REPORT

Historical analysis of peak electricity demand patterns (WP2)

Prepared for National Grid ESO

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1. Executive summary

Overview

This report presents findings from a statistical analysis of the main drivers of peak electricity demand in Great Britain. Key conclusions drawn from the analysis are summarised below.

The literature reviewed in WP1 suggested that multiple linear regression analysis is well suited to long-term, multi-year peak demand forecasting, therefore we chose to focus on this approach during WP2.

Within the project timeframe, a partial least squares (PLS) linear regression model for peak electricity demand was developed, incorporating various demand drivers including weather, socioeconomic, economic, technology and behavioural factors.

The results of this analysis suggest that peak demand from historical drivers can be modelled to an acceptable degree of accuracy using the PLS linear regression model.

The model was able to predict historical peak demand with a degree of accuracy comparable to other methodologies reviewed in the WP1 literature review, obtaining a mean average percentage error (MAPE) of 5.4% compared with a MAPE of 1.4% to 7.9% seen in the literature

Further refinements to the regression model through the consideration of additional demand driver datasets and or the use of a different combination of demand drivers could yield further improvements in accuracy.

Key takeaways

Overall, the regression analysis of historical demand drivers showed that:

1. Temperature was the most significant driver of peak demand out of all the demand drivers captured in the regression model
2. The next most significant drivers of demand were day of week and seasons, suggesting a strong behavioural contribution to peak demand historically

The study of the future peak demand contributions from new demand drivers such as battery electric vehicles, heat pumps and hydrogen electrolysers showed that:

1. In the event of no time-shifting of demand from these new technologies, the magnitude of their peak demand contributions could increase significantly over time to more than double current peak demand levels by 2050
2. In the next 5 years, peak demand will only be minimally affected by new demand drivers, causing an additional contribution to peak demand of up to 15GW in total by 2027

The resulting ranges of peak demand obtained from the regression model in the next 5 years and up to 2050 are summarised below:

Combination	Peak demand in 2027 (5 years)	Peak demand in 2050 (~30 years)
Existing drivers & EVs	45-55 GW	51-97 GW
Existing drivers & heat pumps	43-52 GW	28-86 GW
Existing drivers & hydrogen	42-47 GW	24- 59 GW

Overall, the modelling of peak demand cannot be purely based on a statistical approach, and will require a hybrid approach, due to:

1. The emergence of new peak demand drivers in the coming years
    - In this study, the effect of new demand drivers on peak demand had to be considered separately to historical demand drivers because the new demand drivers could not be captured in the regression model (due to little or no data on these drivers being available as of yet)
    - There are limitations of a statistical approach in capturing emerging time-shifting or reduction in peak demand as a result of the increase uptake of smart technologies
    - These peak demand contributions would need to be modelled using a non-statistical method such as bottom-up modelling
2. Gaps in historical demand driver datasets limit the robustness of any statistical models developed
    - In this study, some data had to be processed either via extrapolation or interpolation before inclusion in the regression model due to a lack of data of a consistent granularity or timescale across all demand drivers
3. Challenges in identifying and quantifying all possible behavioural demand drivers
    - In this study, we included a retail electricity price index and time dummies for day of week and seasons in order to capture some behavioural elements within the regression model
    - However unexplained drivers that contribute to the recent decline in peak demand, appear not to be captured fully in the resulting regression model. We believe that some of these might be due to additional behavioural drivers, not captured here
4. The need to consider possible inflection points, where statistical correlations between demand drivers break down
    - This study did not consider any likely inflection points, beyond which statistical correlations behind drivers and peak demand may breakdown. However, it is likely that these points will occur in the future

Comparisons against the average cold spell (ACS) methodology – the purpose of this study was to form a view on the drivers of peak demand through the analysis of historical data. As such, it focused on a PLS linear regression model, which considers additional demand drivers explicitly within a statistical model compared with the ACS methodology, which considers the effects of drivers within a single basic demand component and a residual demand component. Both models consider temporal effects (day of week, season) and weather effects. The ACS model in its current form determines peak demand by taking the median of 20,000 winters simulated based on 30 years of winter weather data. This study does not seek to replicate this methodology, and instead considers the effects of temperature as additional sensitivities.

Areas for further study

Areas that NGESO should consider for further study include:

- Exploration of additional demand drivers to include in the model
- Exploration of different combinations of demand drivers and the resulting model accuracy

- Modelling of demand based on temperature from global climate model forecasts for GB for a deeper understanding of potential year-on-year changes to future peak demand
- Additional day of week time dummies (to account for different weekdays, special events, etc.)
- Bottom-up modelling of behavioural demand drivers
- The consideration of inflection points in the future demand driver trends
- The consideration of the effects of increasing uptake of air-conditioning with increasing heat pump adoption on summer peak demand
- The potential for a purely statistical demand-forecasting methodology once smart meter penetration reaches a critical value/a certain proportion of total electricity consumers

2. Introduction

This report provides a summary of the results of an analysis of historical demand drivers and peak electricity demand in Great Britain, undertaken for the National Grid Electricity System Operator (NGESO). It follows on from the literature review of peak demand forecasting methodologies, delivered to NGESO in the first phase of this study.

It serves to provide a foundational view of how peak demand forecasting could be based on analysis of existing and new peak demand drivers, that could be built upon with further research to develop a comprehensive peak demand forecasting methodology.

The peak demand in this study is the highest demand in a half-hour period in a given year, referred to as annual peak demand.

Overview of report sections

The report summarises the methodology used in the analysis, key results for historical and future peak demand, along with additional considerations of how peak demand might change moving forward:

- Section 3 covers the methodology used to analyse the relationship between key demand drivers and peak demand
- Section 4 covers the results obtained by conducting a statistical review of the link between historical demand drivers and historical peak demand (2009-2021)
- Section 5 covers the results obtained by using the regression model from Section 4 to consider what future peak demand might be based on a continuation of the historical trends, and also considers the effect of additional demand drivers like electric vehicles (EVs), heat pumps and hydrogen on peak demand
- Section 6 provides commentary on additional considerations in how peak demand might change moving forward, given the increasing uptake of smart technologies and storage technologies
- Section 7 shares conclusions from the study, a discussion of the challenges and limitations experienced in undertaking the analysis and further research areas

3. Overview of analytical methodology

3.1 Regression analysis

1. **Collation of demand driver data:** Through the literature review conducted in WP1, key demand drivers were identified from across weather, economic, socioeconomic and technological factors
    - An extensive search for publicly available datasets in these categories was undertaken
    - The data obtained are for the UK and taken to be representative of trends in Great Britain (GB), as GB-specific datasets could not be obtained
    - Data sources are detailed in Table 1 (Section 4)
    - ***Raw data inputs are provided in the 'Regression model databook.xlsx' file that accompanies this report***
2. **Collation of electricity demand data:** Half-hourly demand for Great Britain was obtained from the datasets published by NGESO and ELEXON
3. **Data processing methodology:** For the data to fit into a regression model, it needed to be processed to be in the right level of granularity as the peak demand data included in the model – processing was done for daily peak demand regression and annual peak demand regression
    - Daily peaks
        - Half hourly demand data in GW - the maximum half-hour demand within each day was selected as the daily peak demand
        - Temperature data was taken at daily granularity
        - Other demand drivers were either at monthly or yearly granularity and were re-sampled to daily granularity and/or linearly interpolated to obtain missing values
        - Time dummies are added in, in a binary format of 0 or 1, for season (winter/spring/summer/autumn) and day of week (weekday/weekend)
        - All demand and driver data are then merged according to the timestamp
    - Yearly peaks for Residential, Commercial and Industrial demand
        - Samples of residential/commercial/industrial demand profiles at half-hourly granularity for different combinations of day of week and season were obtained from ELEXON
        - From here a representative year demand profile is synthesised for each consumer segment (residential/commercial/industrial) before normalising them to a mean of 1
        - The yearly maximum value of this normalised demand pattern is identified and multiplied with the annual MW residential, commercial, and industrial demand to get the peak demand by consumer segment by year
        - The demand drivers that are available at monthly or yearly granularity are then linearly interpolated or averaged as appropriate to obtain a yearly value
        - All demand and driver data are then merged according to the year timestamp
    - ***Processed daily and yearly data inputs, referred to as the 'training' data, are provided in the 'Regression model databook.xlsx' file that accompanies this report***

4. **Linear regression analysis:** In order to analyse the correlations between demand drivers and peak demand, a suitable linear regression method was identified and applied against the data processed in Step 2 above
    - Initially a range of regression methodologies including Ordinary Least Squares (OLS), Partial Least Squares (PLS), Principal Component Regression (PCR) and Ridge Regression were analysed
        - One of the key limitations with the data is that many variables are correlated with each other (e.g. GDP vs income)
        - Many regression techniques struggle in this situation, particularly OLS, and so the PLS method was selected because it mapped both the explanatory demand drivers and response (peak demand) variables to new vector spaces such that all are completely independent, thus removing the issues around correlation
        - The added benefit of the PLS method was the ability for the model to then utilise projections of the same combination of demand drivers to produce projections of future peak demand
    - PLS can reduce the number of variables (much like principal component analysis) and so has a parameter of the number of independent components. For this study, PLS with 5 components was selected with the justification that there was no significant increase in accuracy and an increased risk of overfitting beyond the point of using 5 components
    - The regression analysis was conducted using a standard Python package for PLS linear regression
        - ***The Python script used is provided in the Appendix (Section 8.4) and in the zipped folder 'Regression model code.zip' that accompanies this report***
5. **Model validation:** In order to ascertain the accuracy and validity of the model, a number of metrics from the regression exercise were analysed
    - The main metrics used to validate the performance of the regression model have been the R^2 value and Mean Absolute Percentage Error (MAPE). The R^2 value can be interpreted as a metric for how much of the variation in the original data can be explained by the changes in the explanatory variables. The MAPE then indicates the level of certainty in results
    - Additional validation analysis was done via cross-validation. This involved removing a portion of the original training data set and retraining the model before subsequently testing against this reserved test set. Here, 13-fold cross validation for daily peak data was used because the dataset contained 13 years of data – so each test removes a single year of data before fitting around the remaining 12 and then testing against the original removed year. The metrics defined above were obtained for each combination. An interesting observation occurs around 2020 where the model struggles more to predict daily peak demand due to the Covid pandemic
    - No cross validation was done for the yearly peaks due to the significantly smaller sample sizes (1 datapoint per year)
6. **Forward projections of peak demand:** The regression model was used to project what peak demand could look like based on potential future trends of historical drivers
    - To forecast peak demand within a year, forward projections of each explanatory variable (demand driver) are fed into the regression model
        - For the time dummies, peak demand is assumed to occur on a winter weekday
        - For temperature, a range of values for the coldest day over a given winter each year is modelled, looking at the coldest day of the coldest winter, the coldest day

of the most mild winter and also some hypothetical "extreme" cases taking these two scenarios and making them more extreme by making them colder/warmer by one standard deviation of temperature in winter (detailed in Table 3)

- Overall two sets of projections are explored; one extrapolating the demand drivers based on the entire timeline, and a second case plateauing some demand drivers (detailed in Table 2)
- ***Regression model outputs are provided in the 'Regression model databook.xlsx' file that accompanies this report***

3.2 Future demand driver analysis

1. Historical data collation: Annual historical data for battery electric vehicle (BEV) sales, heat pump adoption and metered embedded generation were located from publicly available data sources
2. Future driver datasets: Annual future (forecast) datasets and demand profiles were obtained from a combination of external and internal sources
3. Peak demand calculation for BEVs and heat pumps: The forecasts from Step 2 were applied to demand profiles for BEVs and heat pumps to obtain annual peak demand from these new demand drivers, assuming that no time-shifting of demand occurred from the smart usage of these technologies. Two cases were explored for each technology – a base case that assumes a linear uptake of these new technologies as the available historical data, and a maximum case that assumes an uptake rate as modelled by the CCC Balanced Net Zero Pathway scenario
4. Peak demand calculation for hydrogen electrolyser peak demand: For the calculation of hydrogen electrolyser peak demand, a slightly different methodology was used where electrolysed hydrogen supply forecasts by the CCC were used as a starting point to determine the total amount of electricity required by the system in each year to produce that amount of electrolysed hydrogen. Based on assumptions of efficiency, flexibility and load factors obtained from Aurora Energy Research, values for the base peak demand and maximum peak demand were calculated. Base peak demand was modelled after the CCC Headwinds electrolysed hydrogen supply scenario and maximum peak demand was modelled after the CCC Balanced Net Zero Pathway scenario
5. ***Raw data inputs and the corresponding outputs for the base and maximum cases are provided in the 'New drivers databook.xlsx' file that accompanies this report***

