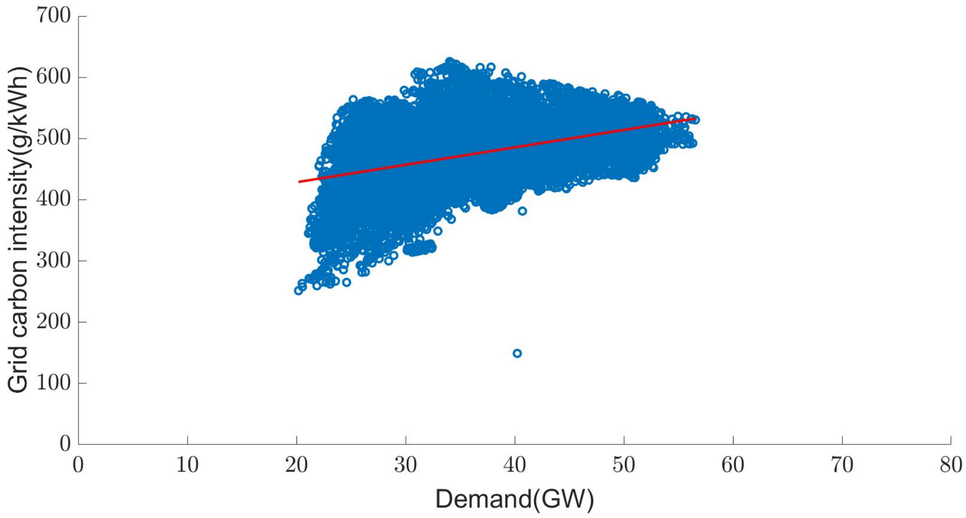


(c) 2011

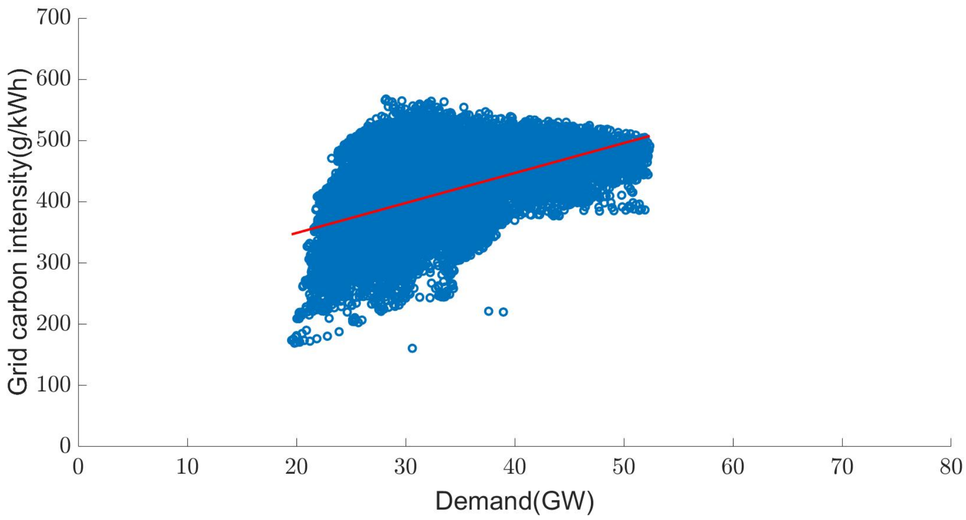
Figure 3.13: Transmission system demand against grid carbon intensity for years 2009 to 2011.



(a) 2012

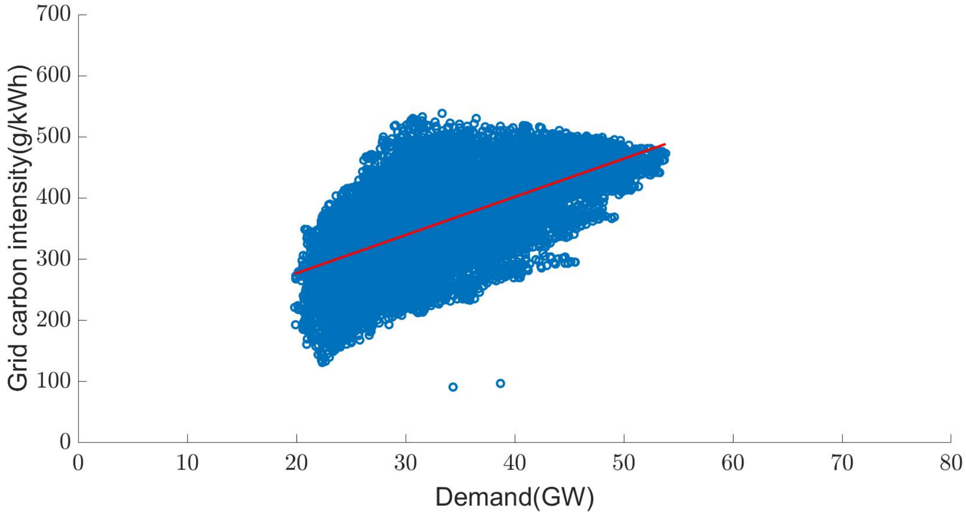


(b) 2013

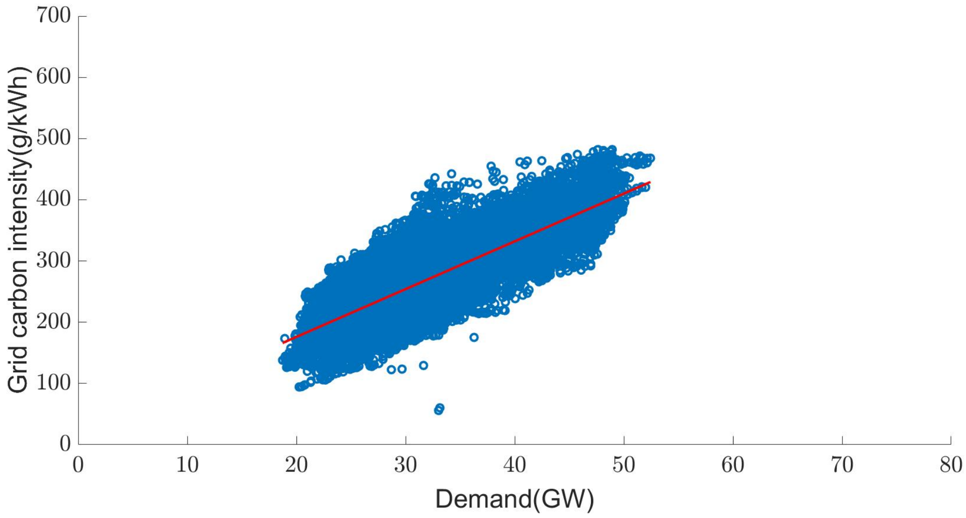


(c) 2014

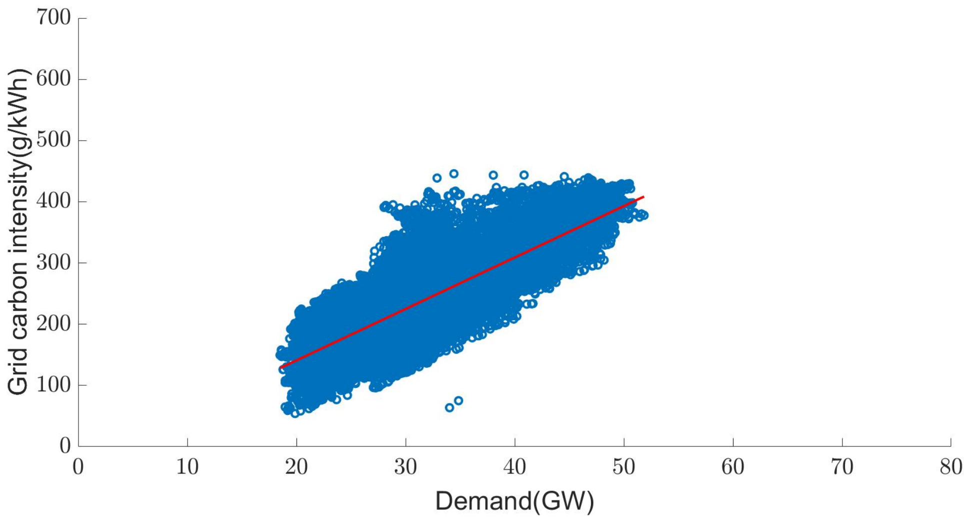
Figure 3.14: Transmission system demand against grid carbon intensity for years 2012 to 2014.



(a) 2015



(b) 2016



(c) 2017

Figure 3.15: Transmission system demand against grid carbon intensity for years 2015 to 2017.

3.9 Summary of findings

	Mean CI	Median CI	Standard deviation	Max CI
2009	443.8	448.6	87.4	626.1
2010	457.9	468.5	69.1	590.0
2011	448.8	453.9	71.9	611.5
2012	505.4	512.5	56.8	647.6
2013	475.0	478.1	50.3	625.6
2014	419.9	431.7	65.4	567.7
2015	360.6	361.2	69.7	538.5
2016	274.1	269.5	66.2	482.0
2017	239.1	229.3	73.7	445.7

Table 3.7: Statistical characteristics for half-hourly grid carbon intensity for years 2009 to 2017 (g/Kwh).

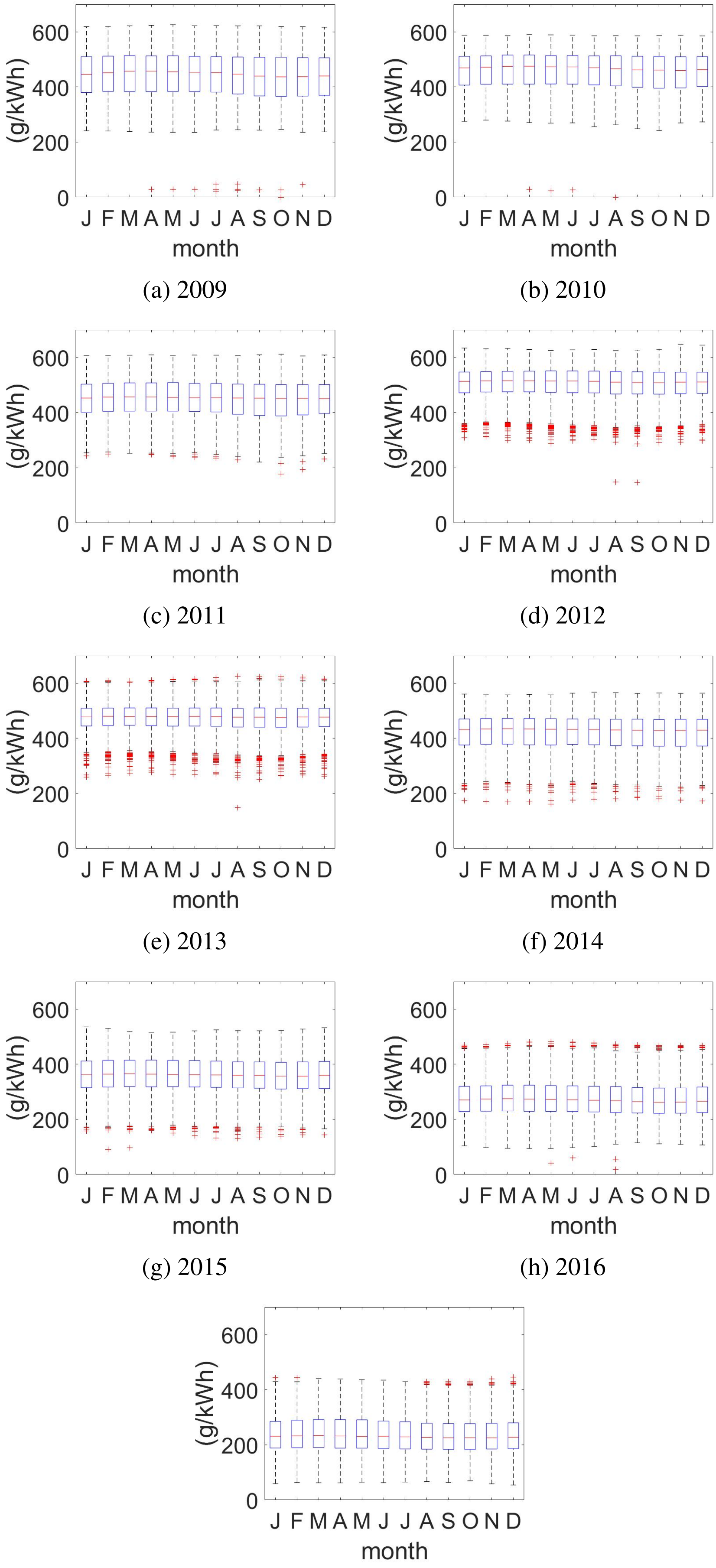
With the drastic decrease of coal generation by 79% and the increased wind penetration by 162% the progress of the GB grid decarbonisation achieved in the space of nine years is evident in table 3.7 and figure 3.16 with a sharp drop of average, annual grid carbon intensity by almost 47% from 443 g/kWh in 2009 to 239 g/kWh in 2017.

Furthermore, the intra-annual variability (measured by the standard deviation in table 3.7) was shown to begin at its highest in 2009, decrease until 2013 following the coal plant closures and then started increasing again from 2014 until 2017 due to increased renewable penetration.

Different plant type carbon factors cause a discrepancy of more than 10% in annual average figures of grid carbon intensity when compared to the DEFRA respective figures. The use of plant carbon factors derived from international literature caused uncertainties of 25% on the half-hourly grid carbon intensity. By contrast, using GB specific carbon factors the noticed discrepancy in half-hourly grid carbon intensity varied from 2% to 3%.

Average half-hourly grid carbon intensity follows a consistent pattern of energy use profile throughout the day in all years but the same does not apply for the average monthly intensity. Although it generally is lower in warm months (spring and summer) than in colder ones (autumn and winter), there is not a consistent intra-annual trend.

Finally, the half-hourly change of grid carbon intensity is shown to be significant, reaching 50% of the total annual average in certain cases. Hence, the results of this analysis indicate that grid carbon intensity widely varies not only during the year but also during the day. Thus, the use of a single carbon electricity factor for annual calculations is shown to fail to capture the true behaviour of grid carbon intensity and ends up to under-represent the reality.



(a) 2009 (b) 2010

(c) 2011 (d) 2012

(e) 2013 (f) 2014

(g) 2015 (h) 2016

(i) 2017

Figure 3.16: Distribution of grid carbon intensity for years 2009-2017

Chapter 4

A GB power system model: the mixed integer linear programming approach

4.1 Introduction

This chapter addresses objectives 2 *"Apply power system model(s) to establish grid carbon intensity uncertainty under varying renewable resource inputs and future power station capacity projections"*.

This chapter introduces and describes the Unit Commitment and Economic Dispatch power system model functions and then illustrates how they have been simulated with two different modelling approaches. Mixed integer linear programming approach is the selected solution method for the Unit Commitment problem (see section 2.6.2). The Economic Dispatch problem has been simulated with a non-linear optimisation method. Additionally, a benchmark version of the model has been built utilising the heuristic method of Priority list for the Unit Commitment part and the same non-linear optimisation for the Economic Dispatch part.

These two algorithms are combined to reflect and simulate the operation of Great Britain electricity grid. The input dataset of the model comprises of total demand, power unit operational characteristics and wind and solar generation data while the output is electricity grid carbon intensity in either hourly (sections 4.5 and 4.7) or half-hourly resolution (sections 4.6 and 4.8).

The aim of this chapter is to examine the behaviour of grid carbon intensity under different weather, capacity and demand assumptions, or in modelling terms, when different input parameters are adjusted. Table 4.1 summarises which model parameters remain unchanged and which get adjusted across each section of the chapter.

	Installed capacities	**Demand**	**Wind & Solar generation**
Section 4.5	fixed	fixed	variant
Section 4.6	variant	fixed	fixed
Section 4.7	fixed	fixed	variant
Section 4.8	fixed	variant	fixed

Table 4.1: Fixed and variant parameters in model runs for each chapter section.

4.2 Method

In order to create time-series of grid carbon intensity in half-hourly resolution a GB power system model was designed. The core model comprises of two algorithms that simulate the basic energy modelling functions, unit commitment and economic dispatch. While both functions are implemented in MATLAB the UC algorithm uses an external solver (CPLEX by IBM[1]) to improve computational times. All simulations were conducted on an Intel Core i7-5600U @ 2.60GHz processor.

The UC algorithm uses as inputs the system demand that has to be met and the operational characteristics of the units and produces as output which units are going to be used in each half-hour at minimum system cost. The ED algorithm uses as input UC's output and allocates generating power among the selected units.

Following the runs of the UC and ED algorithm, the output is time-series of generated power for each power station in half-hourly resolution. Consistently with the applied method in chapter 3, grid carbon intensity can now be calculated using equation 2.1.

[1] https://www.ibm.com/uk-en/analytics/cplex-optimizer

The following sections detail the formulation of the algorithms for the Unit Commitment and the Economic Dispatch functions.

4.2.1 The Unit Commitment solution

The literature research indicated that mixed integer linear programming (MILP) is an ISO certified (Streiffert *et al.*, 2005), suitable (Pfenninger *et al.*, 2014) and computationally efficient (Delarue & D'haeseleer, 2007) approach for the problem of Unit Commitment.

To form the UC problem as an algorithm, a binary choice of "on" and "off" commitments for each generator at every time-step needs to be computed, where the following requirements must be met. The committed generators:

- must meet at least the forecasted demand (plus reserve) when operated at minimum;
- must be "on" for a minimum amount of time, and
- must be "off" for a minimum amount of time.

The mathematical formulation is as follows:

$$\min_x f^T(x) \text{ subject to } \begin{cases} x(t) \in Z \\ P_{\max}(i) \cdot x(t) \geq -(D_{for}(t) + R(t)) \\ P_{\min}(i) \cdot x(t) \geq D(t) \\ x(t) \in \{0, 1\} \end{cases} \tag{4.1}$$

where:

- $f^T(x) = (N_i \cdot C_{average}(i)) + (N_{start-ups} \cdot C_{start-up}(i)) + (N_{shut-downs} \cdot C_{shut-down}(i))$: cost function that includes an average running cost for each unit and all costs associated with start-up and shut-down events
- $x(t)$: integer variable taking values 0 or 1

- $P_{\text{max}}(i)$: the maximum operating capacity of unit i
- $P_{\text{min}}(i)$: the minimum operating capacity of unit i
- $D_{for}(t)$: forecasted demand at every time-step
- $R(t)$: fixed reserve at every time-step

MATLAB's integer programming solver requires the following formulation:

$$\min_{x} f^T \cdot x \text{ subject to } \begin{cases} A \cdot x \leq b \\ A_{\text{eq}} \cdot x = b_{\text{eq}} \\ lb \leq x \leq ub \end{cases} \tag{4.2}$$

The assigned parameters are:

- x: the search vector
- f: the cost function that includes running and start-up/shut-down costs
- A: inequality constraint matrix
- b: inequality constraint vector
- A_{eq}: equality constraint matrix
- b_{eq}: equality constraint vector
- lb and ub: lower bound and upper bound for x

The x vector is a concatenation of three equal sized vectors: the first contains the binary "on" and "off" commitment, the second contains the flags indicating generator "start-ups", and the third contains the flags indicating generator "shut-downs"

$$x = [c^T \; u^T \; d^T]$$

where:

- c : vector containing binary commitment choice ("on" or "off")

- u : vector containing powering up flags (from “off” to “on”)
- d : vector containing powering down flags (from “on” to “off”)

After the population of the vectors, the algorithm is set to use an external solver (CPLEX by IBM). This selection was made to achieve more efficient computational times. The output is a matrix containing only 0s and 1s for each time-step indicating which units are going to turn on (1) and which units are to remain off (0).

4.2.2 The Economic Dispatch solution

Using the UC’s output, the ED part regards the allocation of power outputs among the available units at minimum cost fulfilling the following constraints:

- the sum of the power outputs must meet the real demand (plus reseve) for every time-step;
- the power output of each generator should not be below the minimum generation characteristic of the unit;
- the power output of each generator should not be above the maximum generation characteristic of the unit.

The mathematical formulation is as follows:

$$\min_{x} f^T(x) \text{ subject to } \begin{cases} \sum_{i=1}^{N} P_i = D_{real}(t) + R(t) \\ P_{min}(i) \leq P(i) \leq P_{max}(i) \end{cases} \tag{4.3}$$

where:

- $f^T(x) = (N_i \cdot C_{running}(i))$: the cost function that includes only the running cost for each unit
- P_i: the power output of unit i
- $D_{real}(t)$: real demand at every time-step

- $R(t)$: fixed reserve at every time-step
- $P_{min}(i)$: the minimum operating capacity of unit i
- $P_{max}(i)$: the maximum operating capacity of unit i

MATLAB's nonlinear optimisation solver requires the formulation:

$$\min_{x} f^T \cdot x \text{ subject to } \begin{cases} A \cdot x \leq b \\ A_{\text{eq}} \cdot x = b_{\text{eq}} \\ lb \leq x \leq ub \end{cases} \tag{4.4}$$

where the assigned parameters are:

- x: the search vector
- f: the cost function that includes the variable running cost
- A: inequality constraint matrix
- b: inequality constraint vector
- Aeq: equality constraint matrix
- beq: equality constraint vector
- lb and ub: lower bound and upper bound for x

The ED algorithm optimising over the cost function produces a matrix that contains power output for each generator for every time-step.

The UC was run first for each day of the year, and then ED runs for all available-to-commit units for each half-hour separately. Figure 4.1 illustrates the input and output datasets for the UC and ED optimisation algorithms. UC input datasets are matrix A $[N \times a]$ where N is the number of units and a is the number of operational characteristics for the units (see table 4.2) and array D $[d \times 1]$ where d is the length of the demand array. After the MILP optimisation is complete, the UC output is the binary matrix B $[N \times d]$ where each unit is shown to be on (1) or off (0) for each time-step. This matrix B is then used as the ED input where the second optimisation takes place and the output is matrix P $[N \times d]$ where each unit has been allocated with a power output for every time-step.

Finally, it is reminded that in order to obtain grid carbon intensity datasets, power gets converted to energy and then equation 2.1 is used to calculate grid carbon intensity CI at time t:

$$CI_t = \frac{\sum_{n=1}^{N} c_n \cdot E_{n,t}}{\sum_{n=1}^{N} E_{n,t}}$$

where n is the fuel type index, N_n is the total number of fuels, c_n is the carbon factor for different fuels and E_n is the generated energy corresponding to each fuel type n at time t. The following carbon factors (g/kWh) for each plant type (Staffell, 2017) (found in table 3.1) have been used:

- Coal: 937
- CCGT: 394
- OCGT: 651
- Nuclear: 0
- Wind: 0
- Solar: 0

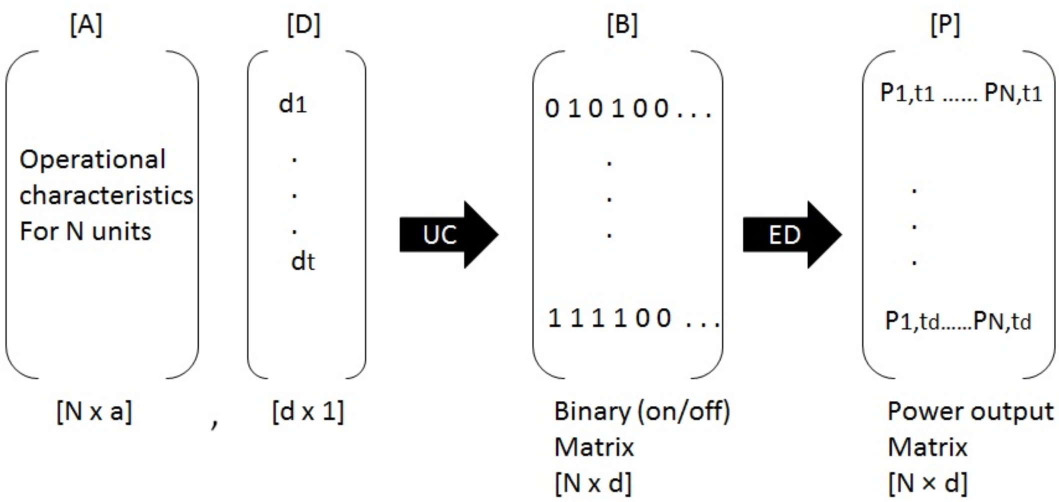


Figure 4.1: Input and output datasets in UC and ED.