4. Analysis of existing drivers of peak electricity demand

4.1 Overview of historical demand trends

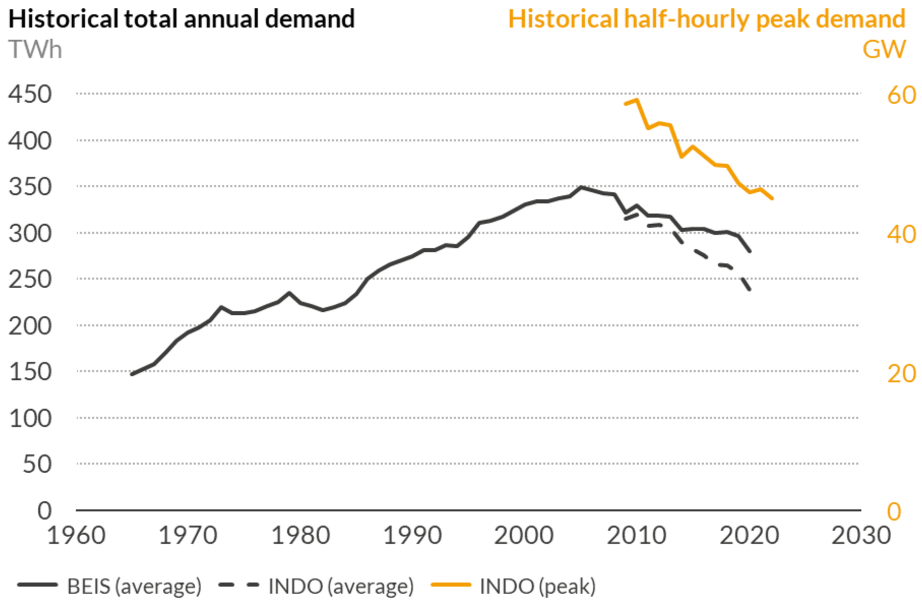
In order to understand how peak demand may change moving forward, it is first important to understand what has driven changes in peak demand historically.

Figure 1 shows the historical annual half-hourly electricity demand for Great Britain based on datasets available from the Department of Business, Energy & Industrial Strategy (BEIS) and Elexon (via the National Grid Electricity System Operator, NGESO). The black solid line shows the historical annual average half-hourly electricity demand calculated from the annual electricity demand dataset published by BEIS, covering electricity consumption from the industrial, domestic, public administration, transport, agricultural and commercial sectors for 1965 to 2022[1].

The orange line is the annual peak half-hourly demand from the half-hourly dataset published by NGESO and Elexon from 2009 to 2022. The black dotted line is the annual demand from the same dataset (NGESO/ELEXON). This demand dataset covers the total electricity demand in GB, including transmission losses but not including non-end consumer demand such as pumped storage and interconnector demand[2]. This is also known as Initial Demand Out-turn (INDO). Note that due to a lack of available data, the trend shown in Figure 1 does not include demand met by behind-the-meter embedded generators even though this also makes up a portion of total electricity demand.

Annual average electricity consumption in the UK has grown since 1965, mainly following the growth in socio-economic factors such as national GDP and industrial activity. It reaches a maximum of 349TWh in 2005 then begins to decline, reaching 280TWh by the end of 2020. The reasons for this decline are not well-established but it is believed to be due to improvements in energy efficiency, and changes in consumer and industrial behaviour despite a continually expanding economy. Likewise, the annual INDO average and peak demand follow a falling trend since 2009.

Overall, peak demand has fallen by 13.7 GW from 58.6 GW in 2009 to 44.9GW in 2021. Potential reasons for this include increasingly warmer winters, improvements in energy efficiency coupled with a plateauing of industrial activity and increasing retail electricity prices. These factors are explored further below.



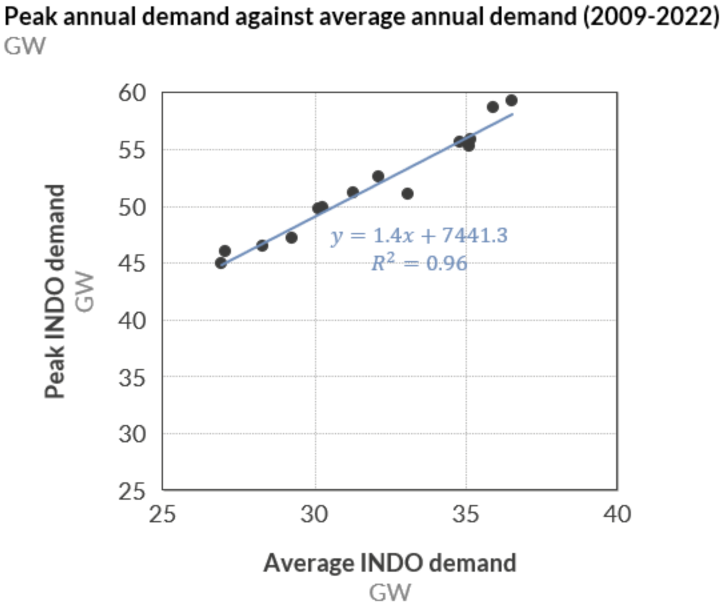
Source: ELEXON, NGESO, BEIS, Aurora Energy Research

Figure 1: Electricity demand trends in GB from two datasets – (a) Total annual final user electricity consumption; and (b) Annual and peak half-hourly Initial Demand Out-turn (INDO)

Between 2009 and 2022, peak demand has maintained a strong linear correlation to average INDO demand, as shown in Figure 2. The major deviations from this relationship have occured in years with unexpected weather. For example, in 2009 and 2010 winters were particuarly cold and peak demand fell significantly above this trendline, reaching 58.6 GW and 59.1 GW respectively. Likewise in warmer than expected winters, such as 2014, peak demand would have been overestimated by this linear relationship, which predicts a peak demand of 53.8 GW as opposed to the actual peak of 50.9 GW.

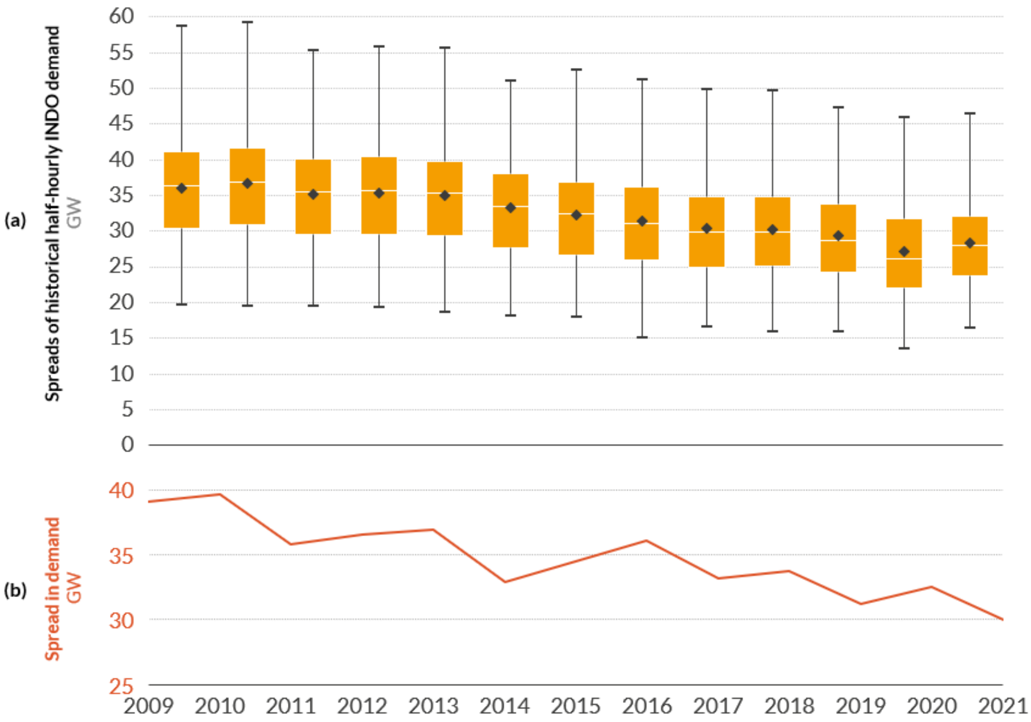
As there is currently a large overlap in drivers of average and peak demand, this near-linear relationship is expected to hold steady in the near future (~5 years). However, the average-to-peak demand relationship is likely to change in the longer term due to the introduction of peak demand time-shifting mechanisms such as demand side management and smart technologies. Furthermore, as winter temperatures may become more volatile due to climate change, this linear relationship may become less reliable.

To understand the range in daily peak demand values each year, box plots of the daily peak demand values each year were created as shown in Figure 3a. As peak demand falls, the annual spread in half-hourly demand (taken from the difference between the maximum and minimum of the daily peak demand half-hours) has also fallen in a similar trend over the years (Figure 3b).



Source: ELEXON, NGESO, Aurora Energy Research

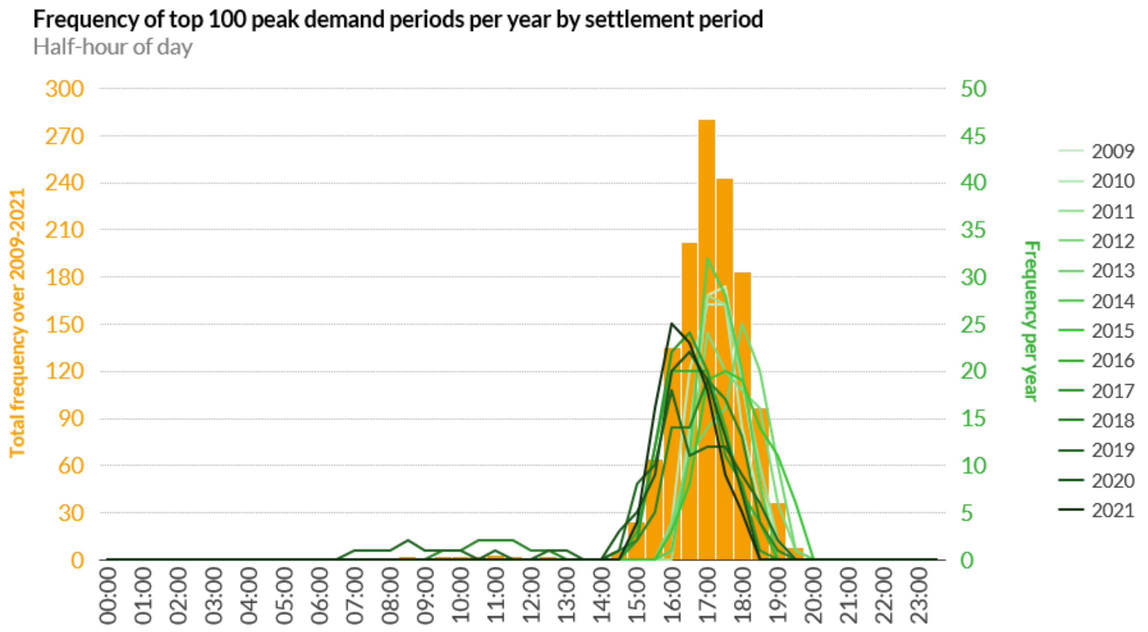
Figure 2: Historical peak to average half-hourly demand with linear best-fit trendline



Source: ELEXON, NGESO, Aurora Energy Research

Figure 3: (a) Spreads of half-hourly INDO demand by year; (b) Spread in demand by year (maximum-minimum demand of the year)

To determine the timing of peak demand since 2009, the top 100 peak demand periods per year between 2009 to 2021 were analysed, daily peak demand has on average occured between 15:00 to 19:30, with the highest frequency of peak periods falling during the evening peak of 17:00 to 17:30 (Figure 4). However, over the years from 2009 to 2021, the evening peak has generally shifted to earlier in the day, with most occurences happening at 4-5pm in 2019-2021. This may be a result of behavioural changes over the years.



Source: ELEXON, NGESO, Aurora Energy Research

Figure 4: Frequency of top 100 half-hour peak demand periods in each year from 2009 to 2021

4.2 Overview of existing demand drivers

This section provides an overview of the existing demand drivers that are believed to have contributed to historical peak demand, and are expected to influence future peak demand. The demand drivers datasets shared here are used in the regression analysis for historical peak demand. Therefore this section illustrates the key driver trends that feed into the regression analysis detailed in Section 4.3.

The key drivers of historical peak demand are identified and listed in Table 1, along with the data sources we have used for each. Table 1 also indicates whether the drivers were included in either the overall or the consumer segment-specific regression analyses. This was determined through a pairs plot analysis (see Appendix) that identified which drivers were highly intercorrelated resulting in some of them being excluded from the regression analysis as they would have skewed the regression results. An example of this is where income data was removed from the overall daily peaks regression as it appeared to be intercorrelated with GDP and population.

Some key observations of the demand driver trends in Figures 5, 6 and 7 are detailed below:

- Over time, the socio-economic drivers (i.e. population, GDP, income and industrial activity) have generally increased as illustrated in Figure 5, with the exception of a sharp drop in 2020 due to the COVID-19 pandemic.

- While monthly average temperatures fluctuate seasonally each year, they have generally been increasing over time, as illustrated in Figure 6a. In particular, the average winter temperatures have risen about 67% in 2022 compared to 2009. Furthermore, there seems to be a possible inverse correlation between minimum winter temperature and peak half-hourly demand as shown in Figure 6b, suggesting the importance of considering the impact of extreme winters on peak demand.
- The remaining technological and behavioural drivers are shown in Figure 7
  - The energy efficiency index trends downwards from 2009-2022 as energy efficiency increases
  - Electricity retail prices increase overall, with the largest increase observed between 2021 and 2022
  - Number of households, average number of bedrooms per dwelling, cumulative non-domestic floor area, and the average number of TVs, fridges and washing machines increase steadily over time

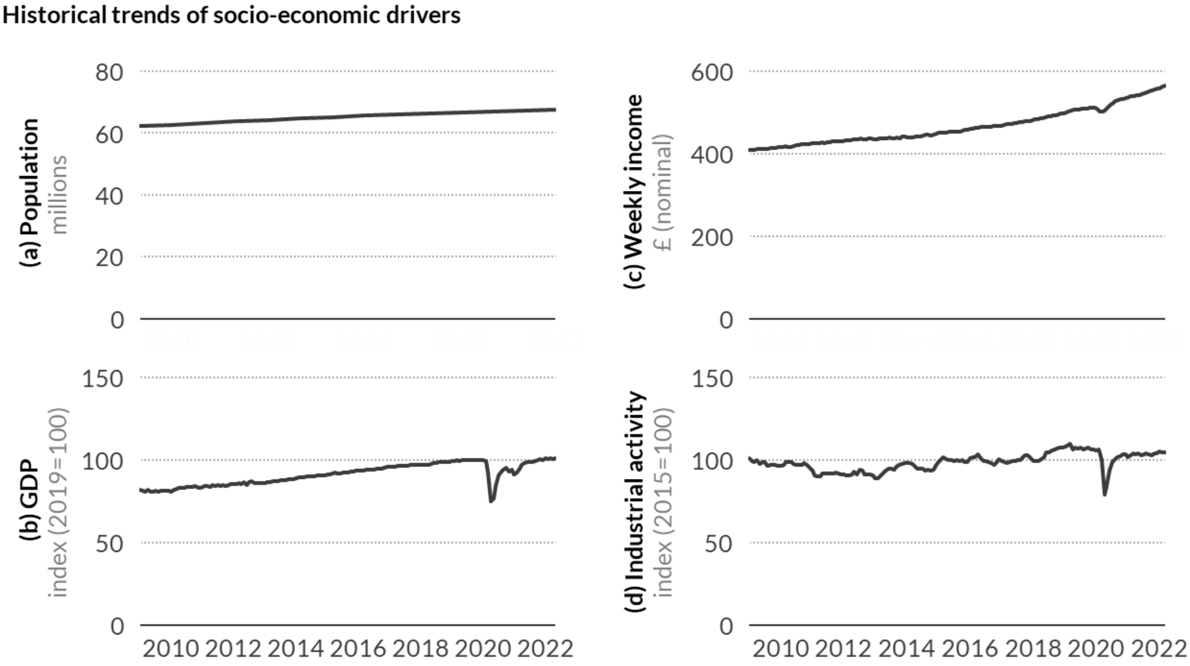
Driver	Data	Source	Included in overall regression?	Included in segment-specific regression?		
				Residential	Commercial	Industrial
Population	Fig. 5	Macrotrends[3]	✓*	✓	✓	✓
GDP	Fig. 5	ONS[4]	✓*		✓	✓
Income	Fig. 5	ONS[5]		✓	✓	✓
Industrial activity	Fig. 5	OECD[6]				✓
Temperature	Fig. 6	Met Office[7]	✓**	✓	✓	✓
Energy efficiency	Fig. 7	EEA[8]	✓***	✓	✓	✓
Electricity retail price	Fig. 7	BEIS[9][10][11]	✓***	✓	✓	✓
Number of households	Fig. 7	UKERC[12]	✓	✓		
Size of buildings	Fig. 7	DLHC[13]; ND-NEED[14]	✓	✓	✓	
Number of appliances	Fig. 7	EEA[15]		✓		
Season	-	-	✓			
Weekday/weekend	-	-	✓			

* Population and GDP were captured together as GDP per capita

** The temperature metric used in the regression analysis is mean daily temperature

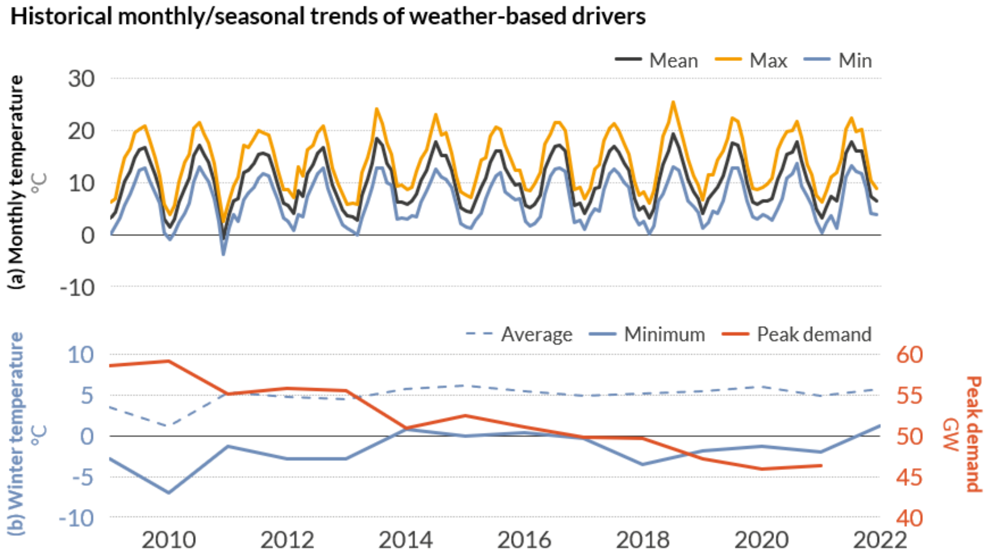
*** For the regression done on overall daily peaks, energy efficiency and electricity retail price were calculated as demand-weighted averages of consumer segment-specific datasets

Table 1: Existing demand drivers used in analysis



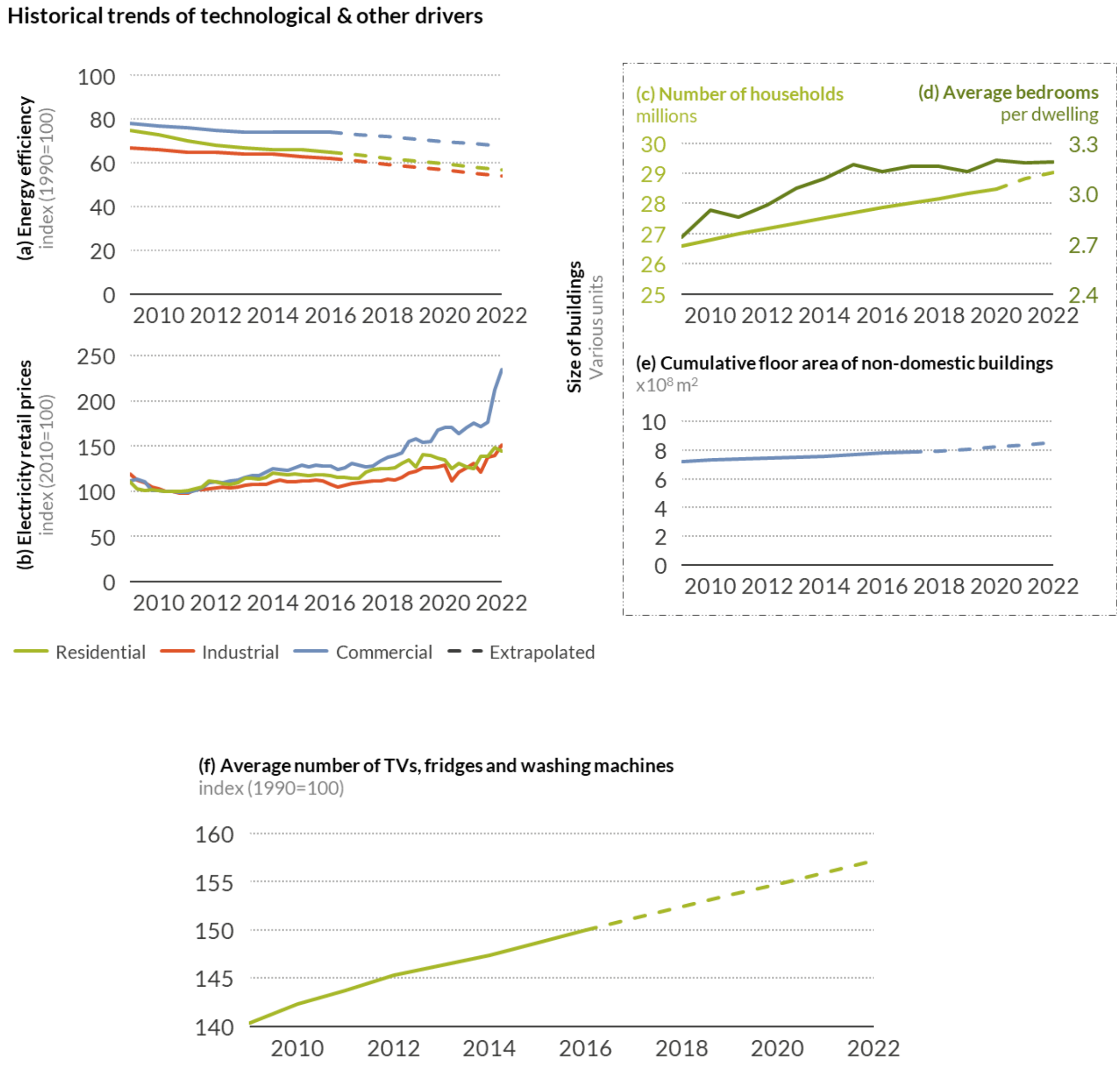
Source: Aurora Energy Research, various sources listed in Table 1

Figure 5: Trends of socio-economic drivers over time. (a) Population; (b) UK GDP index; (c) UK average weekly income (regular pay); (d) UK industrial activity index



Source: Aurora Energy Research, various sources listed in Table 1

Figure 6: Trends of weather-based drivers using daily Central England Temperature data



Source: Aurora Energy Research, various sources listed in Table 1

Figure 7: Trends of technological and behavioural drivers. (a) Energy efficiency index for final consumers in the EU; (b) Electricity retail prices for domestic, industrial, and non-domestic sectors; (c) Number of households used as a proxy for number of residential dwellings; (d) Average number of bedrooms; (e) Cumulative area of commercial (non-domestic) buildings built from 1910; (f) Average number of domestic electrical appliances

4.3 Results of regression modelling between existing drivers and peak demand

This section provides the results of the historical peak demand regression analysis. This regression analysis was conducted for total daily peak demand, residential peak demand, commercial peak demand and industrial peak demand. The residential, commercial and industrial peak demand values were estimated using seasonal demand profiles obtained from ELEXON.