4.3 Design of the input datasets

4.3.1 Operational characteristics for different fuel type units

Table 4.2 presents the operational characteristics for each type of unit that was used in the model. The process of constructing a dataset that realistically reflects the Great Britain electricity grid was challenging as such kind of data (i.e efficiencies of each plant type) is usually commercially sensitive and thus not available to public. For this reason, communication was held with expert team-members of the National Control team of National Grid who advised and provided estimates for efficiency and minimum off-time figures.

The figures for the total installed capacities for different fuels were retrieved from the Digest of UK Energy Statistics, 2017 report (DECC, 2017a) and were cross-checked with the Elexon generation by fuel type data for 2017 (Elexon, 2017). The running cost figures that regard the operational cost of a units when it is online, were obtained from the levelised cost data in the BEIS Electricity generation costs report (BEIS, 2016a). Finally, the start-up cost figures that reflect the required costs to bring a unit online, were based on the work of Bruce (2015), which detailed a GB electricity grid model in 2015.

Fuel Type	**Total installed capacity (MW) (DECC, 2017a), (Elexon, 2017)**	**Efficiency (%)**	**Running cost (£/Mwh) (BEIS, 2016a)**	**Start-up cost (£) (Bruce, 2015)**	**Min off time (h)**
CCGT	31000	50-60	66	10000	6
NUCLEAR	9500	35-50	93	100000	48
COAL	9000	40-50	148	11000	12
OCGT	1000	35-40	162	5000	1

Table 4.2: Operational characteristics for different plant types.

4.3.2 Number of units

In reality, table 4.2 's capacities are allocated among more than 300 generating power stations in GB from which 40 are CCGT, 9 are coal-based, 8 are nuclear and 2 are OCGT (other types are gas/oil, biomass, wind, waste, hydro, tidal and solar) (DECC, 2017a).

For the model runs, the installed capacities of table 4.2 were allocated according to the following scenarios as described in table 4.3. It is noted that an upgrade to a 30-unit version was attempted but was ultimately aborted due to hardware constraints and excessive running time.

Total	CCGT	Coal	Nuclear	OCGT
10	5	2	2	1
20	11	3	4	2
25	14	4	5	2

Table 4.3: Different number of units scenarios.

4.4 Model validation: Benchmarking and mean absolute percentage error as a metric for forecast accuracy assessment

In order to assess and validate the MILP model, the benchmarking approach has been used. Benchmarking is the process of comparing the model's results to existing methods. A benchmarking process can compare the results to the best naive solution or another very simple model (Stein, 2007).

4.4.1 Benchmark model: The priority list approach

To build the benchmark model, the method of priority list has been selected to solve the Unit commitment problem. Priority list is a heuristic solution method where the order of the working units is pre-assigned by the user (Senjyu *et al.*, 2003). The units are classified as baseload (units that are always on), mid-merit or load following (units that turn on when the demand exceeds the baseload) and peak (units that turn on when the demand is high). The list was structured in descending order of the maximum operating limits of the units. For the demand of every half-hourly time step the algorithm “checks” whether the demand can be met with the units that are already on. In this case, the ED optimization function runs for the N units that are working. Otherwise, the next unit in the priority list turns on and the ED optimization function runs for N+1 units. As expected the pre-assigned baseload units are always working while the load-following and peak units turn on when there is need.

Unit no.	**Fuel type**	**Min (MW)**	**Max (MW)**
1	CCGT	1000	9000
2	CCGT	1000	9000
3	NUC	1000	9000
4	COAL	1000	8000
5	COAL	1000	6000
6	CCGT	2000	6000
7	CCGT	3000	4000
8	CCGT	2000	4000
9	COAL	1000	2000
10	OCGT	1000	2000

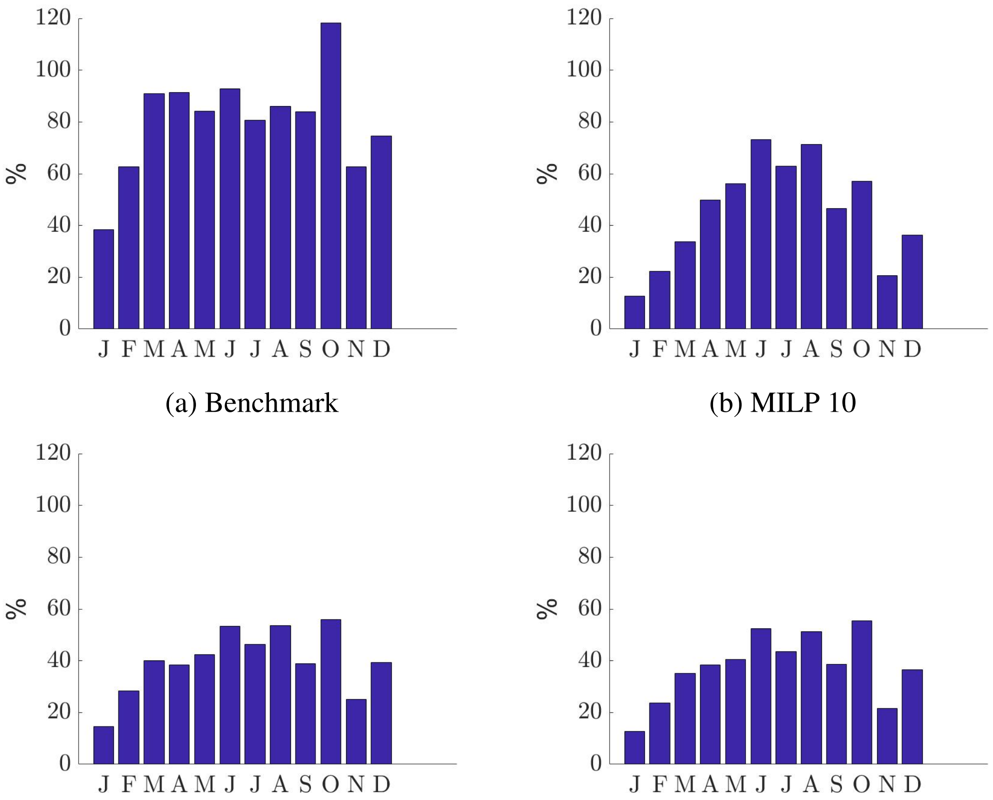
Table 4.4: Benchmark model input units.

4.4.2 Mean absolute percentage error

Mean absolute percentage error (MAPE) is a measure of prediction accuracy of a forecasting method in statistics and is given by the following formula

$$MAPE\% = \frac{100}{n}\sum_{t=1}^{n}\frac{|A_t - F_t|}{A_t} \tag{4.5}$$

where A_t and F_t are the actual and forecasted value at time t. It should be noted that although MAPE is a widely used metric for forecast accuracy assessment, it has inherent flaws especially when it concerns volatile data (i.e double peak punishment). For the purpose of validation of the MILP model, the MAPEs of each month and the total average MAPE, have been calculated for the grid carbon intensity datasets generated by the benchmark model and the MILP model with 10, 20 and 25 units and compared them with real data (Elexon grid carbon intensity 2017- see Data Analysis chapter). It is noted that all simulations have been carried out National Grid's transmission system demand data netting off the Elexon 2017 wind generation.



(a) Benchmark (b) MILP 10

(c) MILP 20 (d) MILP 25

Figure 4.2: Monthly mean absolute percentage errors of model grid carbon intensity versus Elexon grid carbon intensity 2017.

MAPE %	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC	Mean
Benchmark	38.4	62.7	90.8	91.4	84.1	92.7	80.7	86.0	83.9	118.3	62.7	74.5	72.3
MILP - 10 units	12.8	22.3	33.6	49.8	56.2	73.2	62.9	71.2	46.6	57.0	20.8	36.4	41.4
MILP - 20 units	14.7	28.4	40.1	38.4	42.3	53.4	46.3	53.6	38.9	55.9	25.0	39.2	34.8
MILP - 25 units	12.7	23.7	35.2	38.4	40.6	52.4	43.6	51.1	38.7	55.4	21.6	36.6	32.7

Table 4.5: Mean absolute percentage error for benchmark and MILP model.

Table 4.5 shows that the total annual mean absolute percentage error for the 25 unit MILP model reduced to less than half of the error for the benchmark model. Table 4.5 also indicates that the model gives higher error percentage errors for some months (i.e

Jun-Aug-Oct) compared to others. These sensitivities and drawbacks of the forecast can be explained if the omissions and limitations of the model are considered.

4.4.3 Limitations of the MILP model

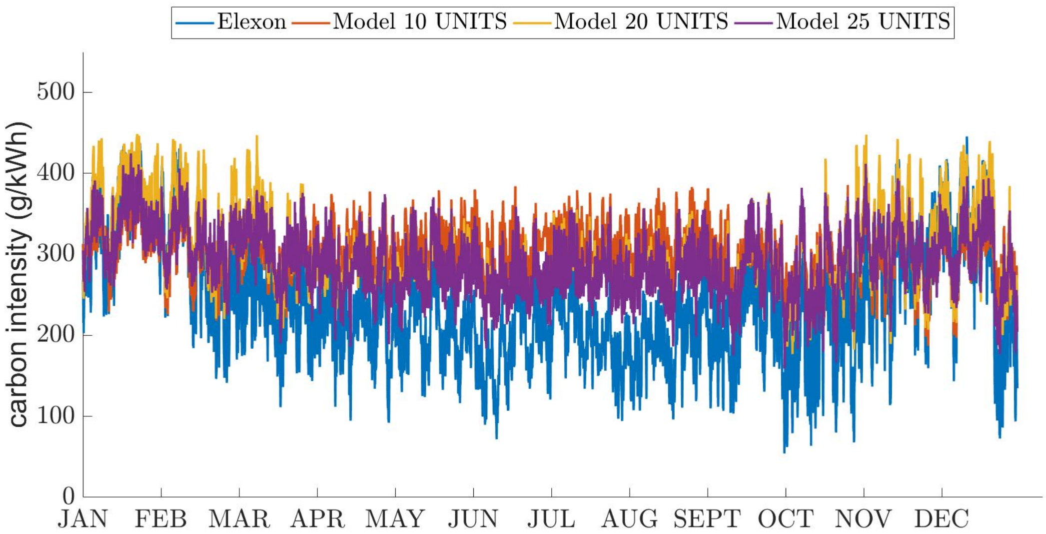


Figure 4.3: Grid carbon intensity of MILP model against Elexon data (2017).

Due to computational efficiency reasons a few parameters have been altogether omitted from the model; Ramping operational constraints, interconnectors and pumped storage have not been simulated and while minimum off time constraints have been built within the model all runs have been carried out without time constraints. The reasons for this are the limited number of units and computational time efficiency.

Figure 4.3 shows the 2017 grid carbon intensity time series for the three MILP versions (10, 20 and 25 units versus Elexon). The model achieves the real-life seasonality of grid carbon intensity as it runs on real demand data. Thus, the decreased variability of the model grid carbon intensity is caused by the small number of units and the lack of seasonality in fuel prices, which results in a less variable fuel mix.

Although there is space for improvement, the MILP'S model performance is shown to be significantly better (40%) than the benchmark's.

4.5 The impact of different weather years on grid carbon intensity

4.5.1 The impact of wind generation on grid carbon intensity

Modern-Era Retrospective Analysis for Research and Applications (MERRA) dataset (Drew *et al.*, 2019a), (Drew *et al.*, 2019b) provides GB-aggregated wind and solar capacity factors in hourly resolution from 1985 to 2015. The annual average figures for both are shown in figure 4.4. For the purpose of this study, three wind "years" have been selected to represent a low, average and high scenario of wind. In specific, 1986 was selected as the high wind, 2011 as the average wind and 2010 as the low wind scenario.

These wind capacity factors datasets have been converted to wind generation datasets using the current wind capacities (see table 4.2) and runs of the 25 unit MILP have been carried out with 2017 National Grid transmission system demand data. It is noted that as the MERRA data is in hourly resolution, grid carbon intensity datasets are in hourly resolution too (as opposed to half-hourly in the remaining sections). Wind and solar have been considered separately in the calculations in order to assess how solely wind and then solar variability affects grid carbon intensity.

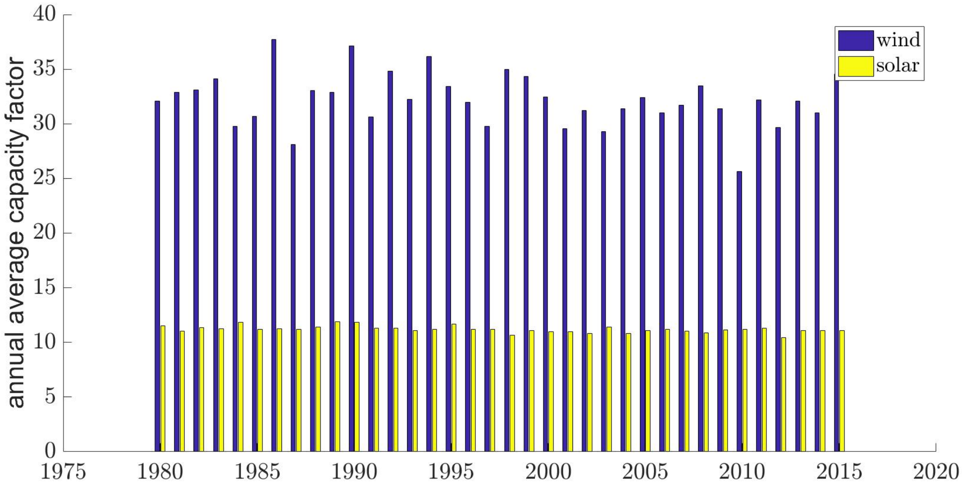
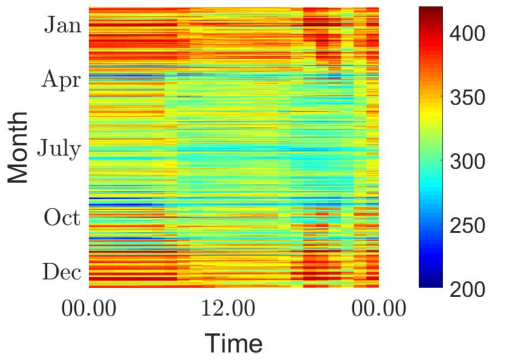
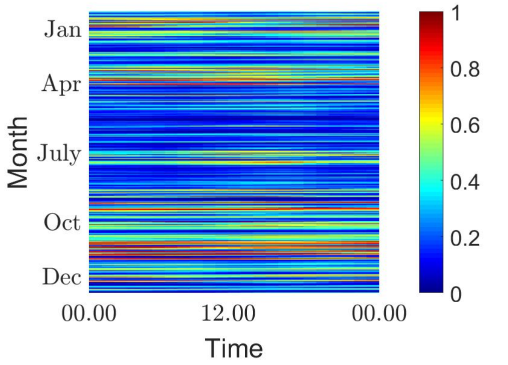


Figure 4.4: Annual average wind and solar capacity factor (MERRA dataset).

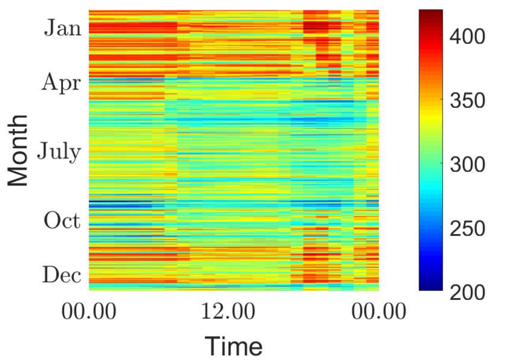
To understand the relationship between wind generation and grid carbon intensity the



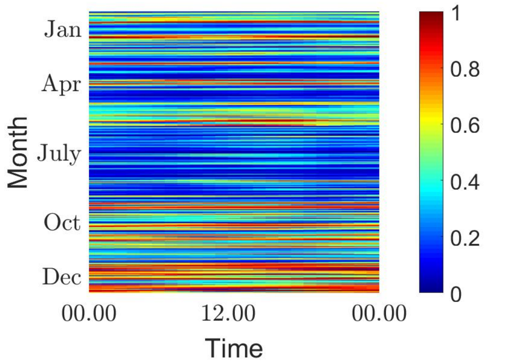
(a) Carbon intensity (g/kWh) - Low wind year



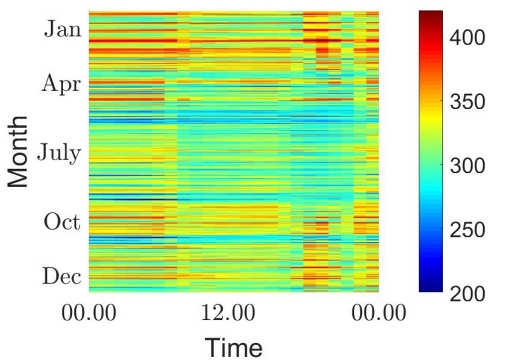
(b) Normalised wind generation - Low wind year



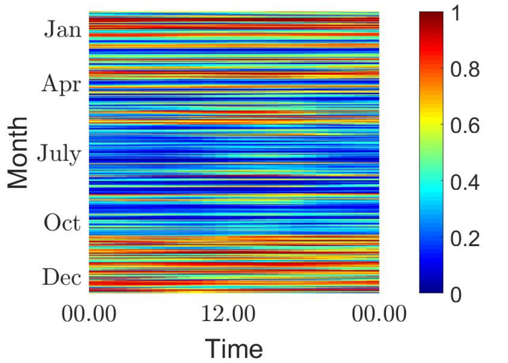
(c) Carbon intensity (g/kWh)- Average wind year



(d) Normalised wind generation- Average wind year



(e) Carbon intensity (g/kWh)- High wind year



(f) Normalised wind generation - High wind year

Figure 4.5: Grid carbon intensity and wind generation for different wind years.

Spearman correlation coefficient ρ has been used:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$$

where d is the pairwise distances of the ranks of the variables xi and yi and n is the number of samples. Spearman's ρ is a rank-based version of Pearson's correlation coefficient, which can be used for variables that are not normal-distributed, more volatile and have a non-linear relationship. Moderate, negative correlation has been noticed in all wind years ranging from -53% to -47% which can also be observed in figure 4.6. This, as expected, means that when wind generation increases grid carbon intensity deceases.

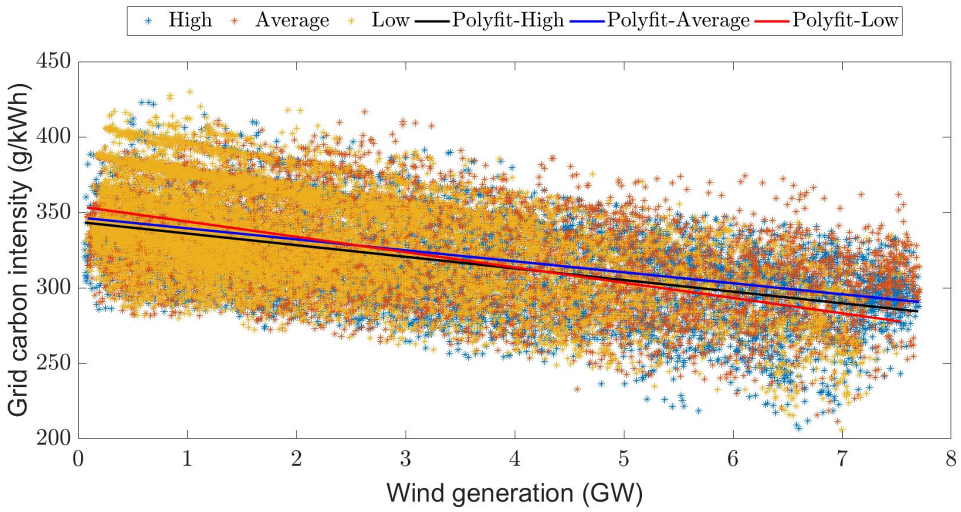


Figure 4.6: Linear fit for wind generation against grid carbon intensity (three MERRA weather years).

Figure 4.5 depicts the normalised wind generation with the respective grid carbon intensity for the three wind years in coloured array plots while table 4.6 presents some of the statistical characteristics for the three time series. The average grid carbon intensity is shown to range only from 318 g/kWh for the high wind scenario to 331 g/kWh for the low wind scenario, while all time series are shown to be similarly "spread" (similar standard deviation 30-33). This difference of 13 g/kWh between the annual averages for the different wind years appears to be negligible and can be misleading about the real impact of wind on grid carbon intensity. The annual average as a metric to understand grid carbon intensity masks the patterns of behaviour that can be noticed only if the whole time series is assessed in higher resolution.

A significant feature can be noticed among the different wind years in figure 4.5; In the low and average wind years, it can be noticed that grid carbon intensity was higher (orange to red-coloured half-hours) for bigger parts of the total year. In specific, it was measured to be higher than 350 g/kWh 2494 times (28% of the year) for the low wind scenario, 2006 times (23% of the year) for the average wind scenario and 1279 times (14% of the year) times for the high wind scenario (table 4.6).

Figures 4.7 and 4.8a present the average grid carbon intensity per hour and per month. Figure 4.7 indicates that different wind generation does not affect the general pattern of average hourly grid carbon intensity which is consistent with the demand pattern (figure 4.11a). Different wind generation is shown to cause an average fluctuation of 13 g/kWh to average hourly grid carbon intensity. On the contrary, average monthly grid carbon intensity does not follow a consistent pattern for all years and the effect of the various wind generation is more evident. Since all three grid carbon intensity datasets have been built using the same demand profile, it is safe to assume that all visible variability between the three profiles on figure 4.8a is caused by the different wind output. For instance, although 1986 (yellow line) was selected as the year with the highest average wind generation, September of the same year displays the highest average grid carbon intensity compared to the other two years. Looking now at figure 4.8b ,which presents the average monthly wind generation, September indeed had the lowest average wind generation across the three scenarios. It is also noticed that the average monthly grid carbon intensity follows the same pattern with the average wind generation in all three wind years. For example, in the case of January, it is seen that an increase of approximately 2000 MW in average wind generation (5000 MW for the high wind year versus 3000 MW for the low wind year) results in a decrease of approximately 30 g/kWh for the corresponding average monthly grid carbon intensity (360 g/kWh for the high wind year versus 330 g/kWh for the low wind year).

	Mean CI	**Median CI**	**Standard deviation**	**Min CI**	**Max CI**	**% of the year CI $\geq$ 350**
Low wind	331	330	33	206	430	28
Average wind	326	325	31	211	417	23
High wind	318	317	30	207	423	15

Table 4.6: Weather years results (wind only).

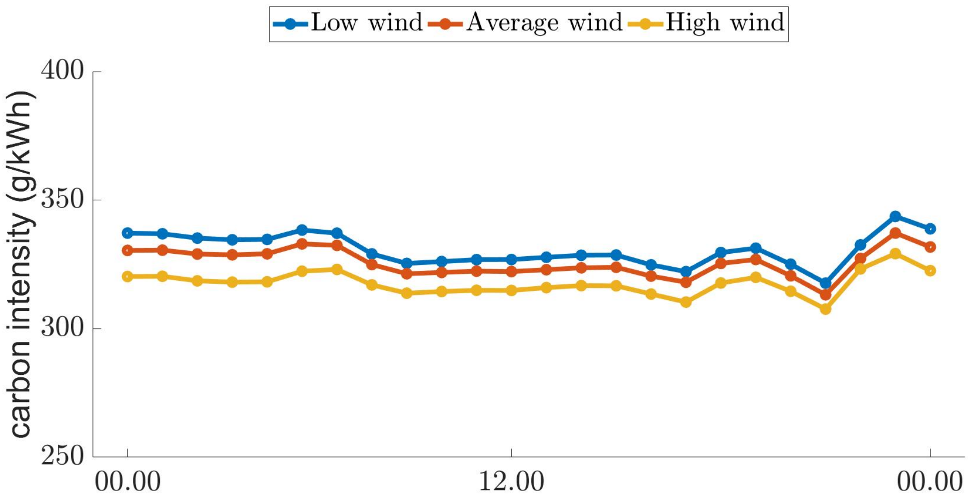
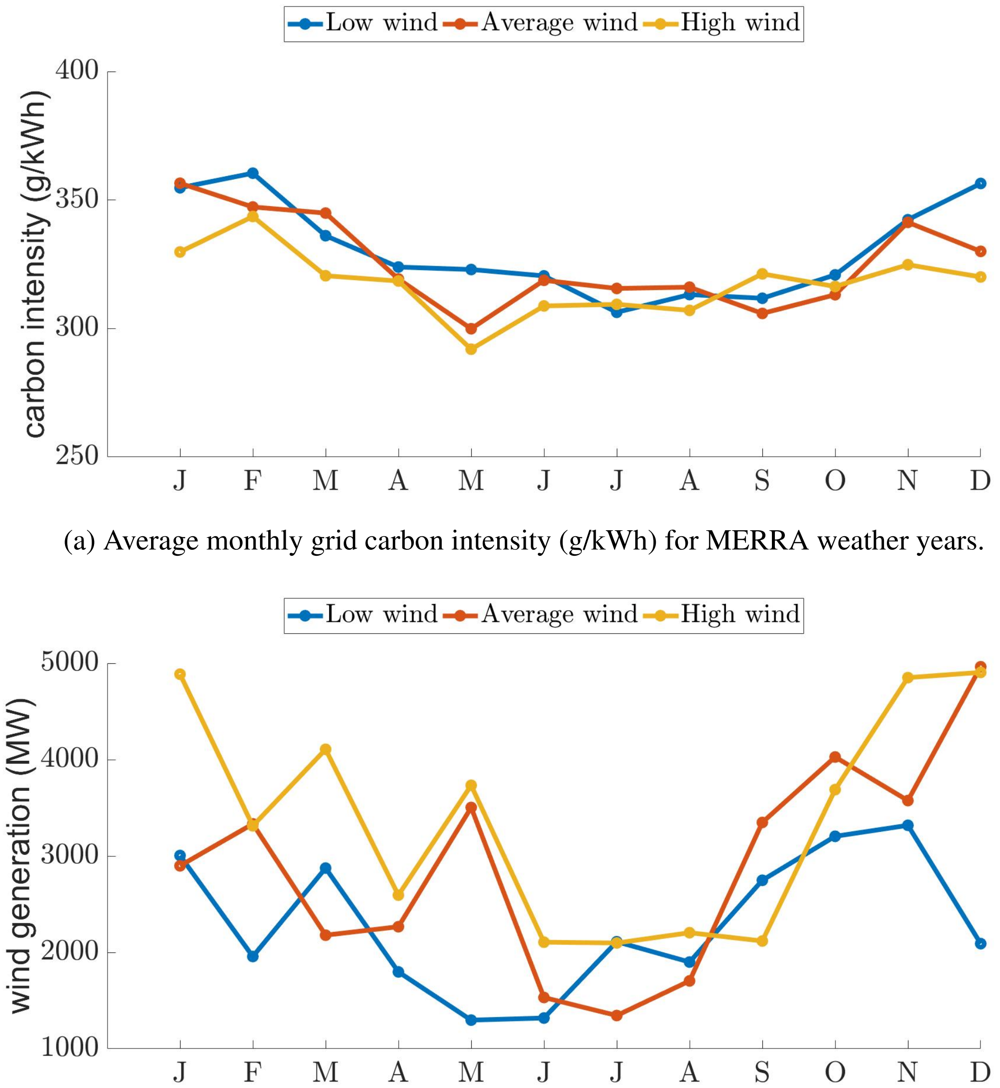


Figure 4.7: Average hourly grid carbon intensity (g/kWh) for MERRA weather years.

4.5.2 The impact of embedded solar generation on grid carbon intensity

While the total installed solar capacity in the UK is 12,493 MW (BEIS, 2017), roughly a total of 574 MW corresponds to major power producers. The remaining capacity represents embedded generators (DECC, 2018c). Embedded generation refers to units connected to the low voltage distribution system as opposed to typically larger sites that are connected directly to the high voltage transmission system (N.G, 2012). Embedded solar generators do not suffer transmission losses, do not participate in the Balancing mechanism and do not require to submit final physical notification (FPN). In simulation terms, this means that this generation is not considered during the plant scheduling and output allocation phases (unit commitment and economic dispatch). Since solar energy is assumed to have zero carbon factor, this type of embedded generation is just added to the total generated energy $\sum_{n=1}^{N} E_{n,t}$ of equation 2.1. In mathematical terms, the relationship between total generated energy $\sum_{n=1}^{N} E_{n,t}$ and grid carbon intensity CI_t is negative linear and as the first increases the second is expected to decrease.

For the purpose of this study, the solar generation profiles of the MERRA 2011, 2010 and 1986 years were included (low wind, average wind and high wind) as embedded generation and grid carbon intensity in hourly resolution was re-calculated.

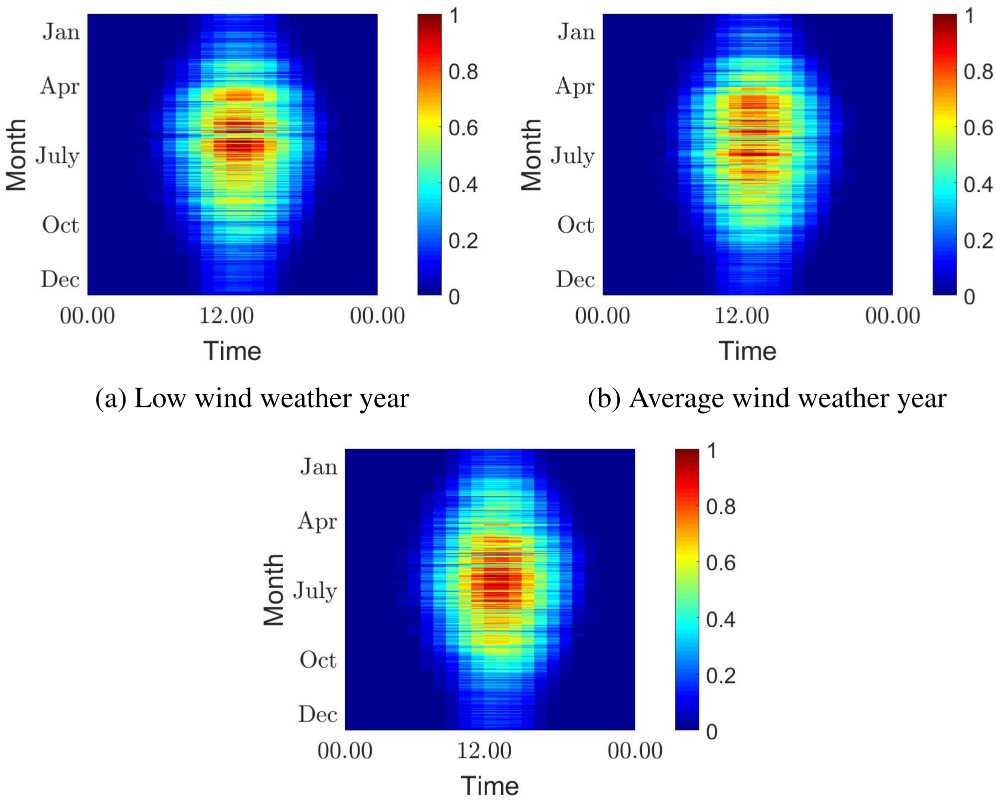


(a) Average monthly grid carbon intensity (g/kWh) for MERRA weather years.

(b) Average monthly wind generation (MW)

Figure 4.8: Average monthly grid carbon intensity and wind generation for MERRA weather years.

Solar generation unlike wind, follows a regular pattern throughout the day peaking from noon to early afternoon when the sun is at it highest point and radiation is most intense (figure 4.9). This solar generation peak causes a drop of 40 to 50 g/kWh in average grid carbon intensity around noon hours, which can be seen in figures 4.10b, 4.10d and 4.10f. For the remaining hours solar generation has little or no impact on average hourly grid carbon intensity. Figures 4.10a, 4.10c and 4.10e present the average monthly grid carbon intensity calculated with and without solar generation for the three MERRA years. Although there is not a consistent monthly pattern, sunnier spring and summer months (especially May and June in all cases) show a decrease of up to $30g/kWh$.



(a) Low wind weather year

(b) Average wind weather year

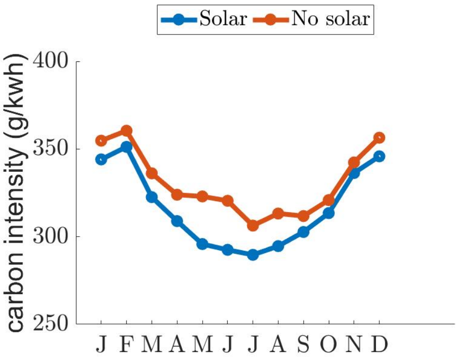
(c) High wind weather year

Figure 4.9: Normalised solar generation for MERRA weather years.

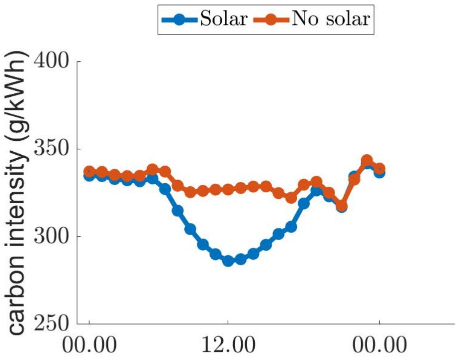
	Mean CI	Median CI	Standard deviation	Min CI	Max CI	% of the year CI $\geq$ 350
Low wind	316	318	37	205	415	19
Average wind	311	311	40	205	421	18
High wind	305	306	37	178	423	12

Table 4.7: Weather years results (wind and solar)

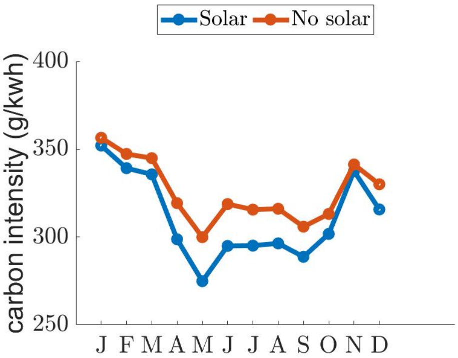
The impact of solar generation to grid carbon intensity is also evident in table 4.7. Comparing it with table 4.6, the mean annual figure decreased approximately by $20g/Kwh$ and the standard deviations increased in all scenarios.



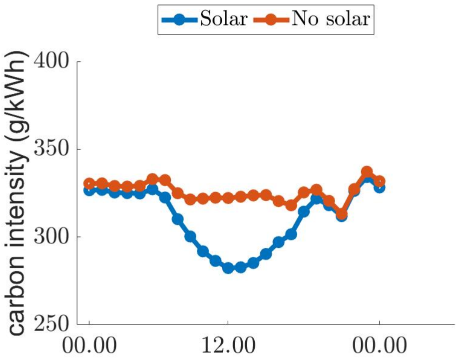
(a) Average monthly grid carbon intensity (g/kWh) - Low wind MERRA year



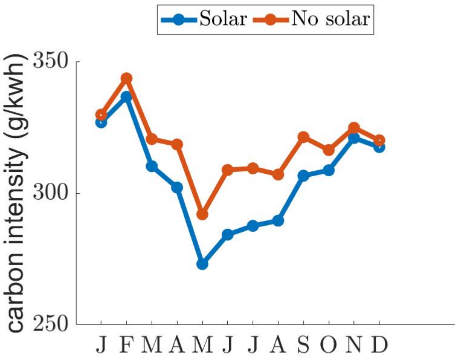
(b) Average hourly grid carbon intensity (g/kWh) - Low wind MERRA year



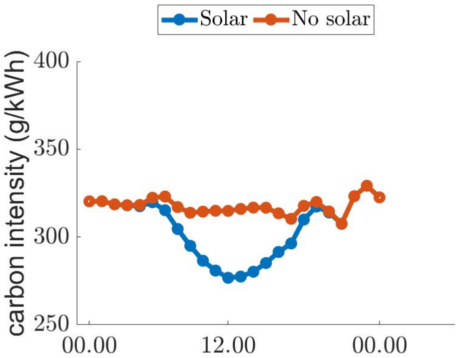
(c) Average monthly grid carbon intensity (g/kWh) - Average wind MERRA year



(d) Average hourly grid carbon intensity (g/kWh) - Average wind MERRA year

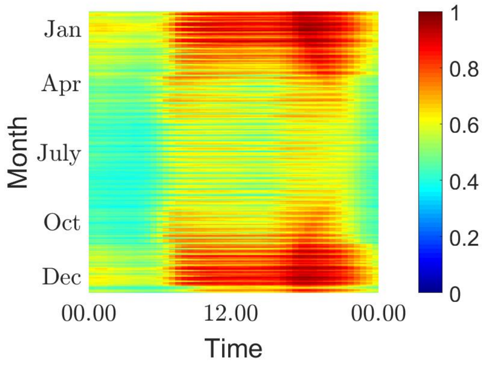


(e) Average monthly grid carbon intensity (g/kWh) - High wind MERRA year

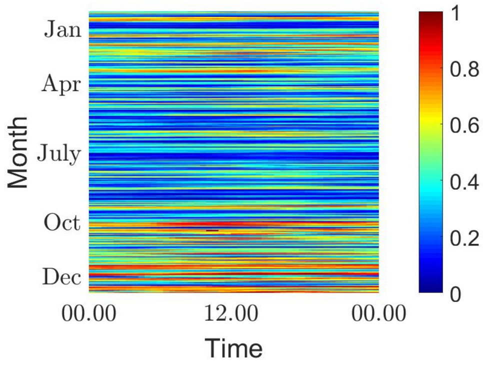


(f) Average hourly grid carbon intensity (g/kWh) - High wind MERRA year

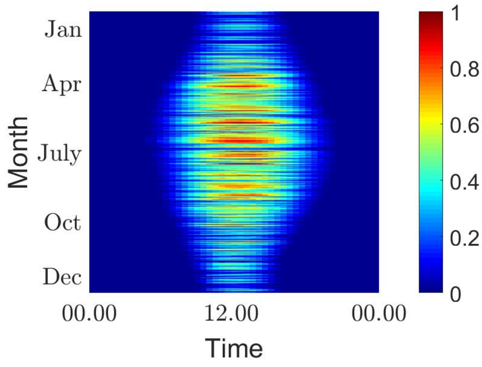
Figure 4.10: Average monthly and hourly grid carbon intensity for MERRA weather years (wind and embedded solar)



(a) Normalised electricity demand 2017.



(b) Normalised wind generation 2017.



(c) Normalised solar generation 2017.

Figure 4.11: Normalised electricity demand, wind and solar generation in 2017.

4.6 The impact of different installed capacities on grid carbon intensity

4.6.1 Baseline input parameters

A baseline grid carbon intensity dataset has been created by running the MILP-25 unit model with adjusted 2017 National Grid transmission system demand data (see figure 4.11a), 2017 Elexon wind data and 2017 National Grid solar data (see figures 4.11b and 4.11c). Figure 4.12 shows that the baseline grid carbon intensity has a range varying from 220 to 400 g/kWh and the median is a little below 300 g/kWh for all months.

The future installed capacity scenarios have been designed on the Future Energy Scenarios' assumptions by National Grid (N.G, 2018a). The same, adjusted 2017 National Grid demand profile has been used for all installed capacity scenarios in order to examine the behaviour of grid carbon intensity. Furthermore, the 2017 Elexon wind profile has been used for all scenarios. For each scenario, a wind generation profile has been created using the 2017 Elexon wind capacity factors and the corresponding to each scenario wind capacities (see table 4.8). It is also noted that the remaining operational characteristics of the units (see table 4.2) remain the same in all capacity scenarios. The future capacities that have been selected and simulated correspond to year 2030. 2030 was selected as an interesting year to examine because coal is eliminated across all scenarios and major changes occur in the installed capacities of renewables.

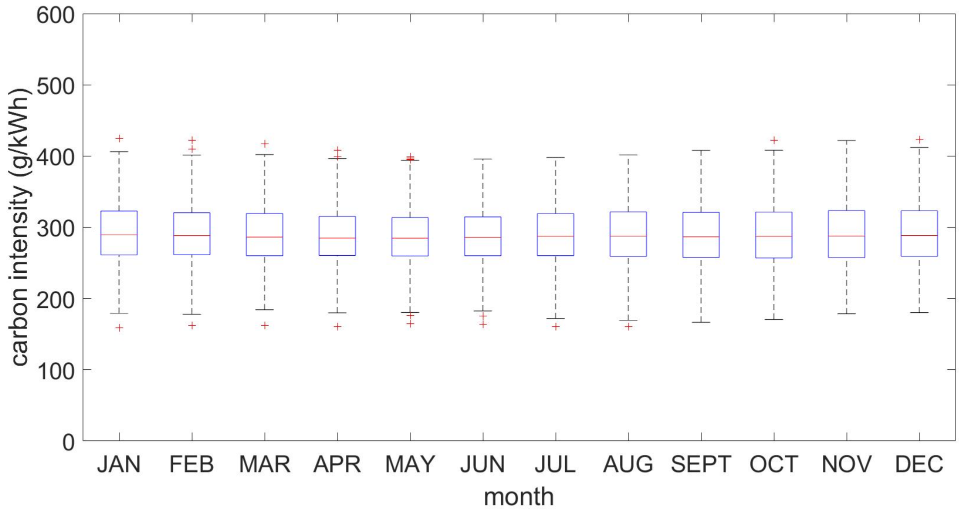


Figure 4.12: Half-hourly grid carbon intensity (g/kWh) for baseline scenario.

4.6.2 National Grid future energy scenarios

National Grid has published documentation on different, credible, energy pathways for the next 30 years and beyond (N.G, 2018a). The four scenarios, namely Community Renewables (CR), Consumer Evolution (CE), Steady Progression (SP) and Two Degrees (TD) have different characteristics and only CR and TD scenarios achieve the 2050 carbon reduction target.

4.6.3 2030 Community Renewables (CR)

The CR scenario achieves the 2050 carbon reduction target through a a more decentralised energy landscape with renewables dominating the picture (N.G, 2018b).

	Current	CR 2030	CE 2030	SP 2030	TD 2030
Coal	9000	0	0	0	0
Gas	31000	31656	43194	41422	30666
Nuclear	9500	2886	1216	2886	9026
Offshore Wind	5098	23585	16835	24805	29935
Onshore Wind	3873	23439	20448	15491	19536
Solar	12493	33037	19773	16429	24275
Storage	2744	9003	6837	5920	8925

Table 4.8: Future Energy Scenarios capacities (MW).

Regarding the installed capacities of interest to this study, coal is eliminated, gas remains at the same levels and nuclear is reduced to roughly a third of its current capacity. Finally, the added onshore and offshore wind capacity increased from 8.9 GW to 46.9 GW while solar increases to 33 GW (table 4.8).

Looking at figure 4.13, the wider range of values is immediately noticed (compared to 4.12) as now there is a lot more of variable wind and solar in the fuel mix. The median has significantly reduced by $150g/kWh$ and for 18% of the year the model runs entirely on carbon free fuels (nuclear, wind and solar) and thus grid carbon intensity is zero (table 4.9). Some seasonality caused by solar can also be seen in the distribution as the median drops in spring and summer months.

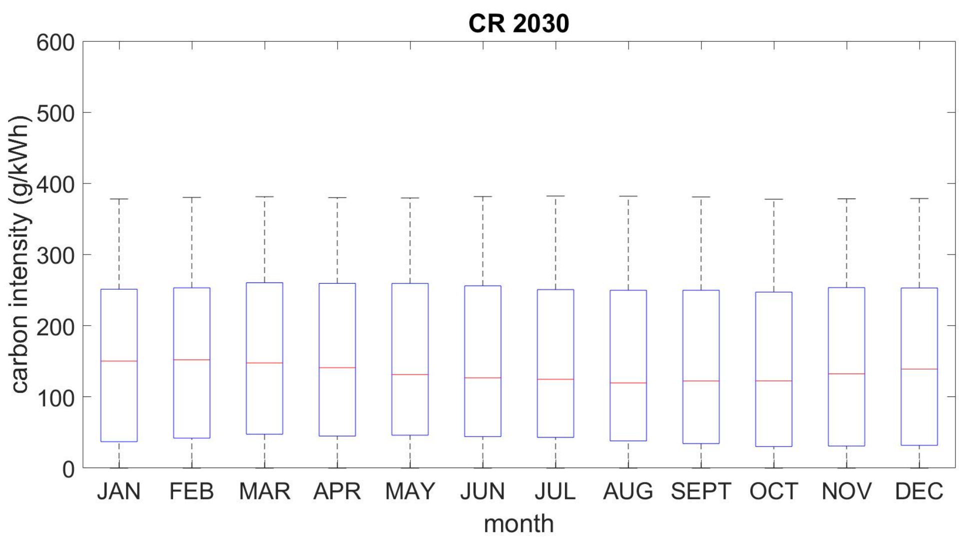


Figure 4.13: Half-hourly grid carbon intensity (g/kWh) for Community Renewables scenario.

4.6.4 2030 Consumer Evolution (CE)

This is a more decentralised scenario which makes progress towards the decarbonisation target but fails to achieve the 2050 target. Generation is focused on smaller scale renewables, with gas and some new large scale nuclear plants providing most of the system flexibility (N.G, 2018b). In this scenario coal is also eliminated from the grid while the gas installed capacity increases from 31 to 43 GW and nuclear decreases to just 1.2 GW. Finally, the total wind capacity also increases to 19.2 GW and solar capacity increases to 19.7 GW. (table 4.8)

In the Consumer Evolution scenario grid carbon intensity has a narrower range compared to Community Renewables, since the renewable capacities are smaller, but still higher than the baseline scenario. The median grid carbon intensity decreased by $130g/kWh$ while grid carbon intensity was zero for 7% of the total year (table 4.9).

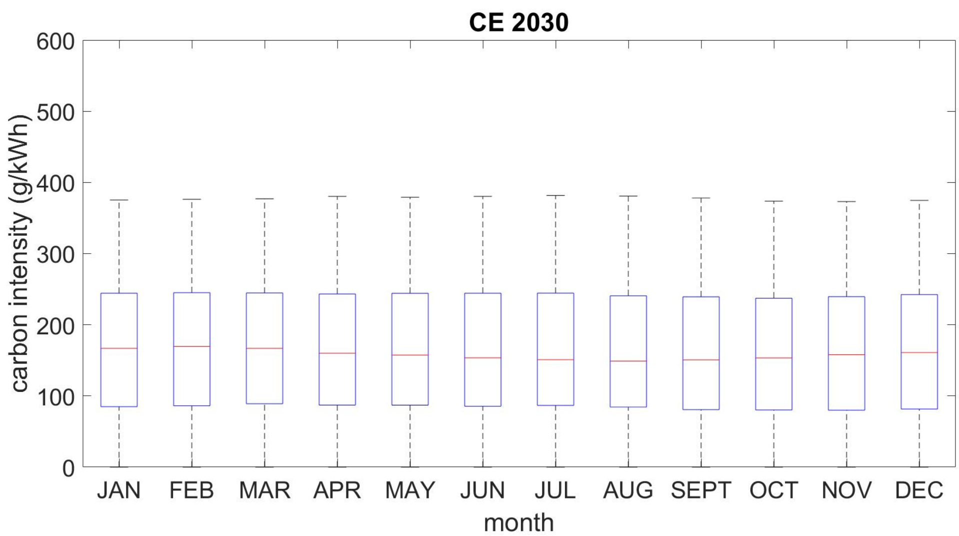


Figure 4.14: Half-hourly grid carbon intensity (g/kWh) for Consumer Evolution scenario.

4.6.5 2030 Steady Progression (SP)

This scenario is more centralised but does not meet the 2050 target. There is greater emphasis on large scale, rather than local, generation. There is development of offshore wind with gas playing an important role in providing system flexibility (N.G, 2018b).

In the SP scenario coal is eliminated from the grid, gas increases to 41.4 GW, nuclear decreases to almost one third of its current capacity, total wind increases to almost 40 GW and solar increases to 16.4 GW (table 4.8).

In this case, the median grid carbon intensity of the year drops to $157g/kWh$, similar to the Consumer evolution scenario and remains at this level across all months. Carbon intensity was measured to be zero for only 7% of the year.