Results obtained include:

- The accuracy of the regression models
- The effect of individual drivers on peak demand within the model
- A regression model that can be used to obtain projections of future peak demand

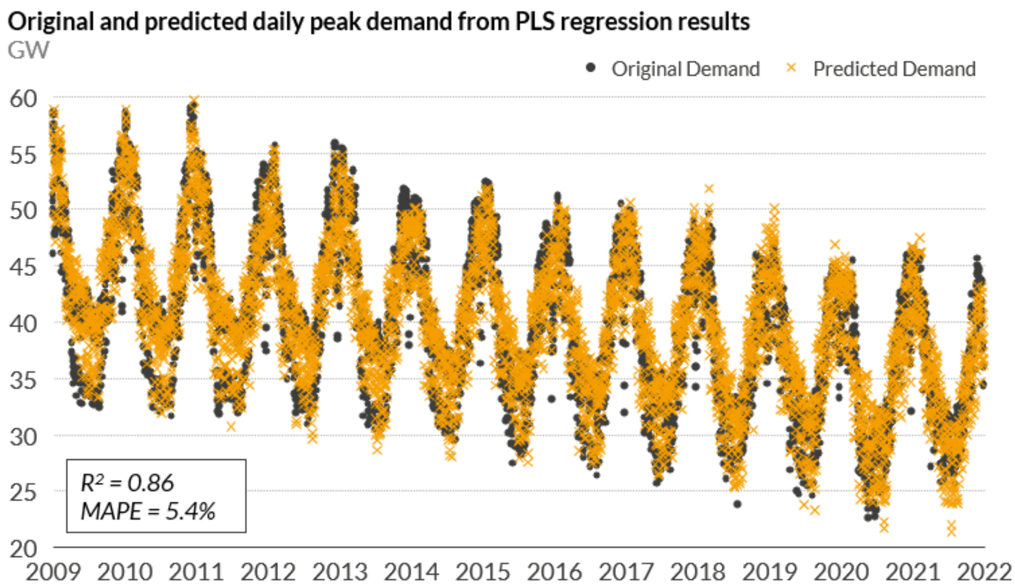
Key results and observations are summarised below.

Total daily peak demand

Figure 8 shows the results of the PLS regression model against the original data for total daily peak demand. With an R^2 value of 0.86 and a mean average percentage error (MAPE) of 5.4%, the model is considered to have a similar performance compared to other demand forecasting methodologies reviewed in the WP1 report (with MAPEs ranging from 1.4% to 7.9%).

The model is generally also able to predict the annual peak demand (the peak daily demand for each calendar year) with acceptable accuracy. However, it does overestimate peak demand for 2018-2021.

In order to minimise effects in the model caused by intercorrelated variables, a driver of GDP index per capita was used, which combines GDP with population. Additionally, the industrial activity index was excluded from the list of drivers in the model as it was seen to interfere with how the model handled GDP index per capita, potentially due to a strong correlation between the two drivers.

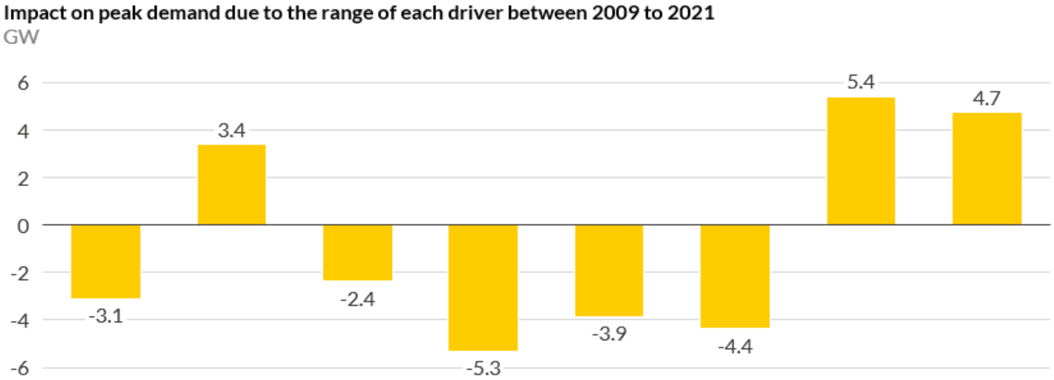


Source: Aurora Energy Research

Figure 8: PLS regression results – original and forecast peak demand values for overall daily peak demand against existing drivers

Figure 9 shows the results of a sensitivity analysis of the various demand drivers on peak demand within the PLS regression model. The positive bars indicate a positive correlation between the demand driver and peak demand, while the negative bars indicate a negative correlation between the demand driver and peak demand. The height of the bars indicate how much peak demand changes for a given range of values for that particular demand driver.

The range for each demand driver tested in this sensitivity analysis was the maximum and minimum values of the historical data from 2009 to 2021 used in the regression model, as detailed at the bottom of Figure 9.



	Energy efficiency index	GDP index per capita	Electricity price index	Minimum winter temperature (°C)	Number of households	Size of non-domestic buildings (m^2)	Season	Day of week
2009-2021 range	63.0 – 73.5	1.2×10^{-6} – 1.5×10^{-6}	98.6 – 186.2	-7.0 – 0.8	2.6×10^{7} – 2.9×10^{7}	7.2×10^{8} – 8.3×10^{8}	spring – winter	weekend – weekday

Source: Aurora Energy Research

Figure 9: Magnitude and direction of the impact on peak demand by each driver, determined by the range of all possible values between 2009 and 2021

Overall, temperature, season (winter) and day of week (weekday) are drivers that contribute most significantly to a change in peak demand between 2009 and 2021, causing changes of -5.3GW, 5.4GW and 4.7GW respectively. GDP index per capita is the driver that represents economic and socioeconomic factors in the model, causing an increase in peak demand of 3.4GW. The energy efficiency index captures the effects of technological improvements on peak demand, causing an overall drop in peak demand of 3.1GW.

Drivers like electricity price index, season and day of week are believed to be good proxies for certain behavioural factors that may influence peak demand. The results of this sensitivity analysis indicate a potentially strong behavioural element in electricity consumption behaviour, which could be explored further beyond this study by NGESO.

It is important to note that regression analysis provides results in the form of correlations rather than causations. It is possible to identify potential causes of the correlations observed, however testing and confirmation of these causations would be difficult. For example, the difference in demand between winter and non-winter peak demand could be caused by factors including daylight hours, heating habits, and potentially other unidentified seasonal behavioural aspects. These potential causes of seasonal peak demand variation could be confirmed through surveys and long-term applied studies (e.g. tracking the behaviours of a sample size of consumers and their resulting demand profiles across a year), but would involve considerable time and cost.

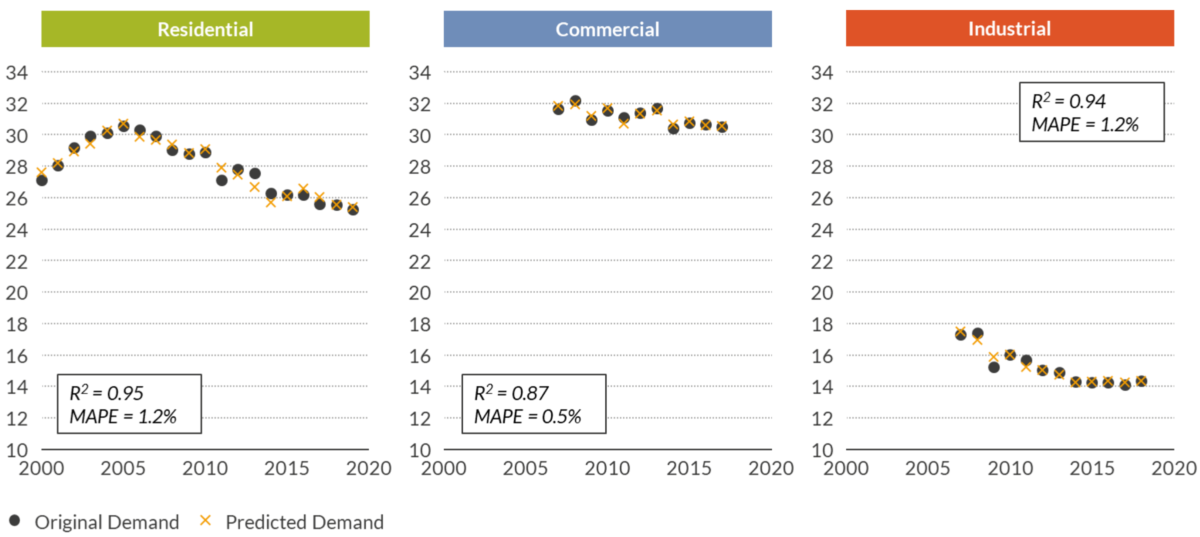
Because of how the PLS model functions, which is to find a least squares solution between actual and predicted values from the demand drivers, the solution obtained does not always provide intuitive relationships between demand drivers and peak demand. The two variables that fall into this category are number of households and size of non-domestic buildings, which cause peak demand to decline as they grow. One probable interpretation of this result is that there remain unexplained drivers that account for the remainder of the decline in peak demand after considering the effect of temperature, energy efficiency and electricity prices, that the model currently attributes to these two variables. This could be explored further by NGESO in an in-depth study of potential behavioural factors that may be contributing to a decline in peak demand, and incorporating them into the regression model.

As such, the model should not be taken as an absolute solution to understanding the relationships between demand drivers and peak demand, but rather a mathematical solution of the best combination of the given variables to obtain the closest approximation of peak demand to actual historical peak demand values. Further study should be conducted to explore the directional aspects of the variables in the PLS model in more depth, but is not covered in this report.

Peak demand for the residential, commercial and industrial consumer segments

Because peak demand consists of demand from residential, commercial and industrial consumers, and each of these consumer groups has a different daily and seasonal demand profile, this study also looked into the correlation between peak demand in each individual consumer group against their respective key demand drivers.

Figure 10 shows the original (calculated from seasonal demand profiles) and predicted peak demand values for the residential, commercial and industrial segments. The PLS regression for each of these peak demand segments produced results of good fit (high R^2 values) and relatively low errors (low MAPE values), indicating promise in the combination of variables included in this analysis to forecast peak demand for each of these consumer segments, as summarised in Table 1.



Source: Aurora Energy Research

Figure 10: Consumer segment-specific PLS regression results – original and forecast peak demand values for overall daily peak demand against existing drivers for the residential, commercial and industrial consumer segments

Shortcomings in this methodology include:

- The lack of available data beyond certain years, resulting in small sample sets
- The lack of data on demand profiles for each user segment, and especially how they change from year-to-year, resulting in an assumed fixed profile each year for this particular analysis. In reality, it is possible that changing behaviours and electricity needs over the years have caused a change in the demand profiles

5. Analysis of existing and new drivers of change in 5 year and 10-30 year horizons

This section explores what future demand trends could look like if there is a continuation of historical trends seen in Section 4, alongside demand from new drivers such as battery electric vehicles (BEVs), heat pumps and hydrogen electrolysers. Trends are analysed first for the first 5 years, between 2022-2027 and then for the period up to 2050.

The results in this section are an exploration of the peak demand using a hybrid approach where peak demand from historical drivers is forecasted by the regression model detailed in Section 4 using projections of future trends of these demand drivers, and non-statistical calculation of peak demand from new demand drivers that were not included in the regression model.

Further refinements and validation to, both, the regression model and the projections of the trends of the demand drivers are required in order to form a definitive view of future peak demand. A discussion of the limitations of the methods used in this study and further research NGESO should consider in further developing their peak demand forecasting methodology is provided in Section 7.

5.1 Trends over the next 5 years

Peak demand from future trends of existing demand drivers

The PLS regression model obtained from fitting the historical demand drivers against historical peak demand was used to assess a potential range for future peak demand. The methodology used in detailed in Section 3.1.

Lower bound (LB) and upper bound (UB) projections are obtained by inserting two varying demand driver datasets created as detailed in Table 2, into the regression model. The LB provides an indication of the future peak demand regression results if all drivers were expected to behave in a similar linear trends as observed historically. The UB provides an alternative indication of the future peak demand regression results if an adjusted view on demand driver trends is made, based on more realistic expectations.