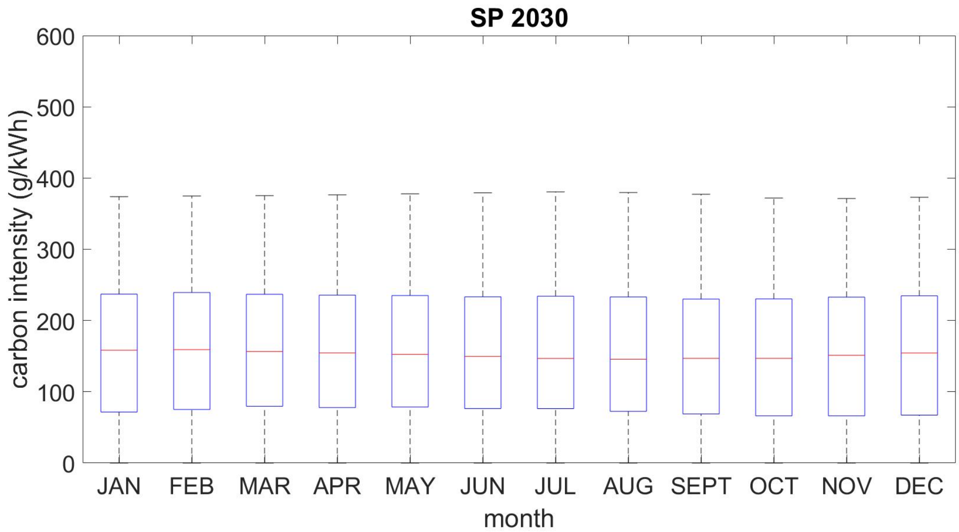


Figure 4.15: Half-hourly grid carbon intensity (g/kWh) for Steady Progression scenario.

4.6.6 2030 Two Degrees (TD)

In this scenario, the decarbonisation target is achieved using larger and more centralised technologies. Generation, such as offshore wind and nuclear, is based more on the transmission network (N.G, 2018b). Lastly, in this scenario while the gas and nuclear capacity remain at the same levels, the total wind capacity increases to, the highest across all scenarios, almost 50 GW while solar increases to 24.2 GW (table 4.8). Under the Two Degrees scenario assumption,grid carbon intensity was found to be the lowest. The increased nuclear capacity in combination with the growth in renewable capacities, caused the median grid carbon intensity of the year to drop to almost $1/3$ of its value in the baseline scenario. Furthermore, the frequency of zero grid carbon intensity figures across the year was the highest (21% of the year).

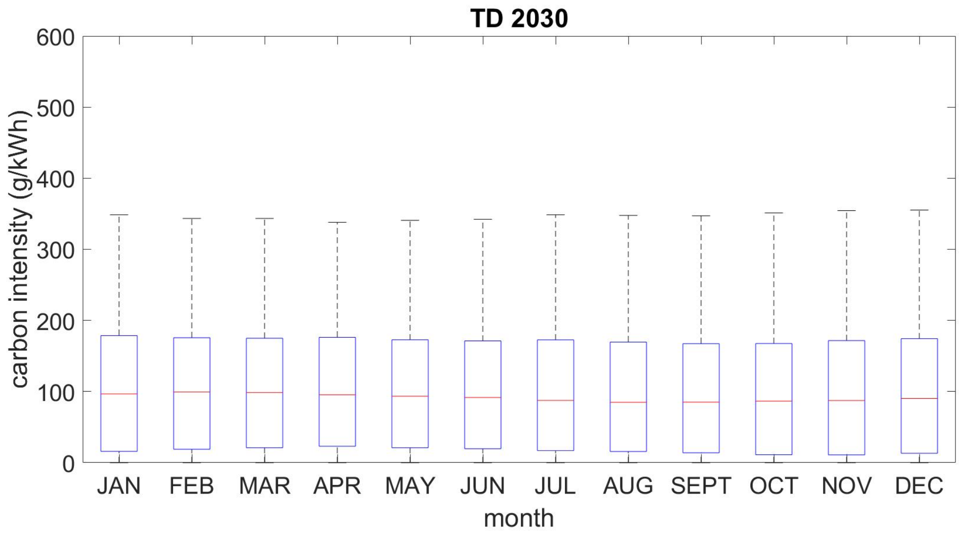


Figure 4.16: Half-hourly grid carbon intensity (g/kWh) for Two Degrees scenario.

4.6.7 Discussion on FES results

In order to understand how the different installed capacities affect the electricity grid carbon intensity, the fuel mix changes under the assumptions of each future energy scenario needs to be examined.

It is reminded that throughout this study the following carbon factors have been used (g/kWh) for each plant type: 937 for coal, 394 for CCGT and 0 for nuclear, wind and solar (Staffell, 2017). Furthermore, grid carbon intensity has been calculated with the following formula: $CI_t = \frac{\sum_{n=1}^{N} c_n \cdot E_{n,t}}{\sum_{n=1}^{N} E_{n,t}}$ (equation 2.1).

Since coal is eliminated in all scenarios, the maximum grid carbon intensity is expected not to exceed $394g/kWh$ which is the carbon factor of CCGT (now, the carbon heaviest fuel in the mix). Furthermore, it is also expected for the grid carbon intensity to drop to zero for some time of the year since there is now enough renewable plant capacity to meet demand.

Table 4.9 summarises some of the statistical characteristics for the grid carbon intensity in each scenario. Maximum grid carbon intensity indeed, does not exceed $394g/kWh$ in all future energy scenarios. Standard deviation, a metric of “spread” is highest in the Community Renewables scenario due to the large amounts of wind and solar in the mix. Consumer Evolution and Steady Progression bore similar results in terms of data distribution and are the less efficient scenarios carbon-wise. Two Degrees assumptions' brought about the most significant reduction in grid carbon intensity with the lowest annual average and the highest frequency of zero values.

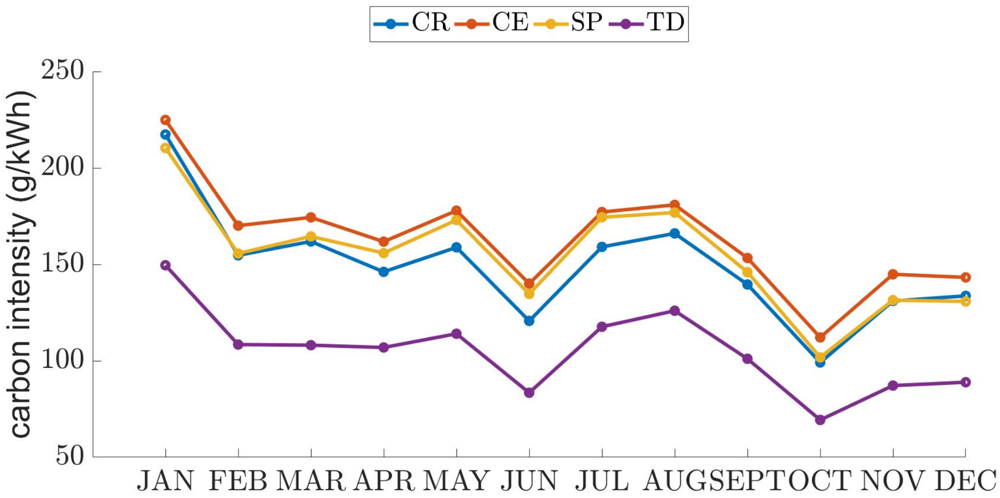
Finally, figures 4.17a and 4.17b present the average monthly and average hourly grid carbon intensity respectively. Since all scenario simulations have been carried out with the same demand and the same weather data, the unchanged annual and intra-daily pattern is anticipated. Average monthly grid carbon intensity has the highest range in Community Renewables scenario and the lowest one in Two Degrees. The drop in average hourly grid carbon intensity around noon is more evident in Community Renewables (blue line in figure 4.17a) where the highest installed solar capacity occurs.

	Mean CI	**Median CI**	**Standard deviation**	**Max CI**	**% the year CI=O**
Baseline	290	287	42	424	0
CR	149	132	119	382	18
CE	163	157	102	382	7
SP	155	152	102	381	11
TD	105	91	91	355	21

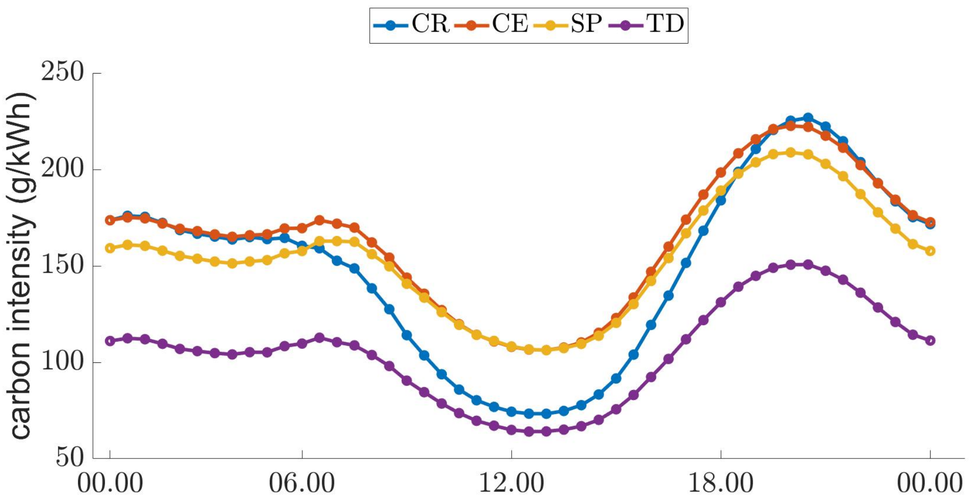
Table 4.9: Future Energy Scenarios results.

In order to perform a just comparison of grid carbon intensities under various installed capacity assumptions, the exact same demand profile had to be used. The problem with using the 2017 transmission system demand data was that in some scenarios and without storage in the model, the total installed plant capacity was not enough to meet demand. Thus, a maximum demand value of 43 GW (as opposed to the real maximum of 51 GW) was selected in order to permit the model to run smoothly across the year in all scenarios. The first approach to solution was to re-scale the real demand profile between the real minimum and the new-found maximum of 43GW but the problem that occurred was that the new demand profile was overall, unrealistically low. For this reason, an adjusted demand profile was used where the upper floor of values was always 43 GW. Hence, some seasonality in grid carbon intensity is expected to be lost due to the trimmed demand data.

The lack of simulated storage system in the model, raises another concern that regards



(a) Average monthly grid carbon intensity (g/kWh)



(b) Average hourly grid carbon intensity (g/kWh)

Figure 4.17: Average monthly and hourly grid carbon intensity for Future Energy Scenarios.

wind curtailment. In reality, National Grid has forecasted installed storage varying from 6 GW to 9 GW depending on the scenario. In the scenarios with the highest installed wind capacities (Community Renewables and Two Degrees) the curtailed wind power reached 20 GW at certain hours. Even if storage systems' function is generally restricted by spacial and time constraints, a simulated storage in the model would at least limit the amount of curtailed wind power.

4.7 The impact of different weather years on grid carbon intensity under future grid assumptions

In a possible future grid where coal has been eliminated and renewable capacities have been vastly increased, the impact of a large amount of wind and solar in the mix on grid carbon intensity is anticipated to be even more evident. As previously discussed, the highest renewable installed capacities occur in Two Degrees across all Future Energy Scenarios. Hence, in this section the installed capacities of the Two Degrees scenario have been simulated alongside the three MERRA weather years.

Figure 4.18 presents the distribution of hourly grid carbon intensity for the three weather years. The medians are 204, 175 and 143 g/kWh for the low, average and high wind years respectively (table 4.10). Since the solar generation profiles are very similar across the three years (figure 4.9), the noticed difference of 60 g/kWh in the median figure can be attributed to the different wind generation. Consistent with previous observations, the range of the grid carbon intensity values increases with the amount of wind in the mix.

It is reminded that for the Two Degrees scenario, the total wind and solar capacities are 49.5 GW and 24.2 GW as opposed to the current capacities of 8.9 and 12.4 GW. As a result, under the TD assumptions the same wind capacity factor profile would result in a much higher wind generation profile. For this reason, in figure 4.19, the negative linear relationship between wind generation and grid carbon intensity is much clearer where the Spearman's correlation coefficient was calculated to vary from -89% to -88% for all years.

Figures 4.20 presents the average hourly and monthly grid carbon intensity for the three weather years under the TD capacity assumptions. Since the used weather data is the same as in section 4.5 a symmetry can be noticed between figures 4.7 and 4.20b and figures 4.8a and 4.20a. Average monthly grid carbon intensity 4.20a seems to follow the pattern of wind generation in figure 4.8b.The cumulative effect of high wind and solar generation is translated as sharper drops and peaks of grid carbon intensity in figure 4.20a

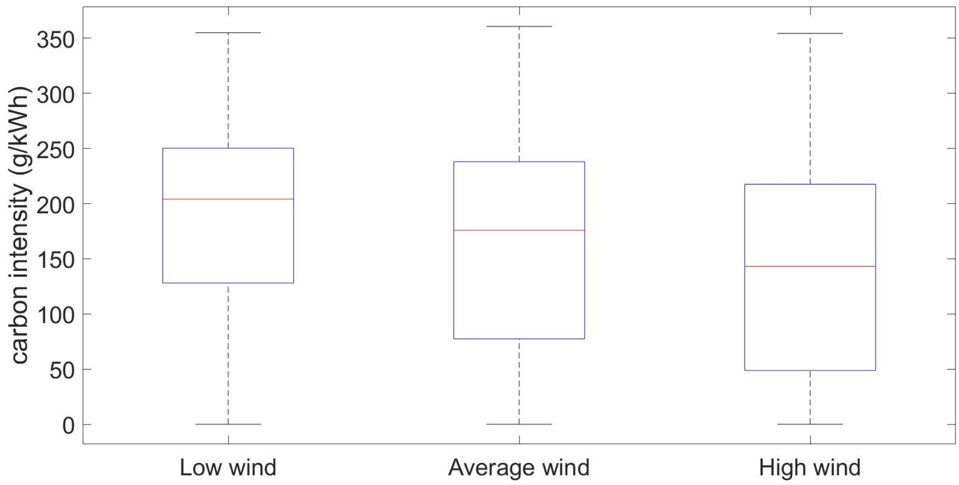


Figure 4.18: Half-hourly grid carbon intensity (g/kWh) for Two Degrees installed capacities and MERRA weather years.

in comparison with figure 4.8a.

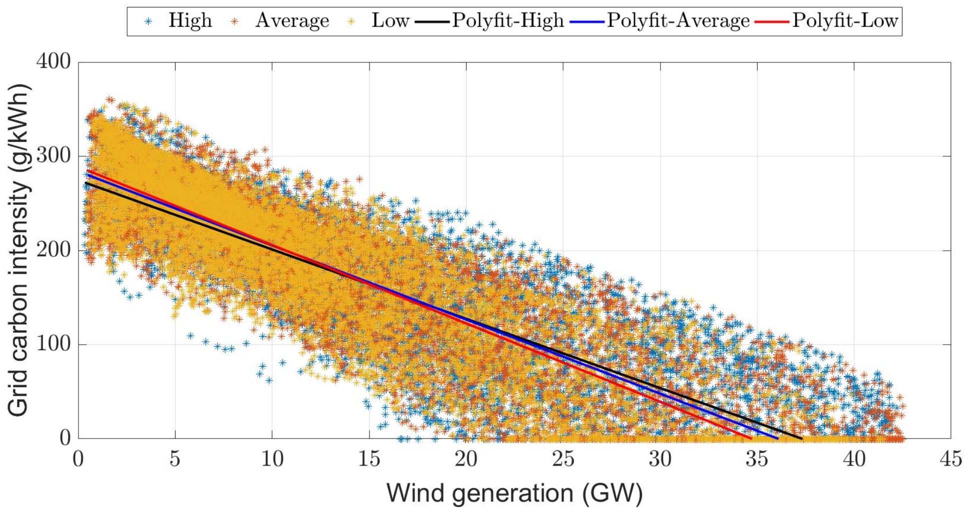
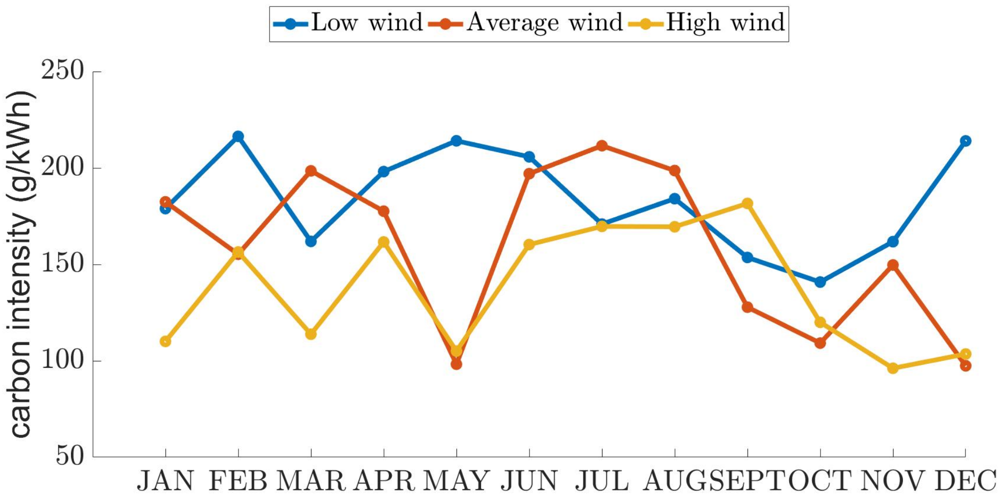


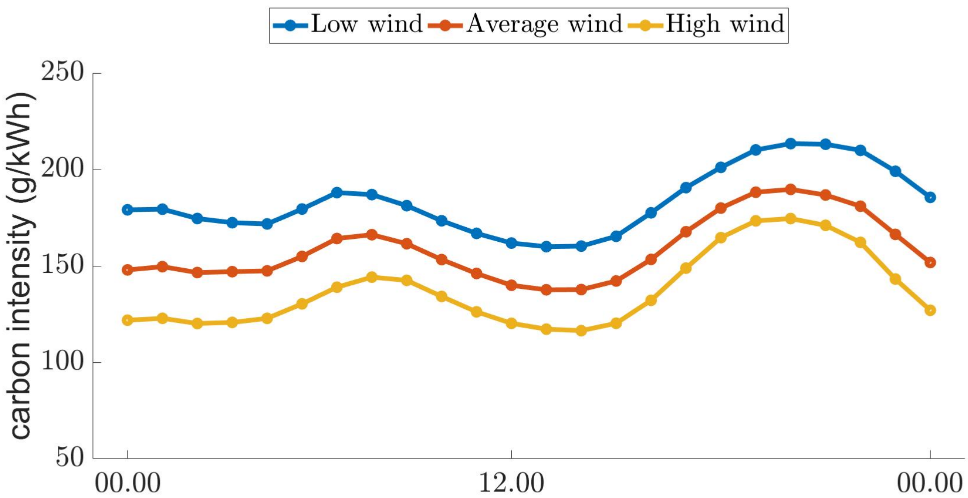
Figure 4.19: Linear fit for wind generation against grid carbon intensity (TD capacities and three MERRA weather years).

Same as before, the effect of the large amount of solar is amplified and can be observed in the pattern of average hourly grid carbon intensity which sharply drops around noon in figure 4.20a.

Finally, table 4.10 presents some statistical characteristics for the three grid carbon intensity time series. Once more, windier years cause an increase to the standard deviation of the grid carbon intensity values, which varies from 88 to 96. Carbon intensity



(a) Average monthly grid carbon intensity (g/kWh)



(b) Average hourly grid carbon intensity (g/kWh)

Figure 4.20: Average monthly and hourly grid carbon intensity for Two Degrees installed capacities and MERRA weather years.

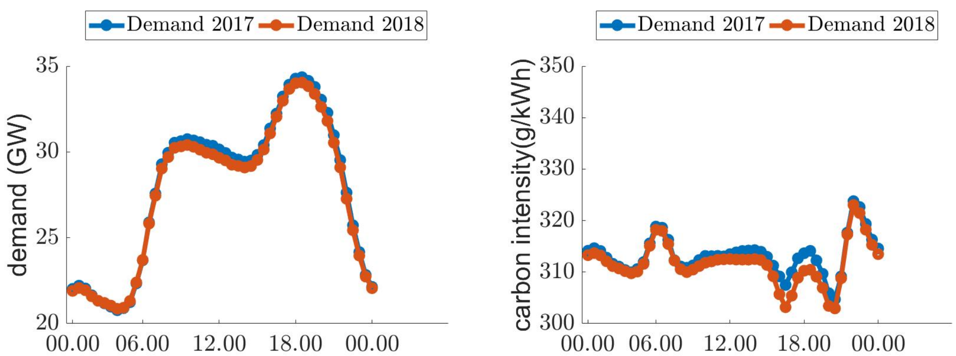
was measured to be zero (there was enough wind on the system to meet demand) for 6%, 13% and 16% of the year for the low, average and high wind scenarios respectively.

	Mean CI	Median CI	Standard deviation	Max CI	% of the year CI =0
Low wind	183	204	88	355	6
Average wind	159	176	98	361	13
High wind	137	143	96	354	16

Table 4.10: Weather years results for Two Degrees scenario.

4.8 The impact of different demand profiles on grid carbon intensity

In order to examine how different demand profiles affect grid carbon intensity, two runs of the 25 unit MILP model with the transmission system demand of 2017 and 2018 were carried out. It is noted that all other model parameters (wind and solar generation) remained unchanged. Spearman's correlation was measured for half-hourly grid carbon intensity. Moderate, positive correlation ranged from 43% for 2018 to 50% for 2017, thus when demand increases grid carbon intensity is expected to increase too. Figures 4.21 and 4.22 show the average hourly and monthly, demand and grid carbon intensity for the demand years 2017 and 2018. In figure 4.21a it can be noticed that average hourly demand in 2018 (red line) demand was slightly lower (by average $200MW$) than in 2017. This difference can also be seen in average hourly grid carbon intensity in figure 4.21b. Carbon intensity was also lower by average $2g/kWh$ across the day in 2018.



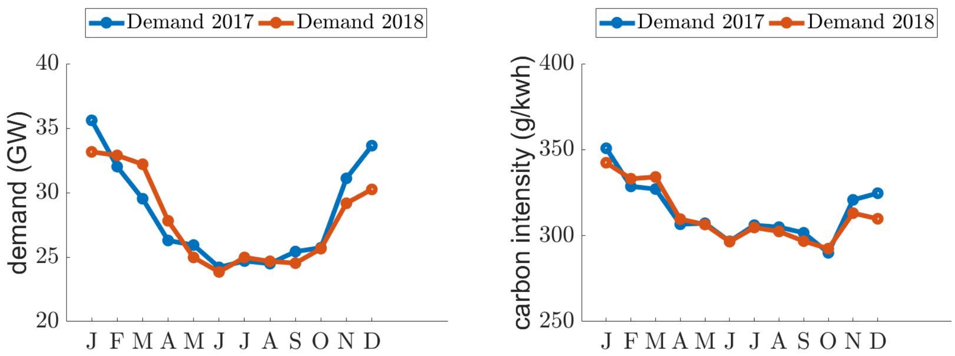
(a) Average hourly demand 2017 and 2018 (GW)

(b) Average hourly grid carbon intensity 2017 and 2018 (g/kWh)

Figure 4.21: Average hourly demand and grid carbon intensity (demand data 2017 & 2018).

Regarding monthly grid carbon intensity, the same pattern of average monthly demand in figure 4.22a can also be seen in figure 4.22b. Average demand was equal or lower in 2018 than 2017, with the exception of February, March and April. The same applies for average monthly grid carbon intensity in the respective years.

However, the relationship between grid carbon intensity and demand is more complex, grid carbon intensity is more dependent on the fuel mix that is being used to meet demand than the value of demand itself. While more renewables penetrate the grid and the fuel mix gets lighter in carbon, an increase in demand would not necessarily cause a higher grid carbon intensity figure.



(a) Average monthly demand 2017 and 2018 (GW)

(b) Average monthly grid carbon intensity 2017 and 2018 (g/kWh)

Figure 4.22: Average monthly demand and grid carbon intensity (demand data 2017 & 2018).

4.9 Summary of findings

This chapter illustrated the modelling process of two basic power system model functions, unit commitment and economic dispatch. The mixed integer linear programming method was applied for the unit commitment function while economic dispatch was solved via non-linear optimisation. This model was simulated with a varying number of units, 12, 20 and 25. Furthermore, using a simple, heuristic solution approach a benchmark model was also built. Monthly average and total annual mean absolute percentage errors were calculated for the resulting grid carbon intensity datasets. The total annual mean absolute percentage error dropped from 72% for the benchmark model to 32% for the 25-unit MILP model which was the version used throughout the rest of the chapter.

Using meteorological, re-analysis data, grid carbon intensity was assessed under the assumptions of different weather years. Although different wind generation was shown to cause minimal difference to the average figures of grid carbon intensity, the frequency of high values of hourly grid carbon intensity during the year widely varied depending on the amount of wind generation. The impact of adding embedded, solar generation to the calculation of average half-hourly grid carbon intensity was more evident around noon hours with a decrease of 40 to $50g/kWh$.

Applying the 2030 National Grid's forecasted plant capacities to the 25-unit MILP model, the behaviour of grid carbon intensity under future energy assumptions was examined. Generally, the elimination of coal from the grid caused a drastic drop to grid intensity while the increased renewable capacities resulted in a more variable annual grid carbon intensity dataset. The scenario that achieved the best carbon benefit was shown to be the Two Degrees scenario where the average grid carbon intensity decreased to $1/3$ of its baseline value and half-hourly grid carbon intensity was zero for 21% of the year.

Furthermore, the Two Degrees installed capacities were ran with the three MERRA weather years in order to investigate the impact of different weather on a renewable dominated grid. The noticed effect of a high wind output year on grid carbon intensity in section 4.5 was shown to be amplified. The same weather years that caused the annual average grid carbon intensity to fluctuate by 10 g/kWh in the current grid, were now shown to result in a discrepancy of up to 50 g/kWh. As expected, stronger anti-correlation was also measured for wind generation against grid carbon intensity.

Finally, different demand profiles were simulated within the model in order to provide insight on how system demand affects grid carbon intensity. The results indicated that a higher demand figure generally causes a higher grid carbon intensity figure, and moderate positive correlation was found between the two. However, grid carbon intensity is more dependent on the fuel mix used to meet demand rather than the demand figure itself. While the grid decarbonises and the fuel mix comprises progressively more of zero-carbon energy sources (wind, solar, nuclear), a higher demand profile would cause a small to none at all increase in grid carbon intensity figures.

Chapter 5

The use of high resolution carbon intensity datasets in real life case studies

5.1 Introduction

This chapter addresses objectives 3 and 4: *"Investigate how time-varying carbon intensity influences carbon assessment in real-life case studies"* and *"Draw on findings derived from real-life case studies in order to establish implications of the dynamic behaviour of grid carbon intensity"*.

With National Grid's initiative of grid carbon intensity API forecast (N.G, 2017), figures of carbon intensity in high resolution have become available to the general public. In this chapter two examples of how to use high resolution carbon intensity datasets (instead of annual averages) and their potential carbon benefits are demonstrated.

The case studies that have been selected represent rapidly-evolving energy areas in the UK. While the electrification of transport is taking place both on national and international level, the future of heating systems in a low-carbon power system is raising several questions.

Although EVs are often referred to as Zero Emissions Vehicles, the electricity used to charge these vehicles still results in carbon emissions from power stations and a carbon intensity that remains significant when allocated to distance driven. With the number of electric vehicles (EVs) set to grow significantly, carbon benefits can be achieved if charging strategy reflects the time varying nature of grid carbon intensity. For this reason, the first case study in this chapter details the design of a carbon optimised charging strategy, compares it with an immediate charge case and then estimates the potential carbon benefits. Liaising with DriveElectric [1], an EV leasing specialists and partners in the WPD EV smart charging project "Electric Nation" [2], provided technical counsel on the selection of characteristics for a typical electric vehicle (charging power, monthly changing needs). The potential carbon benefits are first, estimated using recent, historic grid carbon intensity data from 2017 (section 3.7) and then with simulated 2030 Future Energy annual datasets from section 4.6.

As the British grid decarbonises, the potential carbon benefits of heating systems such as heatpumps and cogeneration/combined heat and power plants (CHP) become uncertain. As discussed in section 2.5.3 the CHP operates with gas while the forecasted fuel mix in some of the National Grid FES is dominated by nuclear, wind and solar (section 4.6). Hence, a scenario where CHP generation displaces grid electricity with a nearly zero carbon content is certainly not favourable from a carbon emissions perspective. For this reason, the second case study uses data from the CHP plant in Whiteknights campus, University of Reading in order to identify a grid carbon intensity threshold where the CHP operation becomes favourable over the grid for a heat demand-led strategy. Similarly to the first case study, the CHP control strategy is first, assessed against recent, historic grid carbon intensity data from 2017 (section 3.7) and then against simulated 2030 Future Energy annual datasets from section 4.6.

The findings of this section are expected to be of interest to DriveElectric and the Estates team at University of Reading to use accordingly in their relevant carbon management plans.

[1] http://www.drivelectric.com/
[2] http://www.electricnation.org.uk/

5.2 Use of high resolution grid carbon intensity datasets to inform carbon optimising strategy for electric vehicles

5.2.1 Design of carbon optimal charging strategy for electric vehicles

The aim of this section is to examine how the dynamic behaviour of grid carbon intensity can be used to inform controlled charging strategies. It is noted that the present analysis focuses on dominant in-use emissions, thus attributing power grid emissions to a charging electric vehicle.

The figures of grid carbon intensity for year 2017 from section 3.7 have been used. It is reminded that the equation for grid carbon intensity is eq. (2.1) while the range of c_n values was derived from column A in table 3.1.

In this case, half-hourly average carbon intensity is allocated to all instantaneous loads. This is a common approach, consistent with encouragement by various advocates to move load to low carbon periods, as for example, would follow from National Grid's published real time carbon intensity forecast (N.G, 2017). It can be argued that vehicle charging represents an additional load and should be accounted for at the marginal intensity. Currently, the marginal plant for much of the year is gas fired (see table 3.5), so a marginal basis would only show small changes in carbon allocation.

The key input parameters are daily mile case, average charge power (kW) and battery size (kWh). In our scenarios a car was modelled with the following representative characteristics, derived from current UK operational practice. In specific, charging power is assumed to be 6kW (typical UK home chargers can achieve 7kW for a fully electric car, however power drawn is not always constant across entire charge cycles, so a representative average is adopted). Finally, the vehicle is assumed to be connected to the charger from 6pm to 7am daily (13 hours per day, 54% of the time). All electricity required is assumed to be taken from the home charger, rather than public or workplace chargers and the vehicle is required to be fully charged on completion of each charge cycle.

Table 5.1 summarises the input parameters for the daily mile case scenarios. The monthly m/kWh values were taken from actual data from 500 Nissan Leaf cars (EVstatus, 2019). Assuming a different daily mile case (20, 40, 60, 80 and 100 miles per day) and a charging power of 6 kW, the daily energy needs in kWh and the number of charging hours have been calculated. The following charging scenarios were devised and modelled using grid

Daily mile case		***100***		***80***		***60***		***40***		***20***	
	m/kWh	Energy need (kWh)	Charg. time (h)	Energy need (kWh)	Charg. time (h)	Energy need (kWh)	Charg. time (h)	Energy need (kWh)	Charg. time (h)	Energy need (kWh)	Charg. time (h)
Jan	2.9	34.5	5.7	27.6	4.6	20.7	3.4	13.8	2.3	6.9	1.1
Feb	3.1	32.3	5.4	25.8	4.3	19.4	3.2	12.9	2.2	6.5	1.1
Mar	3.2	31.3	5.2	25.0	4.2	18.8	3.1	12.5	2.1	6.3	1.0
Apr	3.3	30.3	5.1	24.2	4.0	18.2	3.0	12.1	2.0	6.1	1.0
May	3.4	29.4	4.9	23.5	3.9	17.6	2.9	11.8	2.0	5.9	1.0
Jun	3.4	29.4	4.9	23.5	3.9	17.6	2.9	11.8	2.0	5.9	1.0
Jul	3.4	29.4	4.9	23.5	3.9	17.6	2.9	11.8	2.0	5.9	1.0
Aug	3.5	28.6	4.8	22.9	3.8	17.1	2.9	11.4	1.9	5.7	1.0
Sep	3.3	30.3	5.1	24.2	4.0	18.2	3.0	12.1	2.0	6.1	1.0
Oct	3.2	31.3	5.2	25.0	4.2	18.8	3.1	12.5	2.1	6.3	1.0
Nov	3.0	33.3	5.6	26.7	4.4	20.0	3.3	13.3	2.2	6.7	1.1
Dec	3.0	33.3	5.6	26.7	4.4	20.0	3.3	13.3	2.2	6.7	1.1

Table 5.1: Daily charging needs by month (kWh) and number of charging hours for daily mile case assumptions.

carbon intensity data for 1st January to 31st December 2017:

- Immediate charge (the base case): This scenario captures carbon if charged as soon as the car plugs in (at 6pm). This the base line case as for many drivers the most popular time to charge is when returning from work early evening as identified during the Electric Nation project. Total annual emissions in this scenario are calculated using equation 5.1 where i is the day index, j is the hour index running within the 13-hour charging window, CI_{ij} is hourly carbon intensity and F is the charging factor that represents the charging needs in kWh per hour.

$$C_{total} = \sum_{i=1}^{365} \sum_{j=1}^{13} CI_{ij} \cdot F \tag{5.1}$$

- Carbon optimal: Structured charging by grid carbon intensity (gCO_2eq./kWh) by hour, this scenario charges the EV during the least carbon intensive hour first, then the second lowest etc. This is calculated for 365 days as the CO_2 intensity varies. Total annual emissions in this scenario are calculated using equation 5.2:

$$C_{total} = \sum_{i=1}^{365} \sum_{j=1}^{13} \min(CI_{ij}) \cdot F \tag{5.2}$$

5.2.2 Potential carbon savings for carbon optimal charging strategy against immediate charge under different daily mile case assumptions

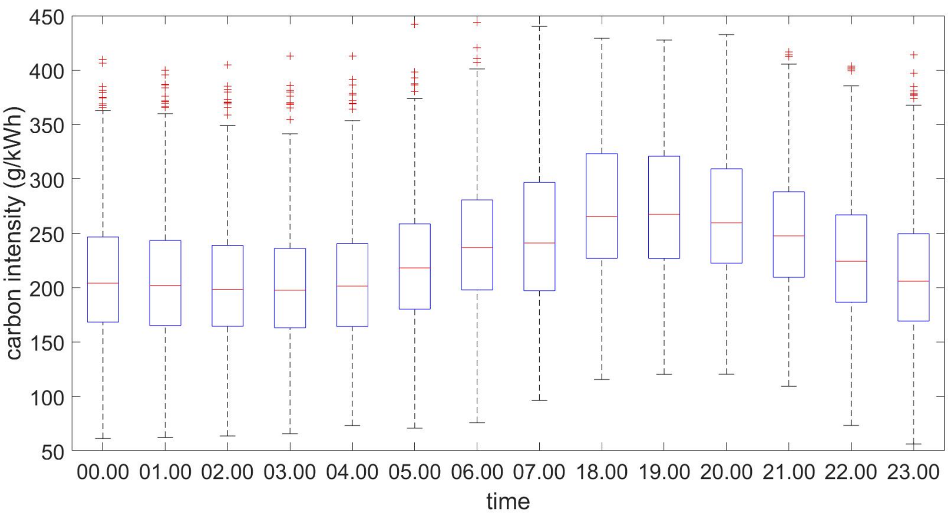


Figure 5.1: Hourly grid carbon intensity during the allowed charging hours.

Time	**00:00**	**01:00**	**02:00**	**03:00**	**04:00**	**05:00**	**06:00**	**07:00**	**18:00**	**19:00**	**20:00**	**21:00**	**22:00**	**23:00**
Median CI	204.1	202.0	198.2	197.7	201.3	218.1	236.8	241.1	265.4	267.3	259.7	247.7	224.3	205.9

Figure 5.2: Median grid carbon intensity during the allowed charging hours.

In order to comprehend the potential carbon saving results under different mile case assumptions it is crucial to comprehend how carbon intensity fluctuates within the allowed charging window. Figure 5.1 shows the hourly grid carbon intensity distribution for the allowed charging window while figure 5.2 shows the values of median carbon intensity for the same hours; it is immediately noticed that the hours between 18.00 and

21.00 are, carbon-wise, the worst to charge as carbon intensity tends to reach its highest values then. The immediate charge scenario assumes the vehicle to begin charging as soon as it gets plugged in at 18.00 for 1 to 6 hours (depending on the mile case assumption). Thus, charging occurs between 18.00 and, at most, 23.00, a time window that includes the most carbon intensive hours. By contrast, the carbon optimal charging scenario selects and allows the vehicle to charge when the carbon intensity is at its lowest (possibly between 23.00 and 04.00 according to the median values in figure 5.2).

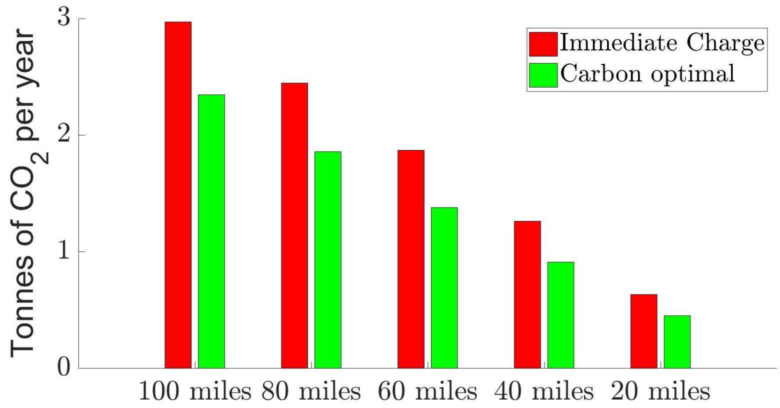


Figure 5.3: Annual carbon emissions for different daily mile case.

Figure 5.3 presents the total, annual carbon emissions for the immediate charge and carbon optimal scenarios. The potential, total, annual % carbon saving ranges from 21% for the 100 mile case, 24% for the 40 mile case, 26% for the 60, 28% for the 80, to 29% for the 20 mile case. The discrepancy between the potential carbon savings for different mile cases can be explained if the number of charging hours and then, the high variability of carbon intensity during these hours are taken into account.

Figure 5.4 shows the total carbon emissions per month for the daily mile case and the charging scenarios which follows the intra-annual carbon intensity trend for 2017. The trend of higher values at winter months should come as no surprise as it has been shown that carbon intensity tends to peak during colder months (section 3.7).

Figure 5.5 shows the potential % carbon saving per month for all daily mile case assumptions if carbon optimal strategy was applied instead of the immediate charge. What immediately stands out in this graph is that the bests carbon savings are achieved in

October, ranging from 35% to 47% while the lowest savings are being noticed in January ranging from 12% to 19%. The level of savings is directly dependent on the variability of grid carbon intensity within the charging hours.

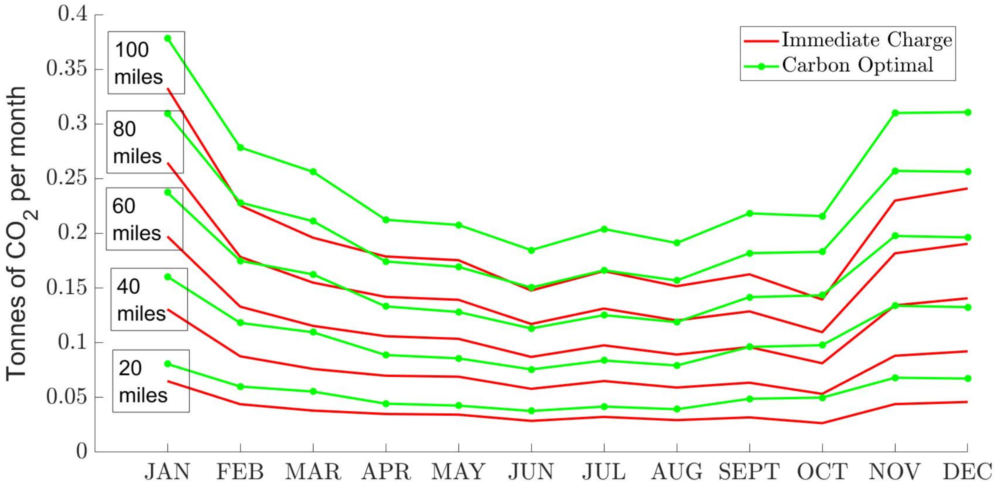


Figure 5.4: Carbon emissions per month for different daily mile case.

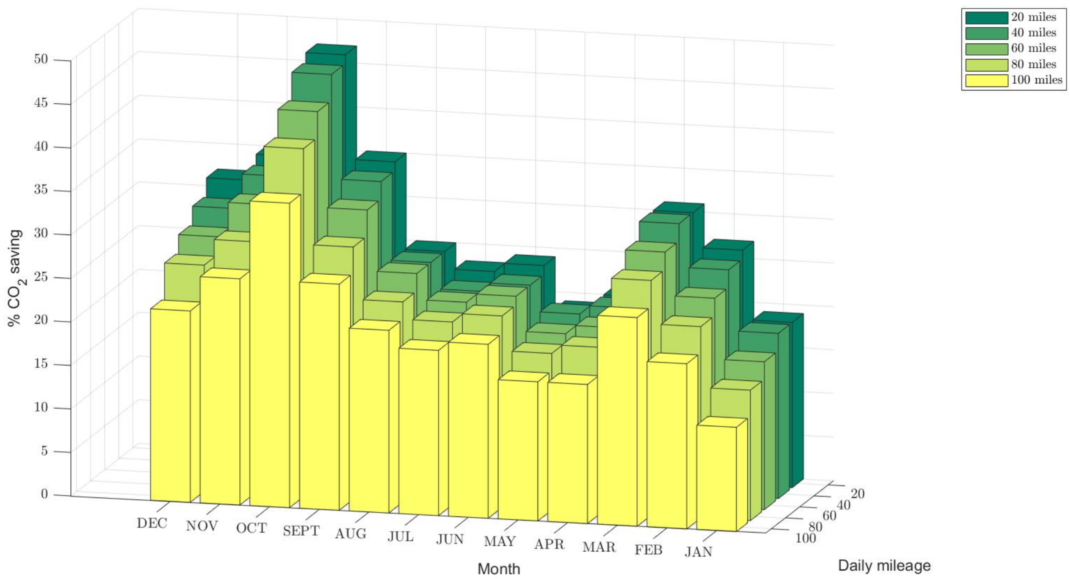


Figure 5.5: % carbon saving per month for carbon optimal scenario against immediate charge scenario.

Finally, figure 5.6 presents the $gCO_2/mile$ figures for the two charging strategies. Here, it can be seen that different mile case assumptions do not cause a large discrepancy in the figures while the potential carbon saving if the carbon optimal strategy is implemented modulates between 17 and 25 $gCO_2/mile$.

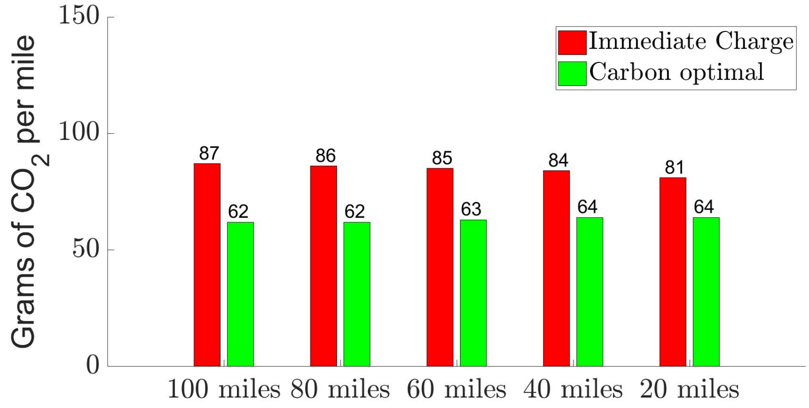


Figure 5.6: Carbon emissions per mile for different daily mile case.

5.2.3 Potential carbon savings for carbon optimal charging strategy against immediate charge for future grid assumptions

As discussed in section 2.5.2 a number of countries have announced phase-out dates for conventional diesel/petrol vehicles in the next ten to twenty years. Furthermore, National Grid's EV Project Director is encouraging the UK to pull forward the UK Government 2040 target (for the banning of the internal combustion engine only car) to 2030 target (HOC, 2018). For this reason, it would be fitting to examine different EV charging strategies under future grid assumptions. The four Future Energy Scenarios by National Grid, Community Renewables (CR), Consumer Evolution (CE), Steady Progression (SP) and Two Degrees (TD) assume different gas, nuclear and renewable installed capacities while across all, coal capacity is utterly eliminated (N.G, 2018a).

Hence, the carbon intensity datasets from section 4.6 have been used in order to assess the potential annual carbon savings under the different installed capacity scenarios for National's Grid Future Energy Scenarios. It is noted that as it has achieved the best carbon benefit in section 5.2.2 the 20 daily mile case assumptions have been selected and used in the present section.

In figure 5.7 it can be noticed that the carbon savings are significantly higher than the ones achieved under the current capacities. The potential future savings are estimated to be 37%, 40%, 43% and 48% for the Consumer Evolution, Steady Progression, Community

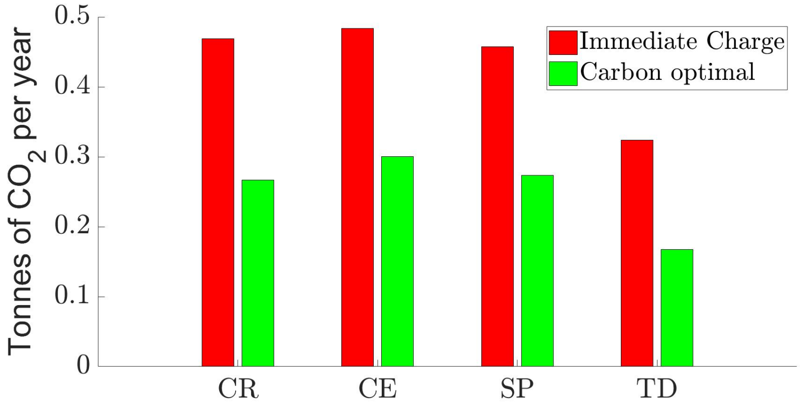


Figure 5.7: Annual carbon emissions for different Future Energy Scenarios.

Renewables and Two Degrees scenarios respectively. The increase in carbon benefit can be as high as 15% compared to the current 29% (figure 5.3) if the Two Degrees scenario materialises. As shown in section 4.6 the increased renewable capacities of all Future Energy Scenarios cause a more variable fuel mix and thus a more variable grid carbon intensity time series. This heightened variability can then be translated in a bigger carbon benefit; Hence, in figure 5.7 the highest carbon savings are observed in the scenarios with the highest wind and solar capacities (Two Degrees/TD and Community Renewables/CR).

Finally, consistently with the results in figure 5.7 a sharper decrease occurs in all cases in figure 5.8 if the carbon optimal strategy is applied. However, it can also be noticed that the gram per mile values for the CR, CE and SP capacity scenarios under the immediate charge charging strategy (63 to 66 g/m) are comparable to the values under the carbon optimal strategy (62 to 64 g/m) seen in figure 5.6. This finding highlights the projected progress of the GB grid decarbonisation. In a little more than 10 years, the grid carbon intensity is forecasted to be so low across the year that an immediate charge strategy is expected to cause similar carbon emissions to a carbon optimal charging strategy that is implemented under the current grid assumptions.

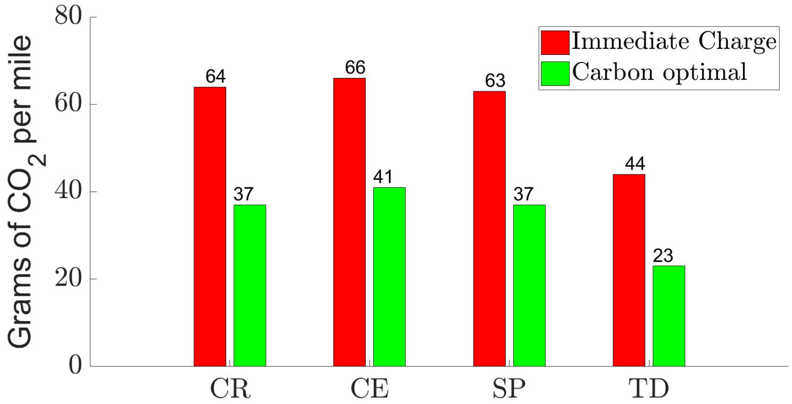


Figure 5.8: Carbon emissions per mile for different Future Energy Scenarios.