Demand drivers	Lower bound dataset for 2022-2050	Upper bound dataset for 2022-2050
Energy efficiency	Linear extrapolation of 2009-2021 trend	Linear extrapolation of 2017-2021 trend
Number of households, cumulative non-domestic floor area	Linear extrapolation of 2009-2021 trend	Growth rate tracks with forecast population growth rate
All other demand drivers	Linear extrapolation of 2009-2021 trend	Linear extrapolation of 2009-2021 trend

Table 2: Explanation of lower bound (LB) and upper bound (UB) projection assumptions

These projections in Section 5.1 do not include demand from new drivers such as battery electric vehicles, heat pumps and hydrogen, which is calculated using a non-statistical approach, with results provided later in this section.

The LB projection is likely better suited for forecasting of trends over the next few years compared to forecasting of very long-term trends (10-30 years), as there is a question of whether historical relationships derived between historical demand drivers and peak demand may continue so far into the future.

Additionally, a set of temperature sensitivities was developed to assess the impact of possible future temperature variations on peak demand. The four sensitivities were intended to cover the range of the coldest winter temperatures experienced historically in the past ten years (maximum and minimum winters), as well as more extreme deviations caused by increased temperature volatility due to climate change (exteme warm and extreme cold winters). These are described in Table 3. A plot of the temperatures that form this dataset is provided in the Appendix (Figure 31, Section 8).

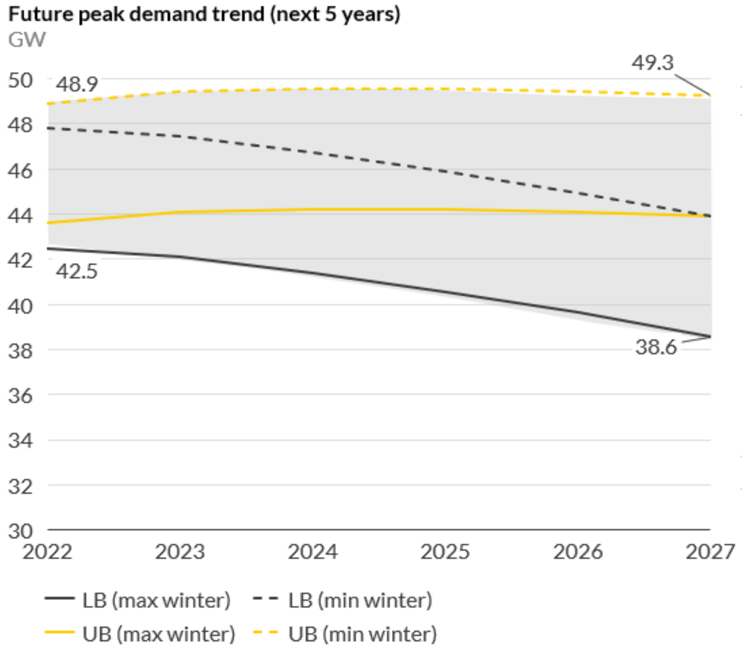
Temperature sensitivity	Temperature (°C)	Description
Maximum winter	0.8	Average daily temperature of the coldest day of the warmest winter between 2009-2021 (i.e. 2014)
Minimum winter	-7.0	Average daily temperature of the coldest day of the coldest winter between 2009-2021 (i.e. 2010)
Extreme warm winter	4.0	Maximum winter temperature plus 1 standard deviation of the coldest daily temperature per year between 2009-2021
Extreme cold winter	-10.2	Minimum winter temperature minus 1 standard deviation of the coldest daily temperature per year between 2009-2021

Table 3: Explanation of temperature sensitivities and associated temperatures

Figure 11 shows the range of projected peak demand in the next 5 years, up to 2027, for the maximum and minimum winter temperature sensitivities for the LB and UB projections. The area between the LB and UB lines illustrate the range of possible values for peak demand up to 2027 suggesting that peak demand could lie within 42.5-48.9 GW in 2022 to 38.6-49.3 GW in 2027.

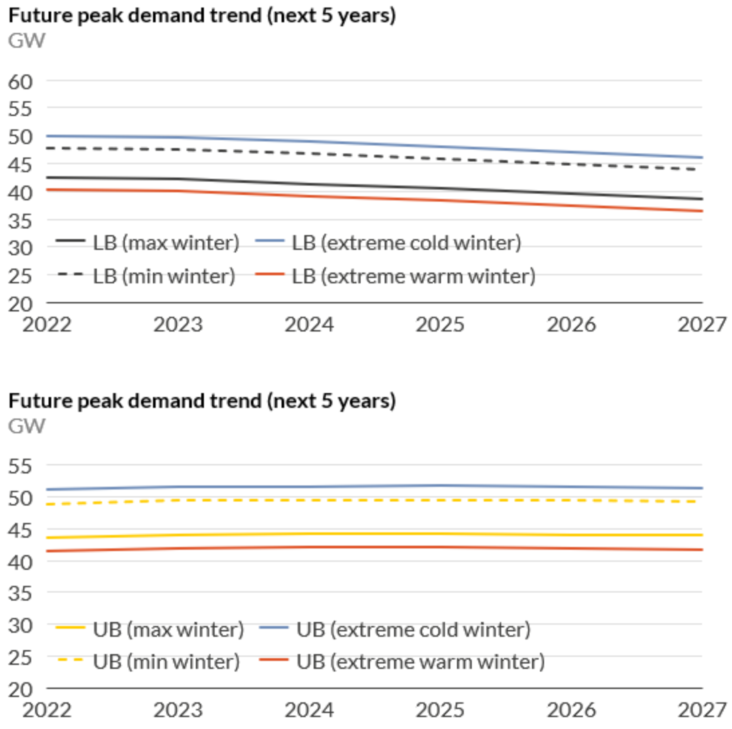
Figure 12 looks at all 4 temperature sensitivities detailed in Table 3, separately for the LB and UB demand driver projections.

It shows an overall change in the potential peak demand range by approximately 2GW each above and below the peak demand for the max winter and min winter projections. Moving forward, NGESO could consider refining the projections based on temperature forecasts from global climate models that take into account climate change effects up to 2050.



Source: Aurora Energy Research

Figure 11: Future peak demand trends based on historical drivers only (LB – lower bound; UB – upper bound; max winter – maximum mean winter temperature from historical dataset; min winter – minimum mean winter temperature from historical dataset)



Source: Aurora Energy Research

Figure 12: Future peak demand temperature sensitivities over time

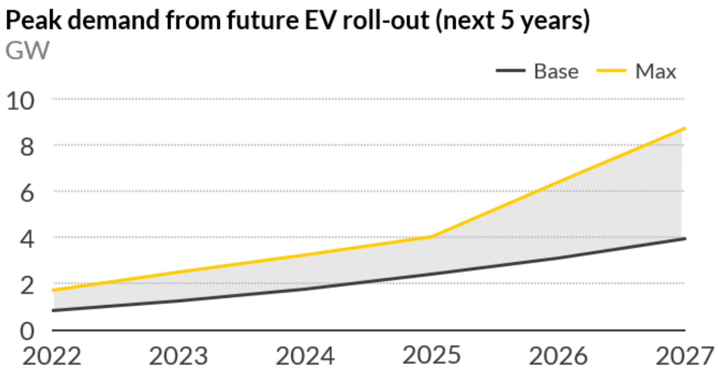
Peak demand from new demand drivers

Moving forward, peak demand is also expected to be influenced by new drivers such as battery electric vehicles, heat pumps and hydrogen electrolysers, where there is limited historical data from which to analyse correlations. This section explores possible future scenarios with varying levels of impact from these new drivers, if there is no time-shifting of demand. The methodology is detailed in Section 3.2. Potential implications of time-shifting of demand are explored briefly in Section 6.

Electric vehicles

The outlook of peak electricity demand from EV charging 2022-2027 is shown in Figure 9. This peak electricity demand from EV charging was calculated using EV roll-out forecasts and residential demand profiles from the Consumer Charging Trials report published as part of the CVEI study[16], assuming normal consumer behaviour with no incentives to charge at particular times of the day. The base case represents a lower-bound of the effect of EV roll-out on peak demand. It is a simple linear extrapolation of the historical trend of BEV sales over the past four years and sees associated peak demand grow about 4.8 times from 0.8 GW in 2022 to 3.9 GW in 2027.

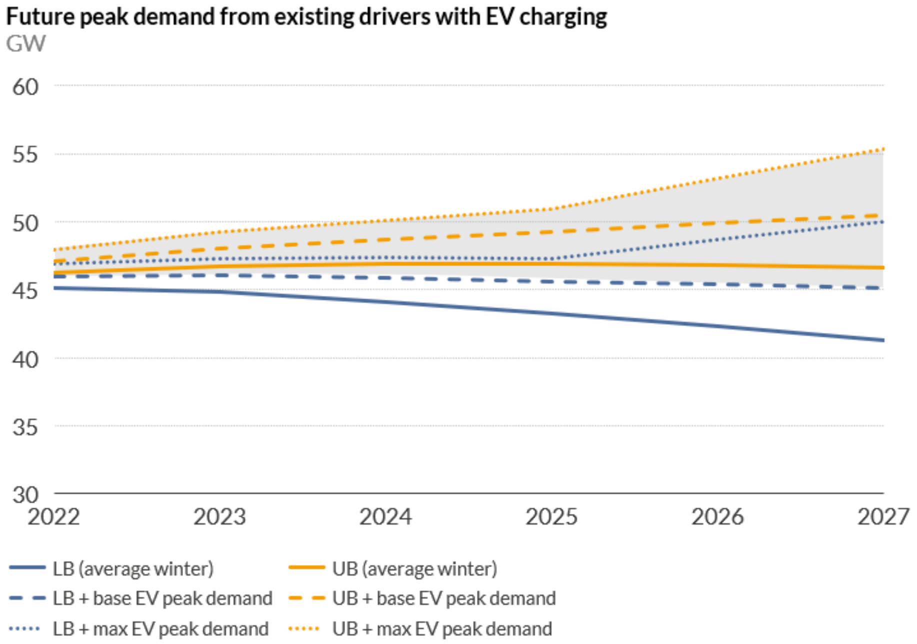
On the other hand, the maximum of this range represents a possible upper-bound in EV roll-out and is based on the *Balanced Net Zero Pathway* scenario developed by the CCC as the recommended scenario that reaches Net Zero by 2050 in the Sixth Carbon Budget[17]. This sees a more rapid scale-up of BEVs in the 2020s to reach an associated peak demand of 8.7 GW in 2027, a five-fold increase since 2022.



Source: Aurora Energy Research

Figure 13: Peak demand from future EV roll-out

Adding the impact of EV charging to the outlook of peak demand in the next 5 years driven by existing drivers, a possible range of peak demand can be estimated, shown in Figure 14, with the potential to reach approximately 55GW by 2027 if there is little or no time-shifting of demand.