5.3 Use of high resolution grid carbon intensity datasets to assess current CHP control strategy - University of Reading

5.3.1 Energy analysis for University of Reading- Whiteknights campus

This section documents the information gathered during a meeting with a member of the Facilities team of the University of Reading regarding the energy generation and carbon reporting procedures the University follows. In terms of company reporting procedures, the University of Reading accounts for their carbon emissions in three main reports:

- Internal annual carbon targets: emissions are being calculated using Carbon Trust methodology and the DEFRA carbon factors;
- The report to Carbon Reduction Commitment (CRC) (for electricity and carbon) is submitted between April and March, and the University pays the fees for the amount of carbon that has been produced (17 pounds per ton);
- The report to Estates Management Record (higher education funding council which collects data from all universities).

To fulfill their reporting obligations the University of Reading gathers the necessary data regarding:

- Electricity: utility bills provide all the information about the demand data (split between generation and transmission/distribution);
- Gas: metering of the CHP unit provide the necessary data;
- Refrigerant gases: Appliances like fridges and air conditioning units may have occasional leaks. Although they do not emit carbon, they still contribute to the global warming;
- Water: Water bills provide the necessary data;
- Business travel: Emissions are being accounted when the University of Reading is covering the expenses of the travel. 25% of the carbon footprint of the university is due to the business travel. Data gathering for travel is the most challenging; University credit cards, travel companies' checks and expense claim forms are used for this purpose.

For the purpose of the analysis, the following have been used: the 2016 campus' electricity demand dataset in half-hourly resolution, the 2016 Elexon carbon intensity dataset also in half-hourly resolution and the 2016 DEFRA carbon factor (412 g/kWh).

Figure 5.9 shows the carbon emissions for the campus calculated using the single DEFRA annual factor and the annual dataset of Elexon carbon intensity. As expected, the time-varying emissions (line in blue) are generally lower than the DEFRA ones since the 2016 Elexon carbon intensity ranges from 150 to 480 g/kWh.

Figures 5.10a and 5.10b show the average carbon emissions calculated with time-varying grid carbon intensity values per weekday and for an aggregated weekday and weekend day for the Whiteknights campus. As anticipated, the emissions significantly drop during the weekend. The weekday profile of emissions in figure 5.10b is a mix of commercial with domestic energy use profile while the weekend day resembles a typical domestic energy use profile.

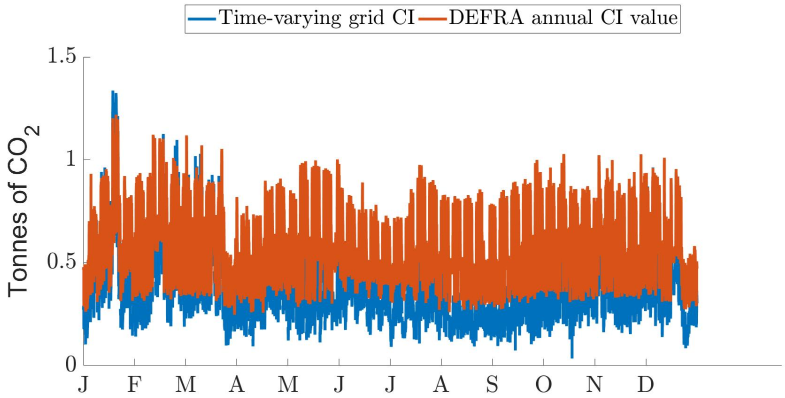
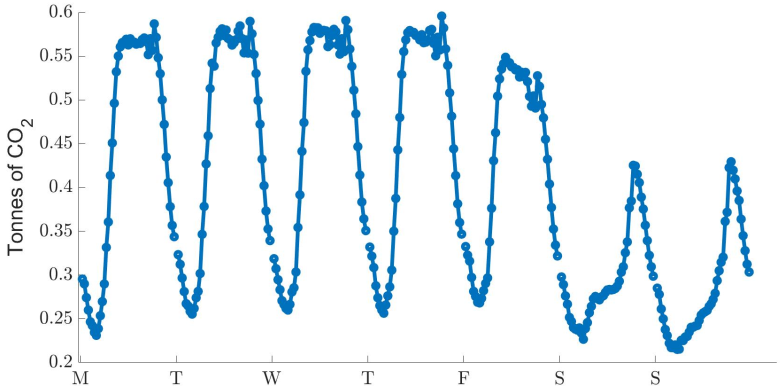
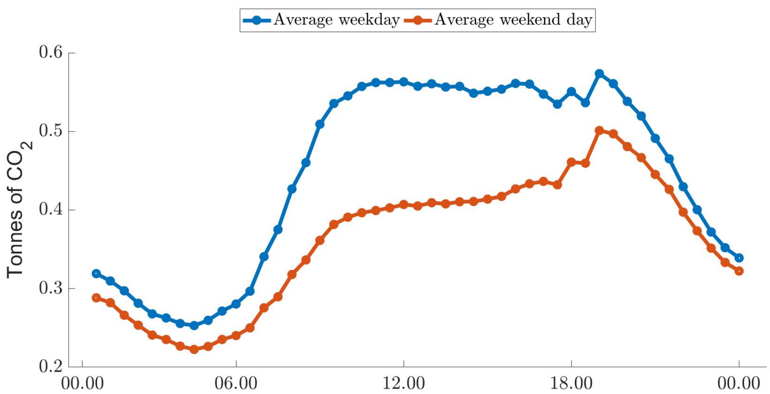


Figure 5.9: Carbon emissions of electricity in Whiteknights campus.



(a) Average carbon emissions per weekday.



(b) Average carbon emissions for typical weekday and weekend day.

Figure 5.10: Average carbon emissions per weekday and for weekday and weekend day for the Whiteknights campus, University of Reading.

5.3.2 Discussion of current CHP control strategy

In October, 2014 The University of Reading installed an 1.1 MWe ICE CHP plant on their Whiteknights campus as part of their carbon management plan and in an attempt to reduce utilities costs. The CHP engine installed is an ENER-G E1160 natural gas driven, internal combustion engine (ICE), which provides an output of hot water and electricity. As seen in table 5.2, the use of CHP for electricity generation in 2016 has led to total cost savings of £235,661 for the university.

With CHP	
Cost of gas to run CHP	£268,601
Without CHP	
Cost of gas to provide equivalent heat in boilers	£105,775
Cost of equivalent electricity from National Grid	£398,487
Annual cost saving	£235,661

Table 5.2: CHP savings for 2016 (source: internal report of UoR).

Although it is unrealistic to expect for the CHP to meet the total energy needs of the campus, the offsetting of some of the electricity grid consumption can potentially lead to significant carbon savings. As (Kelly *et al.*, 2014) highlighted, the preferred use of CHP instead of the grid fuel mix for electricity generation has the potential for carbon savings only in the immediate future. As the electricity grid further decarbonises, the benefits of using gas become less certain.

The University of Reading energy team collects datasets of electricity imported from the grid and electricity generated by the CHP in half-hourly resolution in the Whiteknights campus. These datasets alongside with the 2017 Elexon carbon intensity have been used in this section. The analysis carried out in this section covers a period of 252 days due to missing data in the CHP generation dataset. The missing data are from the following dates: 14 Feb 2018,26 March to 01 April, 19 May to 23 May, 20 August to 27 August, 25 November, 03 December and 16 December to 31 December. Since the biggest part of the data gaps corresponds to holiday periods where the demand is low it is assumed that the effect of this omission on the results is limited. For effective comparison, grid carbon intensity for the missing dates was also omitted from the analysis.

5.3.3 Grid carbon intensity threshold for preferred CHP operation

Two different scenarios have been considered to meet heat demand D_h and electric demand D_e in Whiteknights campus; One pertains a typical gas boiler and importing grid electricity while the second includes solely CHP generation. The electricity carbon emissions in g for the campus at a certain time t are calculated as follows for the two scenarios:

$$E_{grid}(t) = (D_e(t) \times CI(t)) + (D_h(t) \times \frac{185}{0.9}) \tag{5.3}$$

$$E_{CHP}(t) = D_h(t) \times \frac{185}{0.46} \tag{5.4}$$

where $D_e(t)$ is the electricity demand at time t, $D_h(t)$ is the heat demand at time t, $CI(t)$ is the grid carbon intensity in g/kWh at time t, 185 is the carbon factor for natural gas in g/kWh, a representative efficiency of a typical gas boiled is assumed to be 90% (0.9) and the CHP electrical efficiency is 41% while its heat effiency is 46%. It is noted that the carbon factor for gas is not time dependent. Since only in cogeneration plants electrical and heat efficiency can be summed up to provide a total efficiency figure which would equal 87%

$$E_{CHP}(t) = (D_e(t) + D_h(t)) \times \frac{185}{0.87} \tag{5.5}$$

In order to identify the threshold of grid carbon intensity when CHP operation achieves a carbon benefit eq. (5.3) must equal eq. (5.5):

$$(D_e(t) \times CI(t) + (D_h(t) \times \frac{185}{0.9}) = D_h(t) \times \frac{185}{0.46} \tag{5.6}$$

The solution to formula (5.6) is:

$$CI(t) = 196.6 \times \frac{D_h}{D_e} \tag{5.7}$$

However, assuming a steady heat to power output and since the relevant efficiencies are known:

$$\frac{D_h}{D_e} = \frac{0.46}{0.41} \approx 1.122 \tag{5.8}$$

From equations (5.7) and (5.8):

$$CI(t) \approx 220(g/kWh) \tag{5.9}$$

5.3.3.1 Potential carbon saving for heat-demand led CHP control strategy

Subsequently from equality (5.5), the carbon savings in grams at time t can be quantified if the CHP part of each equality is subtracted from the grid part. For the heat led strategy:

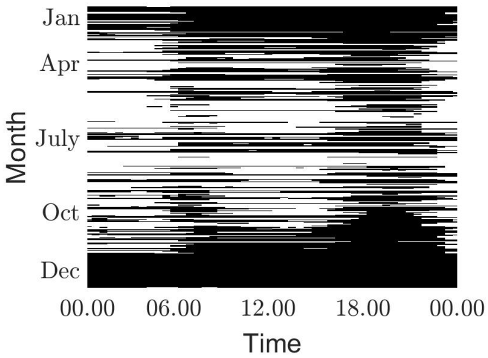
$$S_c(t) \approx (CI(t) - 220) \times D_e(t) \tag{5.10}$$

Since the ratio of heat and electric output is known for the CHP, eq. (5.8), it is noted that the carbon savings in eq. (5.10) can be also written as function of the heat demand $D_h(t)$.

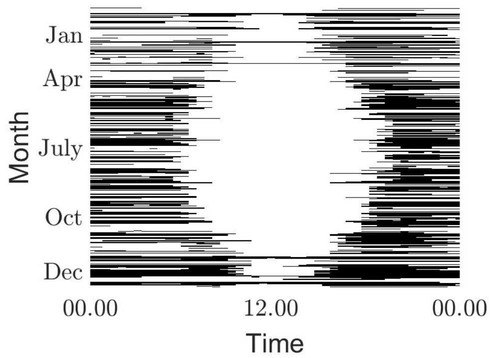
5.3.4 CHP operational window under current and future grid assumptions

Taking into account the drastic changes that the National Grid forecasts for the GB grid and consequently for the grid carbon intensity annual profile, this section seeks to examine how the CHP preferred operational window would change across the year under different installed capacity assumptions compare to the current conditions.

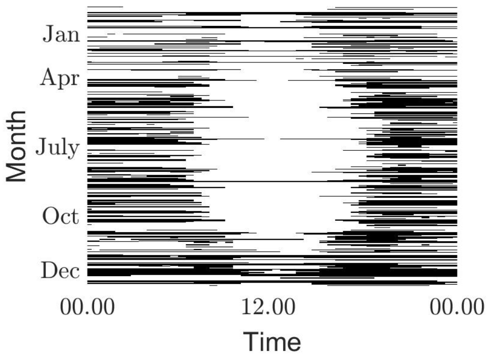
For this reason, the Future Energy Scenarios carbon intensity datasets from section 4.6 and historic Elexon values have been used and examined against the grid carbon intensity



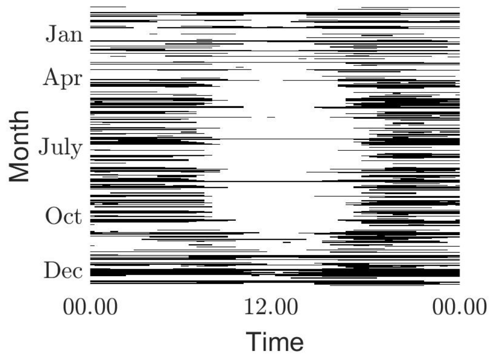
(a) 2017



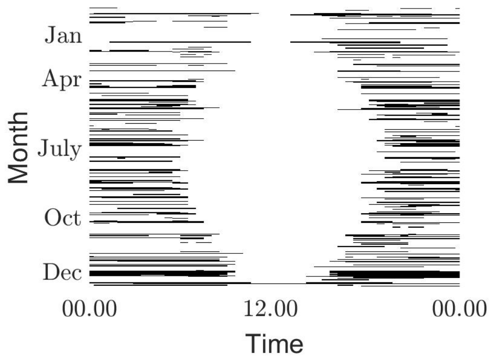
(b) Community Renewables



(c) Consumer Evolution



(d) Steady Progession



(e) Two Degrees

Figure 5.11: Half-hourly binary heatmap of grid carbon intensity when it exceeds the CHP threshold (220 g/kWh) for 2017 and 2030 Future Energy Scenarios.

threshold for the heat-led strategy. Figure 5.11 presents in black the half-hours when the grid carbon intensity exceeds the threshold for 2017 and the simulated 2030 Future Energy Scenarios, Community Renewables (CR), Consumer Evolution (CE), Steady Progression (SP) and Two Degrees (TD) scenarios.

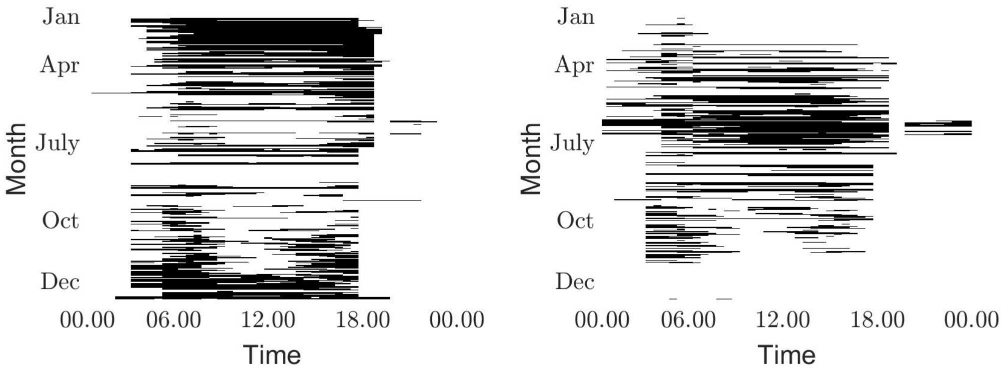
In figure 5.11a, for 55% of the year 2017, grid carbon intensity was measured to exceed the threshold thus allowing a quite wide annual CHP operating window that can achieve a carbon benefit. It is seen that in winter months, particularly January and December, grid carbon intensity remained higher than the threshold across the whole day thus allowing CHP operating opportunity during working hours. For spring and summer months, the effect of solar generation is more evident, although grid carbon intensity is still seen to exceed the threshold for peak demand early morning and early evening hours.

Compared to figure 5.11a, the common feature that immediately stands out in figures 5.11b, 5.11c, 5.11d and 5.11e is the effect of high solar generation. It is reminded that compared to the current 12 GW, the installed solar capacity is projected to increase to 33, 19, 16 and 24 GW for the CR, CE, SP, TD scenarios respectively (table 4.8). As discussed in section 4.6, the high installed solar capacity causes a drastic drop during the hours where solar radiation is at its highest. As a result, grid carbon intensity rarely exceeds the 220 g/kWh threshold during these hours and causes the CHP operational window to significantly narrow during spring and summer months when the sunny hours are extended. However, small differences can be noticed across the four scenarios.

The CHP window across the year was measured to be 32%, 31%, 29% and 14% for the CR, CE, SP and TD scenarios respectively. It is noticed that the Community Renewables scenario offer the longest CHP window across the year while the Two Degrees offers the narrowest. Drawing on table 4.9, the TD scenario was anticipated to provide the least time for CHP operation since the grid carbon intensity takes the lowest values, due to large amount of nuclear and renewables in the mix, compared to the other FES scenarios.

5.3.5 Real and potential annual carbon benefits from CHP operation in 2017, University of Reading

Using real CHP generation data in half-hourly resolution for 2017, its current control strategy was examined against the dynamic behaviour grid carbon intensity for the same year. Figure 5.12 indicates whether CHP was operating when grid carbon intensity was higher and lower than the threshold. The areas in black represent the half-hours when the plant was operating while the areas in white represent the off-time. Of the total operational time across the year, 60% of it was carried out while grid carbon intensity was higher than 220 g/kWh, thus providing a carbon benefit, while the remaining 40% occurred at half-hours when grid carbon intensity was lower than the threshold.



(a) CHP operation when carbon intensity is higher than the threshold. (b) CHP operation when carbon intensity is lower than the threshold.

Figure 5.12: Half-hourly binary heatmaps of CHP operation against the heat-led strategy grid carbon intensity threshold.

Figure 5.13 presents the **real** half-hourly carbon savings in kilograms across the year. From eq. (5.10), it is noticed that the half-hourly carbon saving is dependent on the grid carbon intensity and the CHP generation at each time-step. For this reason, figure 5.14 also presents the half-hourly generation output of the CHP in kWh for the same time. In figure 5.13 it is noticed that January, February, November and December achieved the highest carbon savings. Since the CHP generation remains relatively steady across the year with the exception of June, August and September the high savings can be attributed to the high grid carbon intensity values during these months (figure 3.12i). The average carbon saving was measured to be 36.4 kg, while the maximum was 147 kg and was

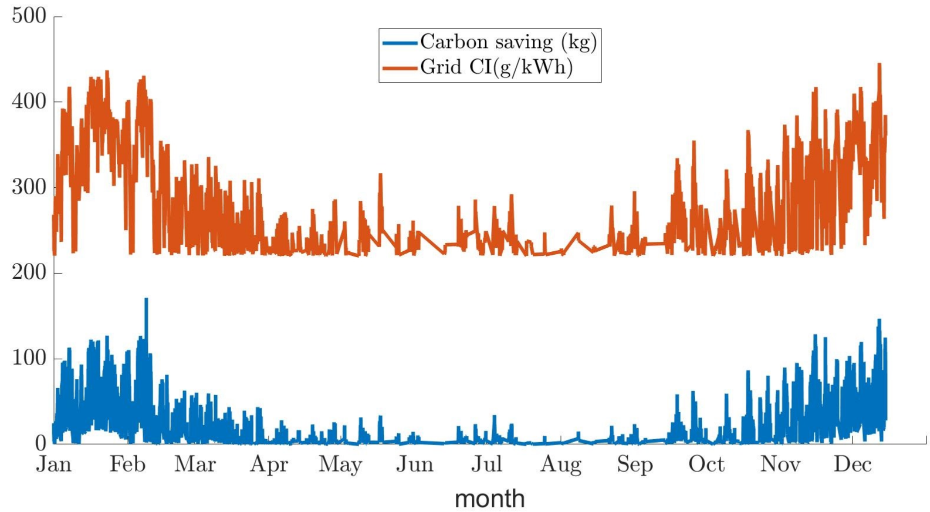


Figure 5.13: Half-hourly grid carbon intensity and carbon saving for CHP operation in 2017.

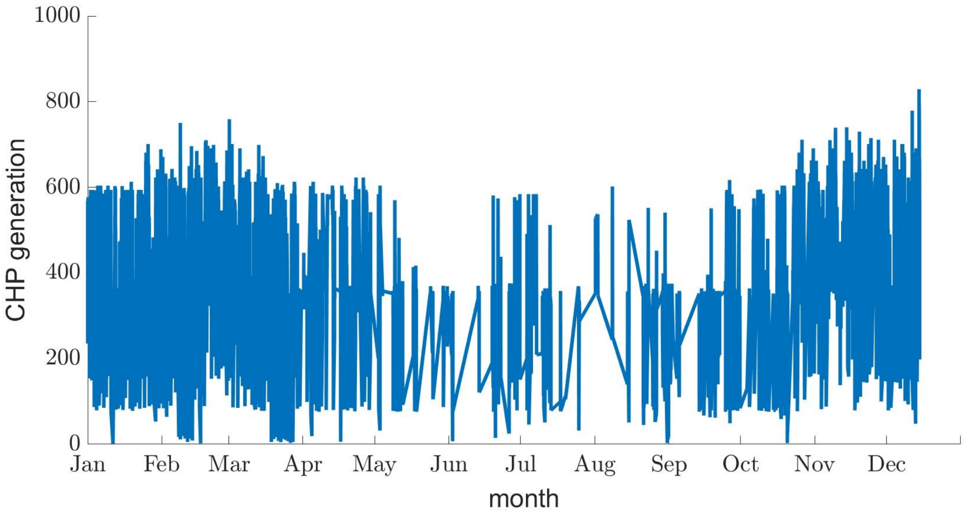


Figure 5.14: Half-hourly CHP generation (kWh) in 2017.

Figure 5.15: Half-hourly grid carbon intensity, carbon saving and CHP generation in 2017.

measured in December. The total annual carbon saving was measured to be 182.7 tonnes.

Furthermore, the half-hours where grid carbon intensity exceeded the threshold but the CHP was not operating were identified. An average CHP generation output of 418 kWh was assumed and figure 5.16 presents the **potential** half-hourly carbon savings in kilograms across the year. Since a steady generation output was assumed, the carbon saving profile (blue line in figure 5.16) develops like the grid carbon intensity for the same hours (red line in figure 5.16). Consistently with figure 5.13, the highest carbon benefits are being observed in January, November and December. The total potential annual carbon saving was measured to be 100.88 tonnes. Hence, it is shown that if CHP was operating during the whole time when grid carbon intensity exceeded the threshold, the total annual carbon saving could increase by 94.8%.

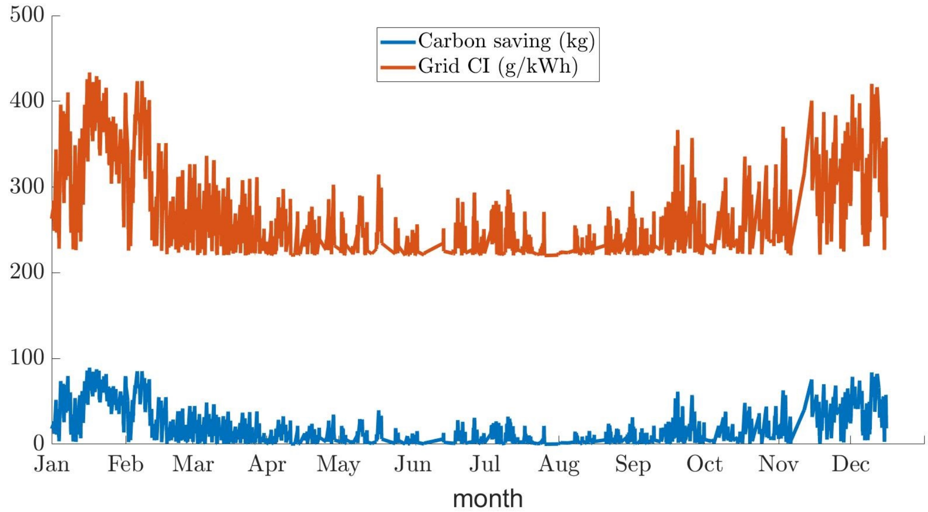


Figure 5.16: Half-hourly carbon intensity and potential half-hourly carbon saving assuming average CHP generation in 2017.

5.4 Summary of findings

This chapter illustrated how carbon intensity datasets in half-hourly resolution can be used to inform real-life applications and point to potential carbon benefits. Two different case studies have been selected in order to represent evolving and interesting energy areas.

In the first case study that concerns the electrification of vehicles, a carbon optimal strategy that allowed a single vehicle to charge during low carbon intensity hours was designed. This strategy was then compared with an immediate charge case when the vehicle charged immediately after being plugged in at 6 pm. Under different daily mile case assumptions the total carbon saving for a year ranges from 21% to 29%. It is noted though that the different daily mile case assumptions did not seem to cause large discrepancies on the $gCO_2/mile$ values for each charging strategy. The ranges were calculated to 81 to 87 $gCO_2/mile$ for the immediate charge strategy and 62 to 64 $gCO_2/mile$ for the carbon optimal strategy. Furthermore, the same carbon optimal strategy was simulated under the 2030 National Grid's Future Energy Scenarios using the simulated carbon intensity datasets from section 4.6. In this case, the carbon savings were much higher ranging from 37% to 48%. The results showed that the higher the installed renewable capacity on the system the higher the carbon benefit. The capacity assumptions for the Two Degrees and Community Renewables scenarios yielded 48% and 43% carbon saving respectively. This was anticipated as the fuel mix that is rich in variable renewables results in a more variant carbon intensity time-series, as shown in chapter 4.