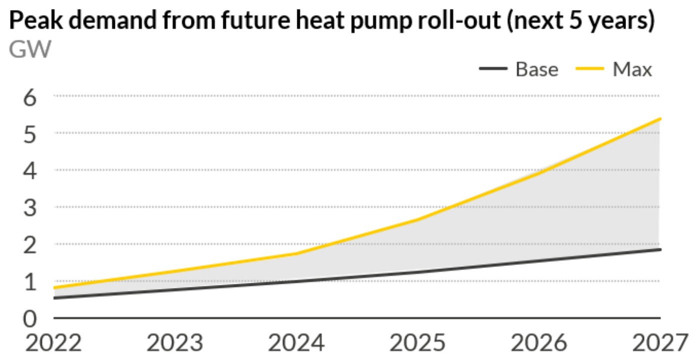
Source: Aurora Energy Research

Figure 14: Range of peak demand from EV charging in addition to the Upper Bound (UB) and Lower Bound (LB) scenarios

Electrification of heat

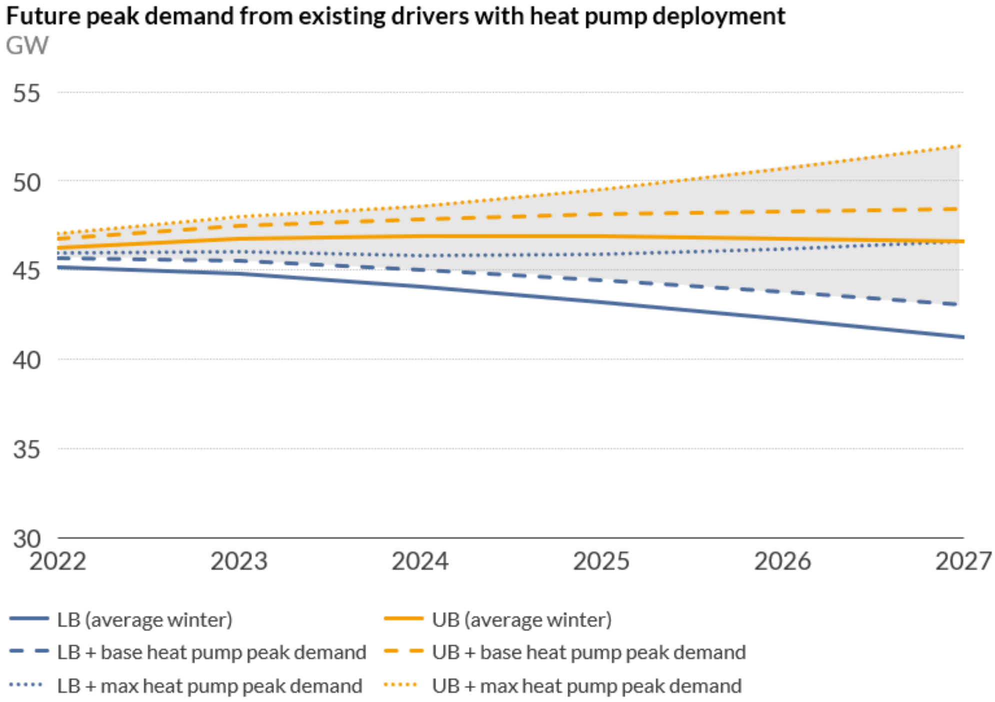
Similarly, peak electricity demand from future residential heat pump roll-out is taken to fall within a range bounded by the linear extension of historical heat pump deployment and the CCC-defined roll-out needed in the *Balanced Net Zero Pathway* scenario, shown in Figure 15. The trend of peak demand due to heat pump deployment was calculated using an assumed unit consumption in MWh, considering a growth in efficiency every year, and a yearly demand profile determined from Aurora Energy Research's multi-client study on heat decarbonisation. The analysis also assumes a simplified average lifetime of 15 years of a heat pump without distinguishing between technology type, such as air source, ground source or hybrid.

In the base case, peak demand from heat pumps more than triples from 0.5 GW in 2022 to 1.8 GW in 2027, while the maximum case peak demand grows over 6.7 times from 0.8 GW in 2022 to 5.4 GW in 2027 (Figure 15). Figure 16 shows the growth in peak demand from existing drivers and new peak demand from heat pumps, reaching up to 52GW in 2027, if there is little or no time-shifting of demand.



Source: Aurora Energy Research

Figure 15: Peak demand from future heat pump roll-out



Source: Aurora Energy Research

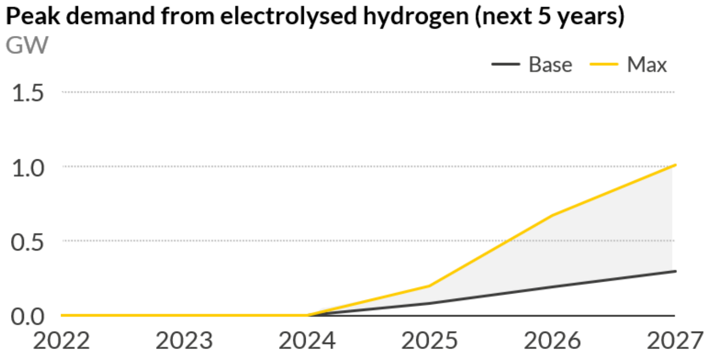
Figure 16: Range of peak demand from heat pump deployment in addition to the Upper Bound (UB) and Lower Bound (LB) scenarios

Hydrogen from electrolysis
A less widely established demand driver, the production of hydrogen through electrolysis was also considered but was determined to have a relatively small impact on peak demand in the short term. As there has been no hydrogen supply from electrolysis at present, the base case for this driver is based on the *Headwinds* scenario developed in the CCC's Sixth Carbon Budget Report[18], the most conservative scenario which assumes a minimal change in societal and behavioural shifts brought about by policy.

Additionally, in the base case, a proportion of electrolysers are assumed to operate flexibly and avoid peak demand periods, with the proportion of flexibly-operated hydrogen electrolysers increasing over the forecast. Peak demand is impacted by inflexible electrolysers only.

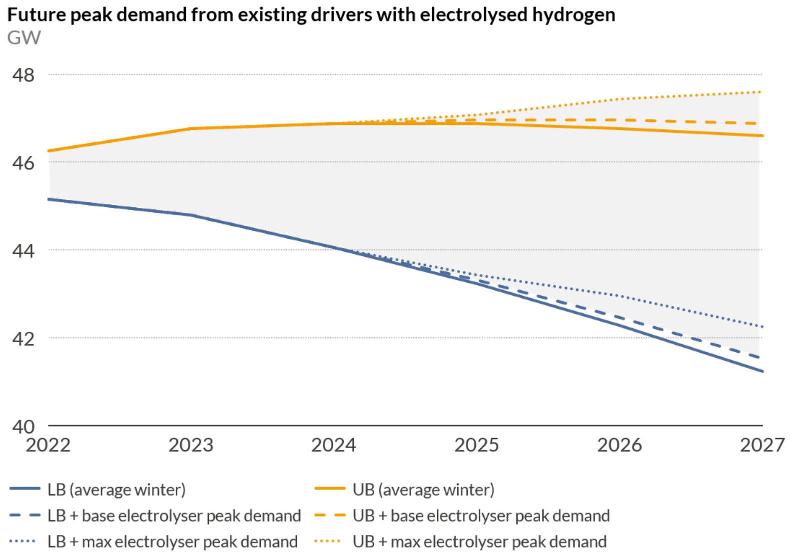
According to forecasts published by the CCC, the supply of hydrogen from electrolysis is expected to remain at zero until 2025, after which it increases to 5.1 TWh and 6.8 TWh in 2027 in the base and maximum cases respectively.[19] Assuming a yearly load factor of 95% for inflexibly operated electrolysers and a constant electrolyser efficiency of 81% quoted from the CCC report, this translates to a peak electricity demand of just 0.3 GW and 1.0 GW in 2027 for the base and maximum cases respectively, shown in Figure 17.

Because hydrogen electrolyser demand grows only slightly in the near term, the effect on overall peak demand is minimal, causing peak demand to potentially reach 47.6GW by 2027 (Figure 18).



Source: Aurora Energy Research

Figure 17: Peak demand from electrolysed hydrogen production



Source: Aurora Energy Research

Figure 18: Range of peak demand from electrolysed hydrogen deployment in addition to the Upper Bound (UB) and Lower Bound (LB) scenarios

5.2 Trends over the next 10 to 30 years

In the longer term, the LB and UB peak demand projections diverge further. These projections explore the possible peak demand ranges, based on two groups of demand driver trends in the long term. Neither of these projections consider inflection points for the demand driver trends.

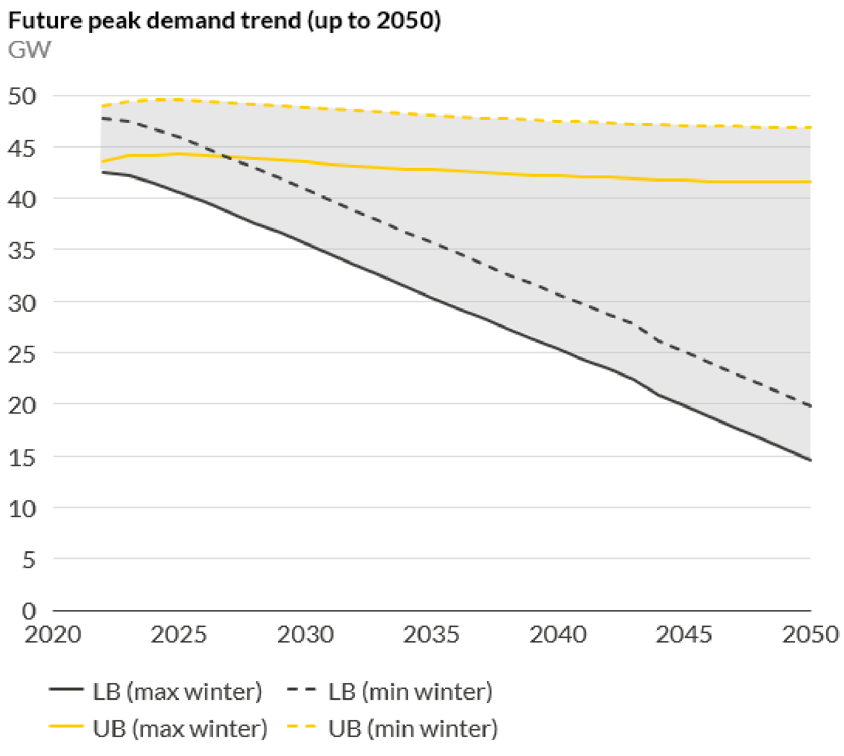
More accurate forecasting of demand driver trends must be explored to obtain greater accuracy in the forecasts for peak demand through the given regression model.

Peak demand from future trends of existing demand drivers

Based on the 2 potential trends of existing demand drivers explored in this study (methodology is detailed in Section 3.1), peak demand is forecasted to lie within the range of approximately 15GW to 47GW by 2050 (Figure 19).

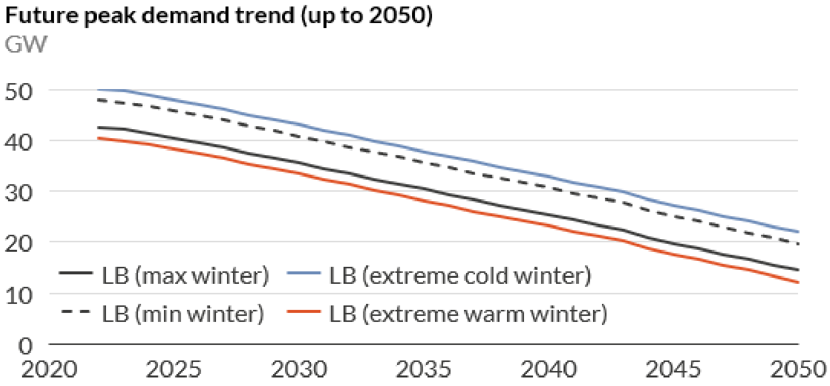
The further into the future projections are, the less likely it is that the same relationships between demand drivers and peak demand will hold, if the likely impact of inflectoin points is considered. As such, it is expected that peak demand is more likely to fall within the higher end of this range as opposed to declining rapidly to 15GW. The line for the lower bound maximum winter condition, is a theoretical indication of peak demand should current driver trends continue linearly into the future, and is not necessarily an indication of realistic expectations of driver trends. NGESO could consider further validation of this using statistical methods.

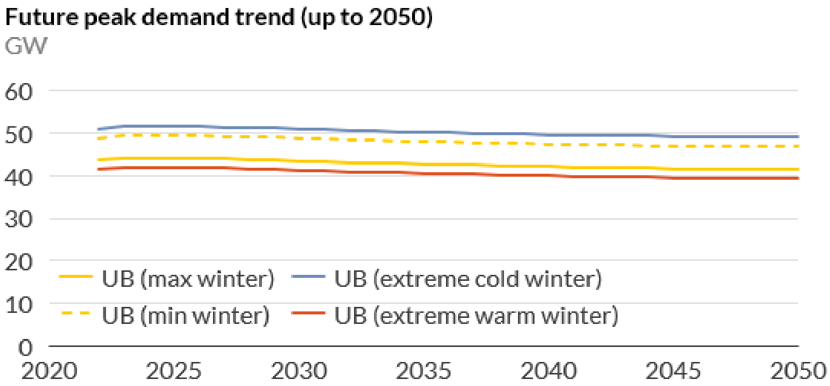
Figure 20 shows the temperature sensitivities explored up to 2050, which causes the possible range of peak demand values to grow by approximately 2GW as a results of a change of 3.2°C (1 standard deviation) on both the higher and lower sides of the range of the coldest and warmest (min winter and max winter) historical daily mean winter temperatures.



Source: Aurora Energy Research

Figure 19: Future peak demand trends (LB – lower bound; UB – upper bound)





Source: Aurora Energy Research

Figure 20: Temperature sensitivities for future peak demand trends

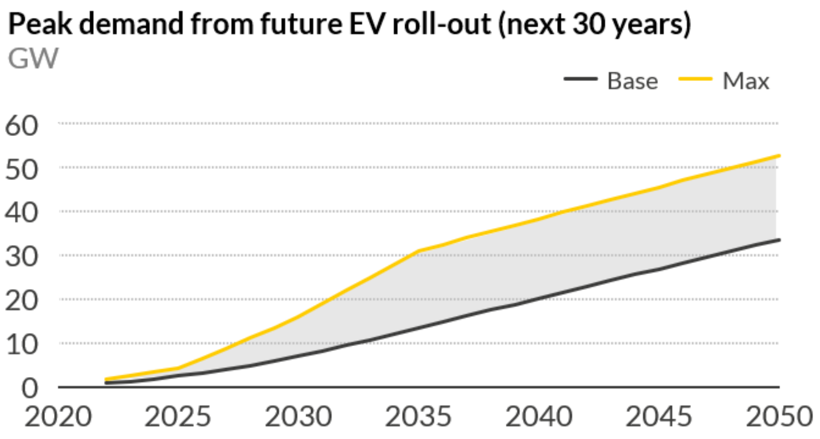
Peak demand from new demand drivers

Electric vehicles

In the longer term, the maximum case sees BEVs making up 100% of new passenger vehicle sales by 2032, reaching an associated peak demand of 21.9 GW in that year and 52.7 GW by 2050. The base case sees a much slower growth in BEV roll-out during that period, resulting in a peak demand of 9.4 GW and 33.5 GW by 2032 and 2050 respectively.

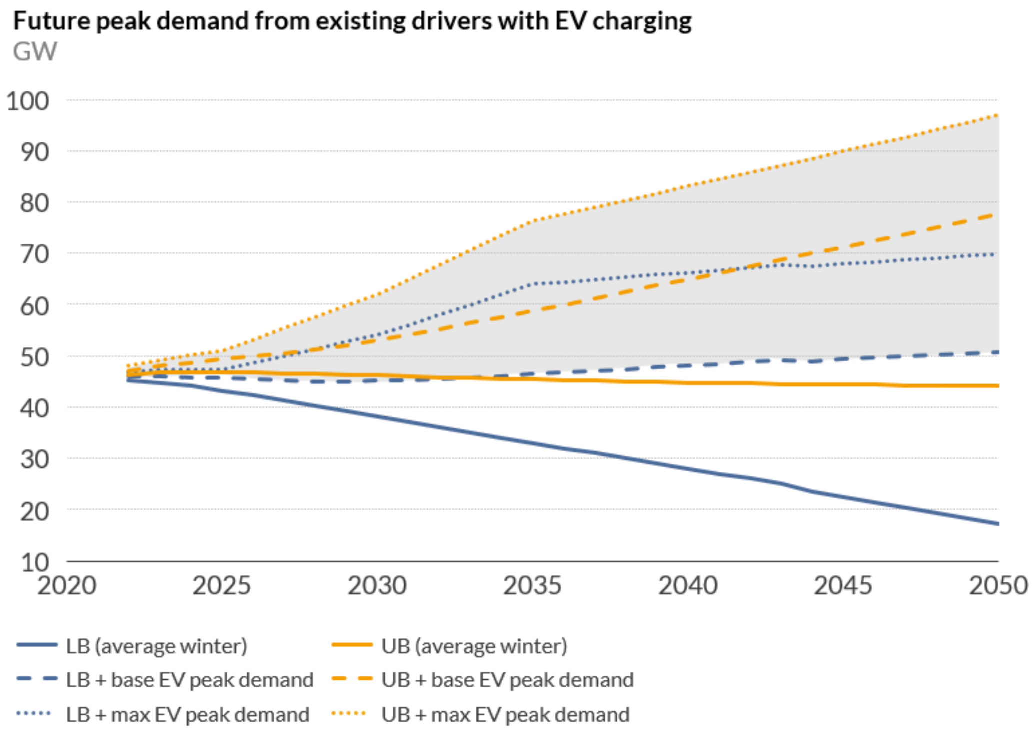
The steep growth of the base case peak demand by 32.7 GW from 2022 to 2050 is reflective of an already fairly established BEV market which is likely to be boosted not only by policy intervention but also increasingly attractive economic and social incentives. BEVs therefore will have a significant impact on peak demand even in the base case where growth simply continues as it has in the previous years.

The effect on peak demand from EV charging in 2050 in addition to the growth caused by existing drivers is an uplift of 33.5-52.8 GW (Figure 22).



Source: Aurora Energy Research

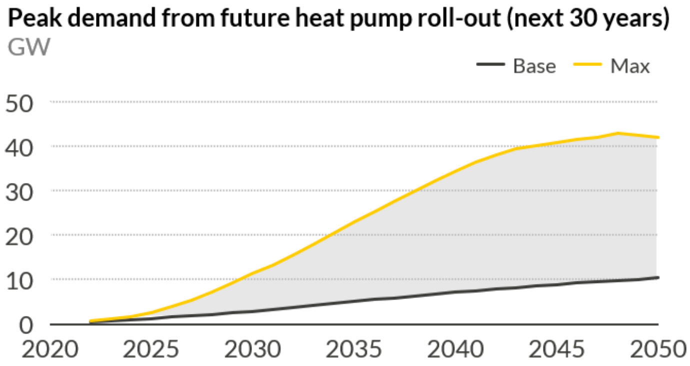
Figure 21: Peak demand from future EV roll-out



Source: Aurora Energy Research

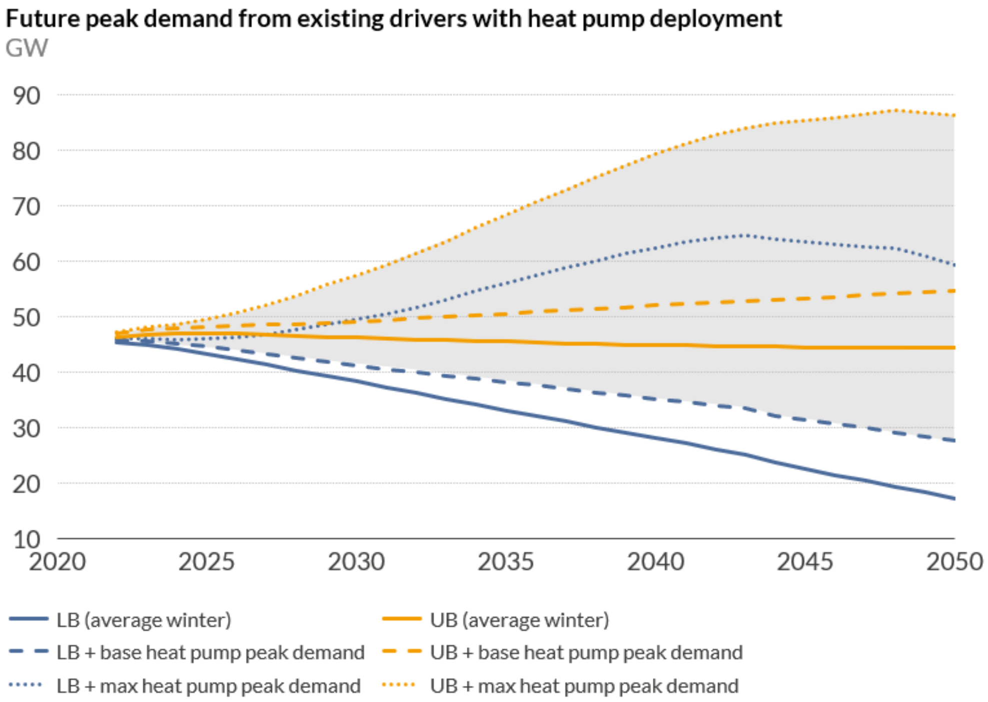
Figure 22: Range of peak demand from EV charging in addition to the Upper Bound (UB) and Lower Bound (LB) scenarios

Electrification of heat
Future heat pump roll-out is one that is more highly variable than BEVs and therefore harder to predict due to its nature of being heavily reliant on government policy instruments. Switching from a gas boiler to a heat pump involves significant upfront costs even with subsidies, which is likely to add uncertainty in whether current heat pump deployment targets will be met.



Source: Aurora Energy Research

Figure 23: Peak demand from future heat pump roll-out



Source: Aurora Energy Research

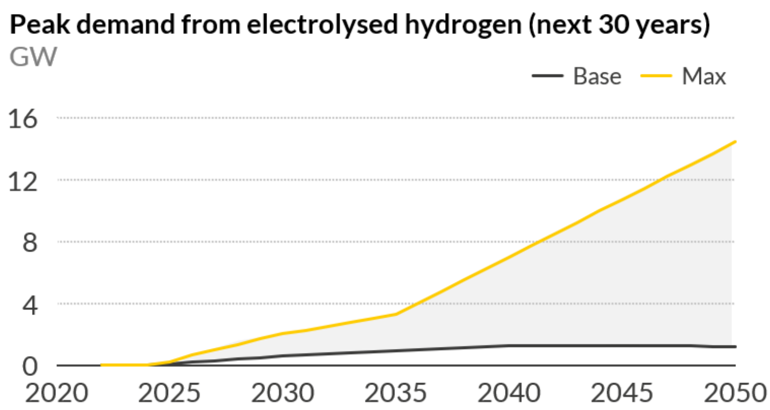
Figure 24: Range of peak demand from heat pump deployment in addition to the Upper Bound (UB) and Lower Bound (LB) scenarios

The base case assumes a conservative view of heat pump roll-out, reaching a total of just 6.3 million heat pumps in homes by 2050, translating to a peak demand of 10.4 GW. In contrast, as a result of a combination of cost effectiveness, wider benefits and consumer preferences determined by the CCC, the maximum case surpasses this figure in 2031 to reach 26 million heat pumps installed by 2050[20]. This translates to a peak demand of 42.1 GW in 2050 which is comparable to that of forecasted EV charging demand. The difference in the base and maximum cases of peak demand in 2050 is fairly large for this reason.

Consequently, future peak demand due to projected heat pump deployment in addition to the growth in existing drivers also ranges widely in 2050. This results in an uplift of anywhere between 23-95% in the Upper Bound scenario and 60-245% in the Lower Bound scenario by 2050.

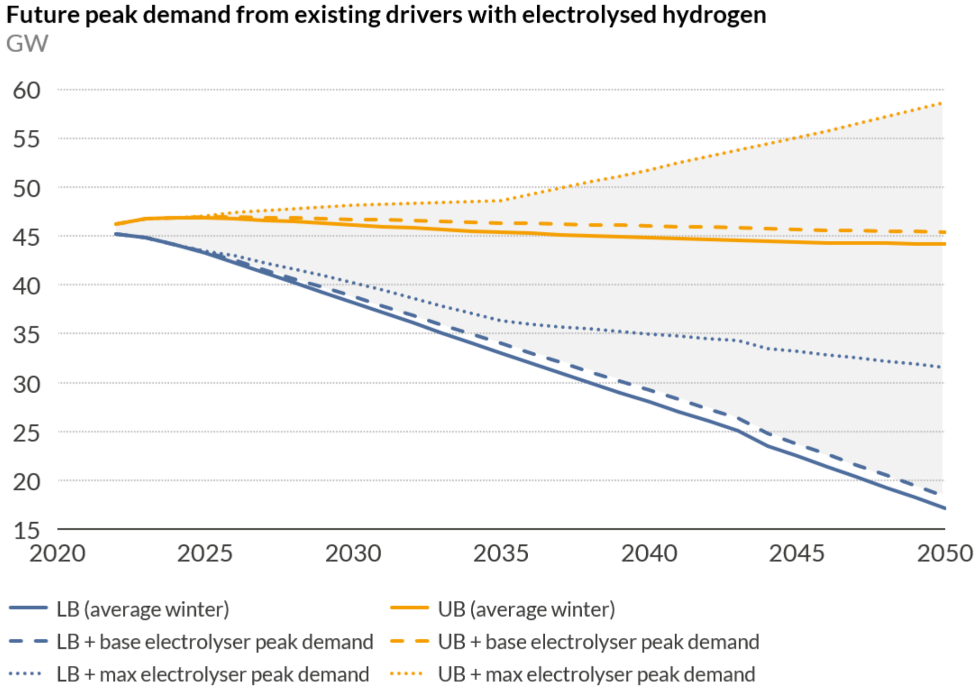
Hydrogen from electrolysis
With the increasing proportion of flexible hydrogen electrolysers in the base case out to 2050, the contribution of electrolysed hydrogen to peak demand remains low despite an increasing supply of hydrogen from electrolysis based on the CCC Headwinds scenario. The maximum case is explored by considering that all electrolysers may choose to operate inflexibly to provide supply projections as per the CCC Balanced Net Zero Pathway scenario. The inflexible operation of electrolysers is considered a possibility due to the increasing need of constant supply of electrolysed hydrogen for certain industrial and transport offtakers coupled with suggestions from electrolyser operators that they may prefer to keep their electrolysers running at a constant pace due to potential operational and economical benefits.