Finally, the second case study looked into the current control strategy of a combined heat and generation plant in the Whiteknights campus, University of Reading. A threshold of carbon intensity was established for a heat-demand control strategy against which the CHP operation was deemed favourable to provide a carbon benefit. In order to explore favourable conditions for CHP operation under current and future grid assumptions, 2017 historic and National Grid's FES grid carbon intensity values were used. Again, all grid carbon intensity time-series including 2017, Community Renewables, Consumer Evolution, Steady Progression and Two Degrees scenarios were assessed against the grid carbon intensity threshold. In 2017, the CHP window was measured to equal 55% of the year, mostly occurring during autumn and winter months and high demand hours. Among the scenarios, Community Renewables offered the widest intra-annual CHP window, measured to be 32% of the year. By contrast, the Two Degrees scenario due to the very low grid carbon intensity values, provided the least time for CHP operation, amounting only to 14%. The University's CHP follows a heat-led strategy so its current schedule was assessed against the 220 g/kWh threshold. The particular CHP was shown to be generating for 60% of its total operational time providing a carbon benefit, while the remaining 40% was carried out when grid carbon intensity was below the threshold.The total annual carbon savings were estimated to be 183 tonnes. However, if the CHP also operated at an average output during the remaining hours, when grid carbon intensity was higher than 220 g/kWh, this amount could increase by 94.8%.

Chapter 6

Discussion and Conclusions

6.1 Thesis summary

This study was designed to investigate the uncertainties in grid carbon intensity introduced by the use of single annual average figures and the arising implications. Although grid carbon intensity has already been investigated by a variety of national and international studies, limited literature was identified that focuses on the time-varying behaviour of grid carbon intensity (Khan, 2018), (Khan *et al.*, 2018). In most cases emissions arising from the grid are described in a single annual either aggregate (Ang & Su, 2016) or average (Goh *et al.*, 2018), (Ang & Goh, 2016) figure. Hence, this study combined historic data analysis, power system modelling and real life case studies aiming to provide insights on the time-varying behaviour of the GB grid carbon intensity that is obscured by the use of a single annual average figure and explore the uncertainties that arise from it.

Although historic data analysis provides useful insights on the "past" of grid carbon intensity, it does not contribute anything to uncover the uncertainties regarding the future and the even plausible present. In equation 2.1 it has already been shown that carbon intensity is largely determined by the fuel mix. Subsequently, the fuel mix is dependent on two factors, the installed plant capacities and the amount of renewables in the mix.

Interestingly, these two factors partly overlap as the amount of renewable energy in the grid is clearly regulated by the installed relevant capacity and the meteorological conditions. In summation, grid carbon intensity is susceptible to changes of the installed capacities and the weather. Therefore, the plausible present regards feasible weather scenarios with the current installed capacities while the future regards capacity projections. In order to address the aforementioned uncertainties, a power system model similar to the one used by National Grid was designed to reflect and simulate the GB electricity grid. The aim was to produce annual carbon intensity datasets under different installed capacity and weather assumptions. Thus, a power system model was built simulating the basic functions of unit commitment and economic dispatch, and then compared with a simple benchmark model.

This far, this study has focused on identifying the historic, current and future uncertainties that affect the grid carbon intensity. Since these uncertainties have been acknowledged, the use of solely a single annual average figure is shown to mask a significant inherent feature of grid carbon intensity, time-variability. Instead, a more nuanced approach such as historic annual datasets in high resolution, can be a more appropriate carbon accounting tool. Therefore, the subsequent question that occurs regards the possible ways high resolution grid carbon intensity can be used. To address the above, two case studies that represent the fast-changing and challenging energy areas of vehicle electrification and cogeneration heating have been selected. While the electrification of vehicles is slowly becoming a reality both on national and international level, the evolution and selection of suitable heating systems in a carbon optimal future is still uncertain.

6.2 Uncertainties in grid carbon intensity and carbon reporting

6.2.1 Data uncertainties

For the historic data analysis, the method that is followed by DEFRA to calculate the annual, average figures of grid carbon intensity using fuel input and power output could not be replicated as generating data is not available in higher resolution. The implemented method, which is consistent with the one followed in the National Grid's grid carbon intensity forecast (N.G, 2017), unveiled the first source of uncertainty in grid carbon intensity calculation. This source regards the assumed carbon factors of different generation plants.

These carbon factors were shown to be inconsistent across the relevant bibliography as they are dependent on whether life cycle emissions were considered, the age and more importantly the efficiency of the relevant plant (tables 2.1 and 2.2). Ideally, in order to estimate grid carbon intensity, the fuel input and power output (alternatively, the efficiency) should be known in half-hourly resolution at a power station level. The carbon factors this study has used are representative of the power station type. In tables 3.1 and 3.2 it can be noticed that a discrepancy of 0.5%, 3.6 %, 0.4% and 0.7% in net efficiency causes fluctuations of 15, 122, 6 and 10 g/kWh in the carbon factors of coal, oil, OCGT and CCGT plants respectively. A range of factors was used to establish an uncertainty range in half-hourly grid carbon intensity, which was shown to vary from 2% to 5% when the factors were GB specific (figure 3.6). The uncertainty range was shown to be significantly higher reaching 25% when wider, international carbon factor ranges and a different methodology were used (figure 3.5). Large discrepancies up to 18% were also noticed in the annual figures that were calculated with different plant carbon factors (figure 3.4) when compared with the DEFRA figures for the same years.

The assumed power station efficiencies were shown to introduce uncertainties ranging from 2% to 25% in grid carbon intensity calculations depending on the range of carbon factors. However, the greatest underlying uncertainty in carbon accounting and reporting, when using annual averages, is the inherent variable behaviour of grid carbon intensity.

6.2.2 Grid carbon intensity variability

Grid carbon intensity is shown to be highly dependent on a number of factors including: the assumed efficiencies/carbon factors and installed capacities for different plant types, demand changes, the weather that dictated the wind and solar output and finally the amount of fossil fuel generation in the mix. All these factors cause high variation, not only on an inter-annual and intra-annual level but also, from one half-hour of generation to next.

Inter-annual variability

The first part of this study, historic data analysis of generation in GB for years 2009 to 2017 demonstrated the progress of the grid decarbonisation that has been achieved in the space of these nine years. Reduced demand, coal plant closures and more renewables on the grid are the main reasons behind this. However, grid carbon intensity displayed a highly dynamic behaviour, not only inter-annually, but also intra-annually and intra-daily. Furthermore, this study showed that the intra-annual variability in grid carbon intensity changes differs from one year to the next, depending on the fossil generation and total annual wind output in the fuel basket. Table 3.7 shows that annual grid carbon intensity variability was at its highest in 2009 (standard deviation was measured at 87.4), reached a low in 2012 (56.8), following the coal plant closures and then started to increase again as renewables penetrated the grid to reach a high of 73.7 in 2017.

Intra-annual variability

Examining the intra-annual pattern of grid carbon intensity, it was shown that there is not a consistent trajectory for the analysed years (figure 3.8). The different weather, fuel mix and demand of each month caused various fluctuations in grid carbon intensity for each year of the analysis. However seasonal trends were detected as warmer months were observed to have lower grid carbon intensity in all cases (figure 3.12).

Furthermore, average monthly wind generation was shown to affect the average figure of grid carbon intensity. Under the current installed capacity assumptions a discrepancy of 40% in average wind generation causes a 10% difference in average monthly grid carbon intensity (figures 4.8a and 4.8b). Finally, high wind generation was shown to affect the frequency of values of low hourly carbon intensity during the year, varying from 15% to 28%, although no significant impact on the annual average figures was detected (table 4.6).

In-day variability

Grid carbon intensity was shown to follow an expected trend during the day, peaking around afternoon, remaining relatively high until midnight and dropping again until 6 a.m. (figure 3.12). Half-hourly grid carbon intensity was also shown to fluctuate by 50%, compared within the same day, to the listed DEFRA annual average in December, 2009 (figure 3.11). However, the reduction of coal and the increased CCGT baseload noticed in the fuel mix of the latest years are shown to limit the in-day variation of grid carbon intensity to 35.5% of the annual average (figures 3.10 and 3.11). Furthermore, the effect of solar generation, even with the current installed renewable capacities was evident in the daily profile of average grid carbon intensity by causing a decrease of approximately 15% around noon hours (figure 4.10).

One could argue that the coal elimination from the grid, as projected by the Future Energy Scenarios (table 4.8) would limit the inter-annual variability. However, the projected renewable expansion is expected to cause a highly variable fuel mix that will amplify the dynamic behaviour of grid carbon intensity. The inter-annual variability of grid carbon intensity under the Future Energy Scenarios assumptions is shown to increase up to 300% when compared to current grid conditions (table 4.9).

Projected variability

Under the National Grid's FES 2030 assumptions, the elimination of coal from the grid caused a drastic drop to grid intensity while the increased renewable capacities created a more variable annual carbon intensity dataset. Notably, the intra-annual grid carbon intensity variablity (measured by standard deviation in table 4.9) was shown to increase by 283%, 242%, 242% and 216% for the Community Renewables, Consumer Evolution, Steady Progression and Two Degrees scenarios respectively when compared with a current capacity scenario.

Furthermore, in many cases, especially for the scenarios with the highest wind and solar capacities, namely the Community Renewables and Two Degrees scenarios (table 4.8), the renewable generation was enough to meet the system demand causing the half-hourly grid carbon intensity to be zero for 18% and 21% of the year respectively. Furthermore, under the Two Degrees capacity assumptions, different weather assumptions were shown to have an even greater impact both on the in-year variability and the frequency of zero values of grid carbon intensity. Both the standard deviation and the frequency of zero values within the year were shown to vary by 10% depending on the wind output (figure 4.10). Hence, the findings imply that while previously the greatest grid carbon intensity fluctuations were caused mostly by major coal plants going online and offline, the future fluctuations are expected to be caused by the fuel mix transitioning from solely renewable generation (with a zero carbon factor) to a solely gas generation (now the heaviest in carbon fuel) and vice versa.

6.3 Implications for carbon accounting and reporting

6.3.1 Recent developments in high-resolution carbon accounting

The findings so far show that the highly dynamic nature of grid carbon intensity and the underlying uncertainties need to be acknowledged. This study proposes that this variability needs not only to be recognised but it should also be used to inform domestic and business energy consumption decision-making. While in the beginning of the project, this time-varying feature was only discussed in a limited number of academic studies, recent years have seen great changes. Two initiatives launched in the last year of the project regard the dynamic nature of electricity generation. While the National Grid forecast[1] provides an indicative trend of high resolution grid carbon intensity up to 48 hours ahead of real-time, Octopus[2] introduced dynamic time of use tariffs in half-hourly resolution a day ahead. Both schemes seek to inform energy consumption behaviour by sharing high-resolution energy data with the public, but a key difference is also detected. Grid carbon intensity forecast makes the information available to any interested party but without any incentive. By contrast, Octopus provides a solid financial incentive and pays domestic customers (it is noted that the company is open to expand to non-domestic level as well) to shift their energy consumption outside peak demand hours. Furthermore, Octopus reports some very interesting findings that can be extrapolated to support the rationale of this study. These findings are (Octopus, 2018):

Energy users engage with their energy and alter their energy consumption behaviour if they are given the appropriate tools. In the case of Octopus, 28% of the domestic customers dropped peak usage from 16% to 11.5% of their total daily consumption (Octopus, 2018). Although no study has been conducted to assess the impact the grid carbon intensity forecast had on altering energy use behaviours, the finding itself is very promising since energy consumers are shown to alter their decisions if armed with adequate and accurate information.

Cost savings are achieved simultaneously with carbon savings. Although the decarbonisation progress of the GB electricity grid has been demonstrated, there is still a significant amount of fossil fuels in the mix. For this reason, peak demand hours, when the wholesale electricity price is high, coincide with the hours of peak grid carbon intensity when fossil plants have to be online to meet demand in the current electricity grid. Thus, if energy consumption gets moved outside the peak window, savings both in cost and carbon terms occur. This finding is further supported by the work in (Papaioannou *et al.*, 2019). Four different charging strategies for electric vehicles were assessed and the results indicated that high cost and carbon savings can be realised if a carbon optimal charging strategy is implemented.

[1] https://carbonintensity.org.uk/

[2] https://octopus.energy/agile/

6.3.2 Proposed demand side management schemes that make use of the time-varying grid carbon intensity

Building up on these two findings, this study seeks to explore ways to respond to the variability of grid carbon intensity, inform energy consumer behaviour and achieve a carbon benefit via two case studies. While the electric vehicles case study regards demand side management on the domestic level, the CHP control strategy represents the business level customers where the implementation gets more complicated on a policy level.

For the electric vehicles, a carbon optimal charging strategy for a single vehicle was designed and then compared with an immediate charge case where the vehicle starts charging at 6 p.m. For the carbon optimal strategy, the lowest carbon intensity hours within a time window were selected as the preferred charging hours for the electric vehicle. Depending on the daily mile case assumptions the potential, annual carbon savings varied from 21% for the 100 mile case, 24% for the 40 mile case, 26% for the 60, 28% for the 80, to 29% for the 20 mile case (figure 5.3). It is shown then that if grid carbon intensity is known in a high resolution, any electric vehicle owner that wishes to contribute to Climate Change mitigation can decide to charge during hours when the fuel mix is cleaner. Insights derived from the National Grid's forecast in combination with a simple charging strategy like the one demonstrated in this study should suffice to achieve annual savings that equate to 0.18, 0.35, 0.49, 0.59, 0.62 tonnes of carbon for the 20, 40, 60, 80 and 100 daily mile case respectively.

The same strategy was also simulated under the National Grid's future energy scenarios 2030's capacities for the 20 daily mile case assumptions. In this case, where renewables dominate the fuel mix, the grid carbon intensity varies even more within the day. Fortunately, the charging strategy can capitalise this amplified variability and achieve higher percentage savings. The projected savings are estimated to be 37%, 40%, 43% and 48% that equate to 0.20, 0.18, 0.18, 0.16 tonnes of carbon for the Consumer Evolution, Steady Progression, Community Renewables and Two Degrees scenarios respectively (figure 5.7). Hence, it is realised that a demand side management measure that includes moving energy consumption from a charging electric vehicle outside peak hours of grid carbon intensity can achieve substantial carbon benefits not only in the current electricity grid but also in forecasted power system conditions.

A different demand side management scheme was explored in the second case study. In this case, the current control strategy of a cogeneration (CHP) plant in Whiteknights campus, University of Reading was assessed. A threshold of grid carbon intensity was established against which, the CHP operation was assessed as favourable or not, in order to achieve a carbon benefit. In contrast with the electic vehicles case study, in this instance the carbon benefit occurs if the highest carbon intensity hours within a time window are selected as the preferred CHP operational hours. Therefore, this demand side management scheme entails the moving of energy generation not consumption, inside and not outside a time window when grid carbon intensity exceeds a threshold. The results of the assessment showed that under the current control strategy, 60% of the total operational time was carried out within the window, thus providing a carbon benefit and resulting in annual savings that reached 183 tonnes of carbon (figure 5.13). However, it was also shown that if the whole extent of the CHP annual window was used, the savings would increase by almost 95% even with an average CHP generation output (figure 5.16).

6.3.3 Recommendations

Two examples of demand side management practices were investigated to factor the variability of grid carbon intensity into energy consumer behaviour and infrastructure planning. However, there is still scope to explore ways to aid the factoring of time-varying grid carbon intensity into such practices.

As previously mentioned, demand side management on the domestic level is more straightforward. Access to high resolution grid carbon intensity data is available on the National Grid's forecast, while a financial incentive is now provided by the Octopus agile tariff. All the essential means are currently in place and available to i.e an electric vehicle owner that wants to avoid charging during carbon intensive hours. However, there is still the uncertainty whether peak demand hours will keep coinciding with peak grid carbon intensity. Although this study showed that even higher percentage savings can occur in the variable future mix if consumption during peak demand hourd is avoided, there is further scope for refinement and introduction of financial incentives that target carbon instead of cost benefits.

By contrast, carbon accounting and reporting on a large business level such as the University of Reading is inherently governed by the national policies and guidelines already in place. Malleability associated with the scope classification (Haslam *et al.*, 2014) and the lack of future emissions accounting (Bebbington *et al.*, 2019) introduce key uncertainties in the carbon reporting process on the business level in the United Kingdom. Noting that the annual average grid intensity values provided by DEFRA do not accurately represent the dynamic balancing of the system, Tranberg *et al.* (2019) highlight the importance of real time electricity carbon accounting. Thus, a demand side management measure, such as the suggested one, will not be implemented even if all the required tools and relevant information are already available. Namely, the CHP case study identified an operational time window that can achieve a carbon benefit whilst forecasted grid carbon intensity in high-resolution is available and sufficient for short-term CHP planning. However, an incentive is absent since the Estates and Facilities team of the University is legally bound to use the annual average carbon figures provided by DEFRA. Hence, it becomes quite clear that to move things forward on large-business demand side management the national policies have to acknowledge the dynamic feature of grid carbon intensity and the great untapped potential of utilising this feature to set and achieve carbon targets. Should high resolution historic grid carbon intensity data become available to large-scale businesses that are legally required to report their Scope 1 and 2 emissions, the carbon accounting process would result in less uncertain insights, more accurate reporting and higher cost and carbon benefits.

6.4 Limitations and future work pathways

Marginal grid carbon intensity

There is a strong argument that marginal emissions have to be recognised and assessed (Hawkes, 2010), (Siler-Evans *et al.*, 2012), (Hawkes, 2014), (Thomson *et al.*, 2017) since using solely system average numbers ignores a key feature of the electricity market function. The remaining uncertainty regards which metric, system average or marginal, should be used in carbon accounting schemes. While it can be argued that marginal intensity is appropriate for assessing small demand interventions in a short-time and system average can successfully reflect longer term substantial mechanisms (Hitchin & Pout, 2002), determination of the marginal mix/plant should also be considered.

This study has focused on system average grid carbon intensity in half-hourly resolution, but also acknowledged the significance of marginal emissions and identified the marginal plant(s) for each year of the historic analysis, covering a period of nine years. In the case of Great Britain the marginal operation has been determined by the prioritisation of coal against gas (CCGT) and vice-versa. The results in table 3.5 indicate that in the earlier years of the analysis (2009-2012) both fuels are in the marginal mix. Coal is seen to dominate the marginal mix in 2012 and since then CCGT is shown to provide the greater proportion of the marginal mix for the remaining years. It is also noted that the last year of the analysis, 2017, had the highest CCGT to coal ratio in the marginal mix. As the carbon factor of coal is twice as high (900 g/kWh) as the CCGT (394 g/kWh) (table 3.1) substantial discrepancies are expected in the marginal emissions for the said years.

The case studies demonstrated in this thesis assessed potential carbon savings from an electric vehicle charging and a CHP control strategy. Both of them could be treated as small demand side intervention and there is argument for the marginal intensity as an additional metric to be examined. At the time of the study, the marginal mix was dominated by gas, thus, marginal emissions are expected to be invariant. However, there is scope for additional calculations using marginal intensity and comparison with the existing results.

Dynamic fuel prices

Although the design of a model from the very beginning is time-consuming, ultimately it was preferred over the use of a ready one already on the market. Acknowledging its limitations, the constructed model would still offer increased flexibility and a deeper understanding of its functions since most purchasable power system models operate by the "black box" principle for commercial reasons. However, due to hardware and computational time constraints, high resolution fuel prices were replaced with a fixed fuel price in the model.

In a similar way to marginal emissions the prioritisation of plant operation has been long dictated by the relationship of gas against coal price. An example to demonstrate the impacts of this relationship is as follows. UK grid carbon intensity peaked in 2012 (figure 3.8) because USA-imported coal provided a cheaper alternative than gas at the time (Staffell, 2017). Furthermore, (Thomson *et al.*, 2017, p. 207) attributes the surge in coal generation in 2012 to an interaction between the Large Combustion Plant Directive and carbon price floor, as generators that were due to be decommissioned rushed to use their allocated hours before the carbon support price rates rose. Although access to historic fuel prices in high resolution is limited and coal elimination from the grid is projected in the next decade, there is scope for refinement of the MILP model and the addition of dynamic fuel prices in order to assess the impact on grid carbon intensity values.

Storage requirements

Although storage technologies do not create carbon emissions by themselves, the stored electricity does not have a zero carbon-factor. The currently used technology of pumped storage has the effect of "time-shifting" carbon emissions. The emissions intensity of storage can be accounted for either with a weighted-average "stock accounting" method (Thomson *et al.*, 2017) or is attributed to the technologies that generated the electricity in the first place (Staffell, 2017).

Furthermore, due to the aforementioned constraints, the simulation of storage was also omitted from the MILP model. National Grid's Future Energy Scenarios project increased storage capacities in order to accommodate the increased renewable share of generation. Incorporating the relevant storage capacities both into the analysis and the model parts would provide more accurate grid carbon intensity estimates and thus, is left for future work.

Future changes in demand

Due to the lack of access to high resolution future demand data, an altered 2017 demand dataset was used to simulate the variety of weather and capacity scenarios. Future grid projections like the electrification of heat and vehicles are anticipated to cause the demand to significantly increase. Access and simulation of relevant demand data would produce more accurate grid carbon intensity figures. However, recent studies have also highlighted the problem of large amount of renewables in the grid without smart system element enabling demand to adapt to supply (Staffell & Pfenninger, 2018). Similarly to the findings of this study (section 4.6.7) net zero demand was shown to regularly occur when the renewable output was high under the Two Degrees capacity assumptions. Recommended measures to avoid a "dumb" operation of the system, shift demand, balance renewables and reduce peak demand include: interconnection, storage and load-shifting from zero-carbon energy, demand-side management schemes ranging from small to large-scale, fleets of electric vehicles with managed and co-ordinated charging and increased electricity and thermal storage capacities (Staffell & Pfenninger, 2018).

6.5 Conclusions

The aim of this study was to "to assess the different sources of uncertainty in historic, current and projected GB grid carbon intensity and make recommendations on factoring its dynamic nature into real life applications". Historic data analysis has shown that the use of a single annual figure of grid carbon intensity masks the high intra-daily variability that occurs. Therefore, it introduces several uncertainties when it is used for carbon accounting and reporting purposes. While a GB grid model was built to simulate various weather outputs and projected capacities, two case studies that used high resolution grid carbon intensity datasets were investigated to estimate the potential carbon benefits. This study's key findings can be summarised as follows.

The historic grid carbon intensity was shown to vary by up to 50% of the annual average figure within the same day in early years of the historic analysis. This variation has dropped to 35% in recent years due to the constantly shrinking amount of coal in the fuel mix (figure 3.10).

The intra-annual variability of grid carbon intensity reached a low in 2013 following the coal plant closures and then started to expand with the increasing renewable penetration (table 3.7).

The intra-annual variability of grid carbon intensity is expected to further expand as the UK power generation mix changes. High installed solar and wind capacities cause the intra-annual variability of grid carbon intensity to significantly increase by 216% to 283% when compared with a current capacity scenario.(table 4.9).

Annual average grid carbon intensity is shown to be a metric that masks the impact of the weather of the year. The effect of different wind outputs is not evident in the annual average figures of grid carbon intensity (table 4.6). However, it is shown to cause high discrepancies in the intra-annual frequency of high/low values that varies from 15% to 28%.

An EV controlled charging strategy that is informed by time-varying grid carbon intensity could achieve 21% to 29% carbon savings under the current grid capacities for daily mile case ranging from 20 to 100 miles. Furthermore, the same controlled strategy under the Future Energy Scenarios assumptions is shown to achieve carbon benefits from 37% to 48%. In this case, the large amounts of renewables in the system cause large in-day fluctuations and many occurrences of zero grid carbon intensity.

A CHP control strategy that factors in the time-varying behaviour of grid carbon intensity could double its carbon benefits if it uses the full extent of the "allowed" operational window. However, the CHP carbon benefit becomes less certain in future capacity assumptions, as the grid decarbonises and grid carbon intensity decrases.

This study has presented strong evidence that high variability, in a time frame that ranges from annual to half-hourly, is a significant feature of the GB grid carbon intensity behaviour. Therefore, the use of single annual average figures for carbon accounting and reporting purposes raises doubts over the accuracy of the estimations. Instead, it is recommended that historic grid carbon intensity should be made available in high resolution to inform demand side management schemes both on domestic and business level.

References

Ang, B.W., & Goh, Tian. 2016. Carbon intensity of electricity in ASEAN: Drivers, performance and outlook. *Energy Policy*, **98**, 170 – 179.

Ang, B.W., & Su, Bin. 2016. Carbon emission intensity in electricity production: A global analysis. *Energy Policy*, **94**, 56 – 63.

Arvesen, Anders, & Hertwich, Edgar G. 2012. Assessing the life cycle environmental impacts of wind power: A review of present knowledge and research needs. *Renewable and Sustainable Energy Reviews*, **16**(8), 5994 – 6006.

Asdrubali, F., Baldinelli, G., D'Alessandro, F., & Scrucca, F. 2015. Life cycle assessment of electricity production from renewable energies: Review and results harmonization. *Renewable and Sustainable Energy Reviews*, **42**, 1113–1122.

B. Hobbs, M. Rothkopf, R. O'Neill H. Chao. 2001. *The next generation of electric power unit commitment models.* Boston: Kluwer Academic Publishers.

Baboukardos, Diogenis. 2017. Market valuation of greenhouse gas emissions under a mandatory reporting regime : Evidence from the UK. *Accounting Forum*, **41**(3), 221–233.

Baldwin, S. 2006. Carbon footprint of electricity generation. *PostNote 268 United Kingdom Parliamentary Office of Science and Technology*.

Barrett, John, Peters, Glen, Wiedmann, Thomas, Scott, Kate, Lenzen, Manfred, Roelich, Katy, & Quéré, Corinne Le. 2013. Consumption-based GHG emission accounting: a UK case study. *Climate Policy*, **13**(4), 451–470.

Bebbington, Jan, Schneider, Thomas, Stevenson, Lorna, & Fox, Alison. 2019. Critical Perspectives on Accounting Fossil fuel reserves and resources reporting and unburnable carbon : Investigating conflicting accounts. *Critical Perspectives on Accounting*.

BEIS. 2016a. *BEIS Electricity generation cost report*. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/566567/BEIS_Electricity_Generation_Cost_Report.pdf. (Accessed on 01/20/2019).

BEIS. 2016b. *Marginal Emission Factor Analysis*. https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/357753/MEF_Analysis_-_Report_FINAL.pdf.

BEIS. 2017. *BEIS 2017 Energy trends*. file:///C:/Users/hy865144/Downloads/BEIS%202017_Energy%20trends_Renewables_Q2%202017.pdf. (Accessed on 03/02/2019).

Bianco, Vincenzo, Scarpa, Federico, & Taglia, Luca A. 2015. Long term outlook of primary energy consumption of the Italian thermoelectric sector : Impact of fuel and carbon prices. **87**, 153–164.

Bosch, Jonathan, Staffell, Iain, & Hawkes, Adam D. 2017. Temporally-explicit and spatially-resolved global onshore wind energy potentials. *Energy*, **131**, 207–217.

Boßmann, T., & Staffell, I. 2015. The shape of future electricity demand: Exploring load curves in 2050s Germany and Britain. *Energy*, **90**, 1317–1333.

Bruce, A. 2015. Impacts of variable renewable generation on thermal power plant operating regimes. *Doctor of Philosophy Dissertation,The University of Edinburgh, Edinburgh*.

Cairney, Paul, Mcharg, Aileen, Mcewen, Nicola, & Turner, Karen. 2019. How to conceptualise energy law and policy for an interdisciplinary audience : The case of post-Brexit UK. *Energy Policy*, **129**(May 2018), 459–466.

Carrión, M., & Arroyo, J.M. 2006. A computationally efficient mixed-integer linear formulation for the thermal unit commitment problem. *IEEE Transactions on Power Systems*, **21**(3), 1371–1378.

CCC. 2015. *Committee on Climate Change: Advice on the fifth carbon budget*. https://www.theccc.org.uk/publication/the-fifth-carbon-budget-the-next-step-towards-a-low-carbon-economy/.

Child, Michael, Kemfert, Claudia, Bogdanov, Dmitrii, & Breyer, Christian. 2019. Flexible electricity generation , grid exchange and storage for the transition to a 100 % renewable energy system in Europe. *Renewable Energy*, **139**, 80–101.

Cleary, Brendan, Duffy, Aidan, Bach, Bjarne, Vitina, Aisma, Connor, Alan O, & Conlon, Michael. 2020. Estimating the electricity prices , generation costs and CO 2 emissions of large scale wind energy exports from Ireland to Great Britain. *Energy Policy*, **91**(2016), 38–48.

Coker, P., Barlow, J., Cockerill, T., & Shipworth, D. 2013. Measuring significant variability characteristics: An assessment of three UK renewables. *Renewable Energy*, **53**, 111–120.

Connolly, D., Lund, H., Mathiesen, B. V., & Leahy, M. 2010. A review of computer tools for analysing the integration of renewable energy into various energy systems. *Applied Energy*, **87**(4), 1059–1082.

DECC. 2011a. *The Carbon Plan: Delivering our low carbon future*. file:///C:/Users/hy865144/Desktop/3702-the-carbon-plan-delivering-our-low-carbon-future.pdf. (Accessed on 10/22/2018).

DECC. 2011b. *The Carbon Plan: Delivering our low carbon future (Executive Summary)*. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/

47614/3751-carbon-plan-executive-summary-dec-2011.pdf. (Accessed on 10/22/2018).

DECC. 2013a. *Environmental Reporting Guidelines*. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/206392/pb13944-env-reporting-guidance.pdf. (Accessed on 11/07/2018).

DECC. 2013b. *Guidance on Combined heat and power*. https://www.gov.uk/guidance/combined-heat-and-power#about-chp. (Accessed on 02/18/2019).

DECC. 2014a. *ESOS - GOV.UK*. https://www.gov.uk/guidance/energy-savings-opportunity-scheme-esos#about-esos. (Accessed on 03/11/2019).

DECC. 2014b. *UK National Energy Efficiency Action Plan*. https://ec.europa.eu/energy/sites/ener/files/documents/2014_neeap_united-kingdom.pdf. (Accessed on 08/11/2019).

DECC. 2015. Annual report. *Digest of UK energy statistics 2015*, **1**, 139–143.

DECC. 2016. *2010 to 2015 government policy: energy demand reduction in industry, business and the public sector - The CRC scheme*. https://www.gov.uk/government/collections/crc-energy-efficiency-scheme. (Accessed on 04/21/2017).

DECC. 2017a. *Digest of UK Energy Statistics (DUKES): Chapter 5, electricity*. https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/633779/Chapter_5.pdf.

DECC. 2017b. *Streamlined energy and carbon reporting - GOV.UK*. https://www.gov.uk/government/consultations/streamlined-energy-and-carbon-reporting. (Accessed on 03/11/2019).

DECC. 2018a. *2018 government GHG conversion factors for company reporting: methodology paper for emission factors - final report*. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/726911/2018_methodology_paper_FINAL_v01-00.pdf. (Accessed on 02/19/2019).

DECC. 2018b. *Digest of UK Energy statistics: Chapter 7: Combined heat and power*. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/729356/Ch7.pdf. (Accessed on 02/18/2019).

DECC. 2018c. *Digest of UK Energy Statistics (DUKES): Chapter 5, electricity*. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/736152/Ch5.pdf.

DEFRA. 2016a. 2016 Government Conversion Factors for Company Reporting. *Methodology Paper for Emission Factors:Final Report*, **1**, 18–33.

DEFRA. 2016b. *2016 Government GHG Conversion: Factors for Company Reporting: Methodology Paper for Emission Factors*. (Accessed on 04/07/2017).

Delarue, E., & D'haeseleer, W. 2007. Energy and Environment conference proceedings Advanced Priority Listing versus Mixed Integer Programming in solving the Unit Commitment problem.

Dogra, R., Nikita, G., & Saroa, H. 2014. International Conference of Advanced Research and Innovation Proceedings Economic Load Dispatch Problem and Matlab Programming of Different Methods.

Dones, Roberto, Heck, Thomas, & Hirschberg, Stefan. 2004. Greenhouse Gas Emissions from Energy Systems, Comparison and Overview. *Pages 77 – 95 of:* Cleveland, Cutler J. (ed), *Encyclopedia of Energy*. New York: Elsevier.

DRAX. 2018. *Balancing for the renewable future - Drax*. https://www.drax.

com/energy-policy/balancing-renewable-future/. (Accessed on 07/01/2019).

Drew, D., Bloomfield, H., Coker, P., Barlow, J., & Brayshaw, D. 2019a. *MERRA derived hourly time series of GB-aggregated wind power, solar power and demand.*

Drew, R.D, Coker, P.J., Bloomfield, H.C., Brayshaw, D.J., Barlow, J.F., & A., Richards. 2019b. Sunny windy sundays. *Renewable Energy*, **138**, 870 – 875.

Edmunds, Ray, Davies, Lloyd, Deane, Paul, & Pourkashanian, Mohamed. 2015. Thermal power plant operating regimes in future British power systems with increasing variable renewable penetration. *Energy Conversion and Management*, **105**, 977–985.

Elexon. 2017. *ELEXON Portal*. https://www.elexonportal.co.uk/basket?cachebust=5crhcnmlcz.

Eltigani, D., & Masri, S. 2015. Challenges of integrating renewable energy sources to smart grids: A review. *Renewable and Sustainable Energy Reviews*, **52**, 770–780.

EVstatus. 2019. *EV Status*. https://evstatus.com/graphs.php). (Accessed on 02/12/2019).

Eyre, Nick, & Baruah, Pranab. 2015. Uncertainties in future energy demand in UK residential heating. *Energy Policy*, **87**, 641–653.

Facchini, Angelo, Rubino, Alessandro, Caldarelli, Guido, & Di, Giuseppe. 2019. Changes to Gate Closure and its impact on wholesale electricity prices : The case of the UK. *Energy Policy*, **125**(October 2018), 110–121.

Fais, Birgit, Keppo, Ilkka, Zeyringer, Marianne, Usher, Will, & Daly, Hannah. 2016. Impact of technology uncertainty on future low-carbon pathways in the UK. *Energy Strategy Reviews*, **13-14**, 154–168.

Fontes, F.A.C.C, Fontes, D.B.M.M, & Roque, L.A.C. 2012. An Optimal Control Approach to the Unit Commitment Problem. 7069–7074.

Foxon, T.J, Hammond, G. P., & Pearson, P. 2010. Developing transition pathways for a low carbon electricity system in the UK. *Technological Forecasting and Social Change*, **77**(8), 1203–1213.

Fthenakis, Vasilis M, & Chul, Hyung. 2007. Greenhouse-gas emissions from solar electric- and nuclear power : A life-cycle study. **35**, 2549–2557.

Gagnon, Luc, & van de Vate, Joop F. 1997. Greenhouse gas emissions from hydropower: The state of research in 1996. *Energy Policy*, **25**(1), 7 – 13.

Galvan, E., Carrasco, J.M., & Portillo, G. 2006. Power-Electronic Systems for the Grid Integration of Renewable Energy Sources: A Survey. *IEEE Transactions on Industrial Electronics*, **53**(4), 1002–1016.

Goh, Tian, Ang, B.W., Su, Bin, & Wang, H. 2018. Drivers of stagnating global carbon intensity of electricity and the way forward. *Energy Policy*, **113**, 149 – 156.

Green, R., & Staffell, I. 2016. Electricity in Europe: Exiting fossil fuels? *Oxford Review of Economic Policy*, **32**(2), 282–303.

Groening, C., Inman, J., & William, R.T. 2014. Carbon Footprints in the Sand: Marketing in the Age of Sustainability. *Customer Needs and Solutions*, **1**(1), 40–51.

Groening, C., Inman, J., & William, R.T. 2016. The role of carbon emissions in consumer purchase decisions. *International Journal of Environmental Policy and Decision Making*, **1**(4).

Grubb, M., & Newbery, D. 2018. Cambridge Working Papers in Economics Cambridge Working Papers in Economics : 1834 UK Electricity market reform and the energy transition: Emerging Lessons.

Hall, Lisa M.H., & Buckley, Alastair R. 2016. A review of energy systems models in the UK: Prevalent usage and categorisation. *Applied Energy*, **169**, 607 – 628.

Haslam, Colin, Butlin, John, Andersson, Tord, Malamatenios, John, & Lehman, Glen. 2014. Accounting for carbon and reframing disclosure : A business model approach. *Accounting Forum*, **38**(3), 200–211.

Hawkes, A. D. 2010. Estimating marginal CO2 emissions rates for national electricity systems. *Energy Policy*, **38**(10), 5977–5987.

Hawkes, A. D. 2014. Long-run marginal CO2emissions factors in national electricity systems. *Applied Energy*, **125**, 197–205.

Hinson, Suzanna, Sutherland, Nikki, & Rutherford, Tom. 2018. Energy Efficiency and the Clean Growth Strategy.

Hitchin, E. R., & Pout, C. H. 2002. The carbon intensity of electricity: How many kgC per kWhe? *Building Services Engineering Research and Technology*, **23**(4), 215–222.

HOC. 2018. *House Of Commons: Oral evidence - Electric vehicles: developing the market and infrastructure.* http://data.parliament.uk/writtenevidence/committeeevidence.svc/evidencedocument/business-energy-and-industrial-strategy-committee/electric-vehicles-developing-the-market-and-infrastructure/oral/80982.html.

Hondo, H. 2005. Life cycle GHG emission analysis of power generation systems: Japanese case. *Energy*, **30**(11-12 SPEC. ISS.), 2042–2056.

IEA. 2017. *International Enegy Agency: Global EV Outlook 2017.* https://webstore.iea.org/global-ev-outlook-2017.

IEA. 2018. *International Energy Agency: Global EV Outlook 2018.* https://www.iea.org/gevo2018/.

Indra al Irsyad, Muhammad, & Halog, Anthony. 2019. Renewable energy projections for climate change mitigation : An analysis of uncertainty and errors. *Renewable Energy*, **130**, 536–546.

ISO4040. 2006. *ISO 14040:2006(en), Environmental management — Life cycle assessment — Principles and framework*. https://www.iso.org/obp/ui/#iso:std:iso:14040:ed-2:v1:en. (Accessed on 10/25/2018).

Johnson, Samuel C, Papageorgiou, Dimitri J, Mallapragada, Dharik S, Deetjen, Thomas A, Rhodes, Joshua D, & Webber, Michael E. 2019. Evaluating rotational inertia as a component of grid reliability with high penetrations of variable renewable energy. *Energy*, **180**, 258–271.

Joos, Michael, & Staffell, Iain. 2018. Short-term integration costs of variable renewable energy : Wind curtailment and balancing in Britain and Germany. **86**(March), 45–65.

Kazarlis, S. A., Bakirtzis, A. G., & Petridis, V. 1996 (Feb). *A genetic algorithm solution to the unit commitment problem.*

Kelly, K. A., McManus, M. C., & Hammond, G. P. 2014. An energy and carbon life cycle assessment of industrial CHP (combined heat and power) in the context of a low carbon UK. *Energy*, **77**, 812–821.

Khan, I. 2018. Importance of GHG emissions assessment in the electricity grid expansion towards a low-carbon future: a time-varying carbon intensity approach. *Journal of Cleaner Production*, **196**, 1587–1599.

Khan, I., Jack, M. W., & Stephenson, J. 2018. Analysis of greenhouse gas emissions in electricity systems using time-varying carbon intensity. *Journal of Cleaner Production*, **184**, 1091–1101.

Lau, E. T., Yang, Q., Forbes, A. B., Wright, P., & Livina, V. N. 2014a. Modelling carbon emissions in electric systems. *Energy Conversion and Management*, **80**, 573–581.

Lau, E. T., Yang, Q., Taylor, G. A., Forbes, A. B., Wright, P., & Livina, V. N. 2014b. Optimization of carbon emissions in smart grids. *Proceedings of the Universities Power Engineering Conference*, 4–7.

Lau, E. T., Yang, Q., Stokes, L., Taylor, G. A., Forbes, A. B., Clarkson, P., Wright, P. S., & Livina, V. N. 2015. Carbon savings in the UK demand side response programmes. *Applied Energy*, **159**, 478–489.

Lave, L.B., & Freeburg, L.C. 1973. Health effects of electricity generation from coal, oil, and nuclear fuel. *Nucl. Safety, v. 14, no. 5, pp. 409-428*.

Lindberg, K B, Seljom, P, Madsen, H, Fischer, D, & Korpås, M. 2019. Long-term electricity load forecasting : Current and future trends. *Utilities Policy*, **58**(April), 102–119.

Malinauskaite, J, Jouhara, H, Ahmad, L, Milani, M, Montorsi, L, & Venturelli, M. 2019. Energy efficiency in industry : EU and national policies in Italy and the UK. *Energy*, **172**, 255–269.

Mclaughlin, Craig, Elamer, Ahmed A, Glen, Thomas, Alhares, Aws, & Gaber, Hazem Rasheed. 2019. Accounting society ' s acceptability of carbon taxes : Expectations and reality. *Energy Policy*, **131**(April), 302–311.

Mohsenian-Rad, H. 2012. *Smart_Grid_Topic_1_Power_Systems.pdf*. http://www.ee.ucr.edu/~hamed/Smart_Grid_Topic_1_Power_Systems.pdf. (Accessed on 04/05/2017).

N.G. 2012. *National Grid operational metering data and renewables*. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/65923/6487-nat-grid-metering-data-et-article-sep12.pdf. (Accessed on 02/06/2019).

N.G. 2017. *National Grid : Carbon Intensity API forecast*. https://www.carbonintensity.org.uk/. (Accessed on 02/12/2019).

NG. 2017. *National Grid: Data Explorer: Demand data 2009-2016*. http://www2.nationalgrid.com/UK/Industry-information/Electricity-transmission-operational-data/Data-Explorer/.

N.G. 2018a. *National Grid - Future Energy Scenarios*. http://fes.nationalgrid.com/media/1357/fes-2018-in-5-minutes-web-version.pdf. (Accessed on 01/27/2019).

N.G. 2018b. *National Grid - Future Energy Scenarios main document*. http://fes.nationalgrid.com/media/1363/fes-interactive-version-final.pdf. (Accessed on 01/27/2019).

Octopus. 2018. *Agile Octopus: A consumer-led shift to a low carbon future*. https://octopus.energy/static/consumer/documents/agile-report.pdf. (Accessed on 03/18/2019).

Odeh, N., Cockerill, A., & Timothy, T. 2008. Life cycle analysis of UK coal fired power plants. *Energy Conversion and Management*, **49**(2), 212–220.

Odeh, Naser A., & Cockerill, Timothy T. 2008. Life cycle analysis of UK coal fired power plants. *Energy Conversion and Management*, **49**(2), 212–220.

Papaioannou, V., Simpson, A., Coker, P., Potter, B., & Livina, V. 2019. Submitted: Variability in the UK grid carbon intensity and how it can inform controlled charging strategies of EVs.

Pean, Emmanuel, Pirouti, Marouf, & Qadrdan, Meysam. 2016. Role of the GB-France electricity interconnectors in integration of variable renewable generation. *Renewable Energy*, **99**, 307–314.

Perry, S., Simon, Klemeš, J., & Bulatov, I. 2008. Integrating waste and renewable energy to reduce the carbon footprint of locally integrated energy sectors. *Energy*, **33**(10), 1489–1497.

Pfenninger, S., Hawkes, A., & Keirstead, J. 2014. Energy systems modeling for twenty-first century energy challenges. *Renewable and Sustainable Energy Reviews*, **33**(January), 74–86.

Rogers, A., & Parson, O. 2017. *GridCarbon: A smartphone app to calculate the carbon intensity of the UK electricity grid*. http://www.gridcarbon.uk/.

Salam, S. 2007. Unit Commitment Solution Methods. *Proceedings of World Academy of Science: Engineering and Technology*, **26**(11), 600–605.

Senjyu, T., Shimabukuro, K., Uezato, K., & Funabashi, T. 2003. A fast technique for unit commitment problem by extended priority list. *IEEE Transactions on Power Systems*, **18**(2), 882–888.

Sharifzadeh, Mahdi, Lubiano-walochik, Helena, & Shah, Nilay. 2017. Integrated renewable electricity generation considering uncertainties : The UK roadmap to 50 % power generation from wind and solar energies. *Renewable and Sustainable Energy Reviews*, **72**(January), 385–398.

Siler-Evans, K., Azevedo, I.L., & Morgan, M.G. 2012. Marginal emissions factors for the U.S. electricity system. *Environmental Science and Technology*, **46**(9), 4742–4748.

Sithole, H, Cockerill, T T, Hughes, K J, Ingham, D B, Ma, L, Porter, R T J, & Pourkashanian, M. 2020. Developing an optimal electricity generation mix for the UK 2050 future. **100**(2016).

Staffell, I. 2017. Measuring the progress and impacts of decarbonising British electricity. *Energy Policy*, **102**, 463–475.

Staffell, I., Brett, D., Brandon, N., & Hawkes, A. 2012. A review of domestic heat pumps. *Energy and Environmental Science*, **5**(11), 9291–9306.

Staffell, Iain, & Pfenninger, Stefan. 2018. The increasing impact of weather on electricity supply and demand. *Energy*, **145**, 65–78.

Stein, RM. 2007. Benchmarking default prediction models: Pitfalls and remedies in model validation. *Moody's KMV, New York*, **1**(1), 77–113.

Streiffert, D., Philbrick, R., & Ott, A. 2005. A mixed integer programming solution for market clearing and reliability analysis. *IEEE Power Engineering Society General Meeting, 2005*, 1–8.

Tauringana, Venancio, & Chithambo, Lyton. 2015. The effect of DEFRA guidance on greenhouse gas disclosure. *The British Accounting Review*, **47**(4), 425–444.

Thomson, R. C., Harrison, G. P., & Chick, J. P. 2017. Marginal greenhouse gas emissions displacement of wind power in Great Britain. *Energy Policy*, **101**, 201–210.

Toke, David, & Fragaki, Aikaterini. 2008. Do liberalised electricity markets help or hinder CHP and district heating ? The case of the UK. **36**, 1448–1456.

Tranberg, Bo, Corradi, Olivier, Lajoie, Bruno, Gibon, Thomas, & Staffell, Iain. 2019. Real-time carbon accounting method for the European electricity markets. **26**(December 2018).

Turconi, R., Boldrin, A., & Astrup, T. 2013. Life cycle assessment (LCA) of electricity generation technologies: Overview, comparability and limitations. *Renewable and Sustainable Energy Reviews*, **28**, 555–565.

UKCCC. 2016. *Meeting Carbon Budgets - 2016 Progress Report to Parliament*. https://www.theccc.org.uk/wp-content/uploads/2016/06/2016-CCC-Progress-Report.pdf.

Van Mierlo, J., Messagie, M., & Rangaraju, S. 2017. Comparative environmental assessment of alternative fueled vehicles using a life cycle assessment. *Transportation Research Procedia*, **25**, 3439–3449.

Varun, Bhat, I. K., & Prakash, Ravi. 2009. LCA of renewable energy for electricity generation systems-A review. *Renewable and Sustainable Energy Reviews*, **13**(5), 1067–1073.

Vijay, A., Fouquet, N., Staffell, I., & Hawkes, A. 2017. The value of electricity and reserve services in low carbon electricity systems. *Applied Energy*, **201**, 111–123.

Vorushylo, Inna, Keatley, Patrick, Shah, Nikhilkumar, Green, Richard, & Hewitt, Neil. 2018. How heat pumps and thermal energy storage can be used to manage wind power : A study of Ireland. *Energy*, **157**, 539–549.

Weisser, D. 2007. A guide to life-cycle greenhouse gas (GHG) emissions from electric supply technologies. *Energy*, **32**(9), 1543–1559.

White, E., & Hough, D. 2016. Energy Policy Overview. 1–20.

Wood, A. J., Wollenberg, B. F., & Sheble, G. B. 2013. *Power Generation, Operation, and Control*. New Jersey: John Wiley and sons.

Wu, Z., Wang, M., Zheng, J., Sun, X., Zhao, M., & Wang, X. 2018. Life cycle greenhouse gas emission reduction potential of battery electric vehicle. *Journal of Cleaner Production*, **190**, 462–470.

Zuijlen, Bas Van, Zappa, William, Turkenburg, Wim, & Schrier, Gerard Van Der. 2019. Cost-optimal reliable power generation in a deep decarbonisation future. *Applied Energy*, **253**(June), 113587.