This results in a peak demand range of 1.2-14.4GW between the base and maximum cases in 2050. On top of the peak demand projection from existing drivers determined by the regression model, this translates to an overall peak demand range falling between 18.3 GW and 58.6 GW in 2050. (Figure 26).



Source: Aurora Energy Research

Figure 25: Peak demand from electrolysed hydrogen production



Source: Aurora Energy Research

Figure 26: Range of peak demand from electrolysed hydrogen deployment in addition to the Upper Bound (UB) and Lower Bound (LB) scenarios

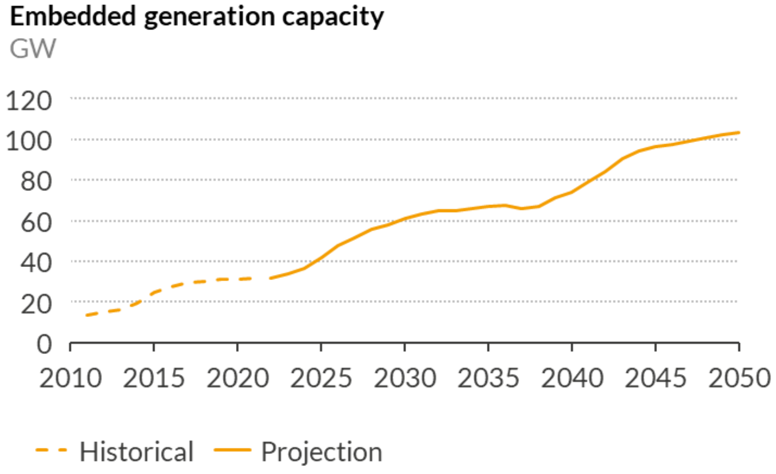
5.3 Embedded generation

By definition, the forecasting of system or end-consumer peak demand by NGESO considers only metered demand, a proportion of which is supported by metered embedded generation. However, a proportion of embedded generation assets are behind-the-meter, and therefore cater to some unmetered end-consumer demand, not captured in this analysis.

The implications of a growth in unmetered embedded generation is that more demand could shift behind-the-meter and therefore cause a drop in the observed metered demand. There is a possibility that this has already been occurring over the past few years, contributing to the declining peak demand observed between 2009 and 2021. However due to the nature of this demand being behind-the-meter, the exact values of demand are difficult to calculate and therefore difficult to consider within any peak demand forecasting models.

The expectation is that behind-the-meter embedded generation will continue to grow in the future, but will take up an increasingly small proportion of total embedded generation as the growth in metered embedded generation is expected to occur at a much greater pace than behind-the-meter embedded generation towards 2050.

Figure 27 shows a combination of the historical embedded generation capacity obtained from BEIS, alongside the projected growth in embedded generation based on Aurora's latest base case power market modelling for GB up to 2050.



Source: BEIS, Aurora Energy Research

Figure 27: Historical and projected embedded generation in Great Britain

6. Other peak demand considerations

6.1 Annual and peak demand

Modelling of peak demand by considering synchronous amalgamation of consumption components

From the observation of available consumer profiles obtained from ELEXON, it is likely that a combination of demand across the residential, commercial and industrial segments would result in the overall system peak demand. An alternative way of modelling peak demand could be to consider demand for these user segments separately through statistical analysis, and explore a suitable weighted combination of these components to form peak demand. One major challenge of this approach is the lack of availability of annual user demand profiles (at least 2 annual profiles per user segment would be needed to identify a simple trend).

This study was only able to obtain user demand profiles for a single year.

Based on profiles obtained from ELEXON for demand from residential, industrial and commercial consumers[21], we can observe the following:

- Peak demand occurs at different times within each of these 3 consumer profiles
- The magnitude of demand per consumer also differs significantly between consumer type – with industrial having the highest demand and the highest peak demand overall, whereas residential has the lowest overall demand and lowest peak demand (this will need to be multiplied by the number of consumers to obtain the total peak demand for each consumer group)
- The seasonal aspect of peak demand is also captured in these profiles where all consumers experience the highest peak demand in the winter compared to other seasons

Modelling of peak demand using a summation of various consumption elements

This study was an exercise in identifying a combination of indicators for weather, socioeconomic factors, technology and behaviour that are likely to drive demand – drivers were identified through the literature review in the first phase of this study, based on known electricity consumption elements. It is possible that there is are additional unexplained behavioural component behind the observed declining peak demand (and overall demand) in GB in recent years.

Behaviours are ultimately linked to the use of electricity due to routine, daylight, weather, etc. across each of the consumer segments. The main challenge lies in identifying demand profiles that enable an understanding of changes in peak demand over time, and what the contributing factors may be. Further work could to to identify the most common behaviour archetypes of each type of consumer (residential, commercial, industrial – which would include transport and heat pump demand, as well as potentially inflexibly operated hydrogen electrolysers). The introduction of smart meters across all consumer segments could provide a solution to obtaining better data on demand profiles of these different consumer segments moving forward. The real time monitoring of peak demand from smart meters would also facilitate a better understanding on the effect of time-shifting of demand from smart technologies on peak demand.

6.2 Effects of time-shifting of demand

Time-shifting of demand will reduce and/or shift demand during peak periods. The challenge is identifying how much of the peak demand will be reduced or shifted.

In order to fully understand the potential for time-shifting that would result in a reduction in peak demand, applied studies need to be conducted to measure actual consumer usage of smart technologies such as EVs, heat pumps and other smart appliances in responding to different prices and or incentives.

One such study conducted by NGESO and Octopus Energy showed that there was a reduction or shift in demand from peak hours as a result of incentives provided to reduce consumption in peak demand periods. Studies like these illustrate the potential for peak demand shaving with the increased uptake of smart technologies.

Fully flexible usage would theoretically result in a flattening of demand, resulting in the maximum possible decrease in peak demand. Behavioural factors may impose a physical limitation to this theoretical limit. Fully inflexible usage would result in the maximum peaks from EV, heat pump and hydrogen demand presented in Section 5. As a result, the annual to peak demand ratio would also change.

Smart technologies

The time-shifting of demand from smart technologies is determined by the flexibility of usage times of these technologies (behaviours) relative to charging times:

- Fully flexible usage times could result in a flattening of demand which would form a lower bound for peak demand from these technologies
- Fully inflexible usage times (where smart technologies are limited to operating inflexibly) will result in an increase in peak demand overall resulting in peak demand levels presented in Section 5 for EVs and heat pumps
- Demand-side management programmes and demand-side response will result in a reduction in peak demand overall
- Annual demand would still increase (regardless of peak demand) due to a larger volume of demand from smart technologies overall – as time shifting is likely to only occur over a scale of hours or days

Additionally, the introduction of incentive programmes, such as smart tariffs, may also result in an overall reduction in both annual average and peak demand as consumers are incentivised to minimize their electricity consumption overall, rather than merely changing their consumption patterns, in order to access lower tariffs under the incentive scheme.

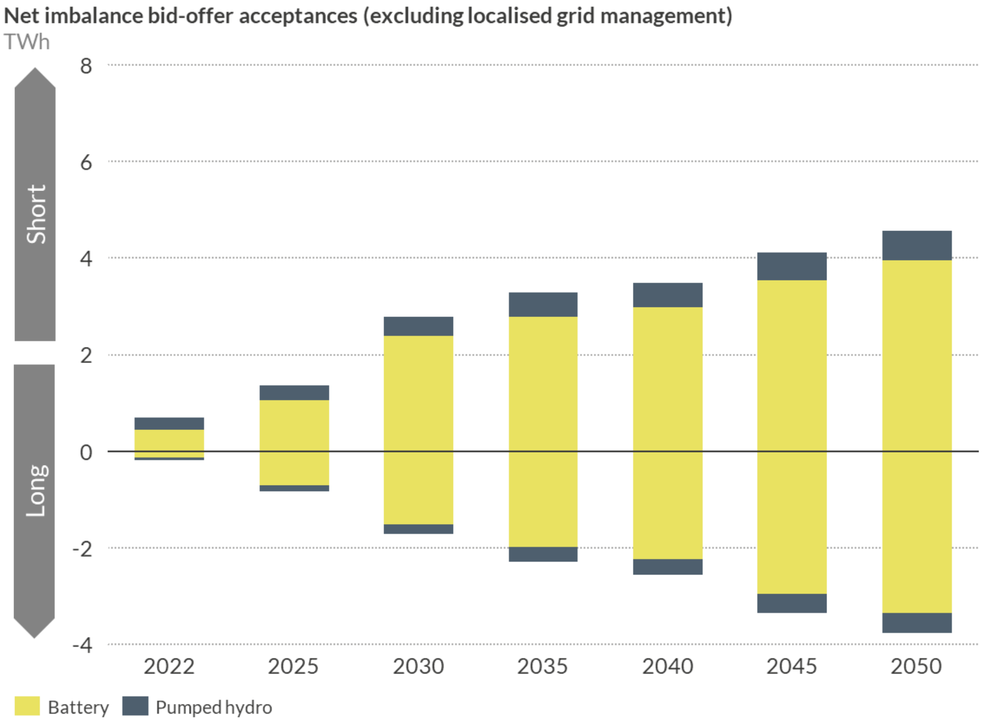
From our analysis in Section 4, we have observed that since 2009, annual peak demand in GB falls mostly within the 4:30-6:30pm period. In February to March 2022, the trials run by Octopus Energy in conjunction with NGESO[22] explored the time-shifting opportunity of various incentives on domestic users with smart meters. They found that out of the 105,320 participants in the trial, the average turn-down per household responding to smart tariffs in the 4:30-6:30pm window was 0.68kWh.

The study estimates potential time-shifting opportunity for residential peak demand based on expected smart-meter growth rates and expected smart tariffs uptake rates. For a 7% uptake of smart tariffs in 2030 with an expected smart meter penetration of 26,800,000, and an average reduction per opt-in during the 4:30-6:30pm window of 0.68kWh, the time-shifting of demand could be 0.6GW per half-hour. This value becomes 1GW and 3.5GW per half-hour respectively for smart tariff uptake rates of 12% and 38%.

A similar study with non-domestic electricity users will yield the time-shifting potential of this group of consumers to inform a forecast of time-shifting of non-domestic electricity demand. This can then be considered against the projections of peak demand assuming no time-shifting, to obtain a holistic view of peak demand shaving from domestic and non-domestic consumers in response to smart tariffs up to 2030 and beyond.

Storage peak shifting

With the growth of renewable electricity generation and grid-connected storage assets, opportunities for these storage assets to shift demand from peak hours will increase as they charge during times of low demand and low wholesale market prices, and discharge during times of high demand and high wholesale market prices. Figure 28 shows Aurora's latest forecast of imbalance bid-offer acceptances in the GB balancing mechanism from storage assets. It shows a growth in imbalance volumes of approximately 8.6 times from 2022 to 2050 from battery and pumped hydro storage assets (total short imbalance volume of 0.7TWh in 2022 and 4.6TWh in 2050).



Source: Aurora Energy Research

Figure 28: Forecast imbalance bid-offer acceptances of storage assets in the balancing mechanism

6.3 The average cold spell (ACS) methodology

Comparisons against the average cold spell (ACS) methodology – the purpose of this study was to form a view on the drivers of peak demand through the analysis of historical data. As such, it focused on a PLS linear regression model, which considers additional demand drivers explicitly within a statistical model compared with the ACS methodology, which indirectly considers the effects of drivers within a single basic demand component and a residual demand component. Both models consider temporal effects (day of week, season) and weather effects. The ACS model in its current form determines peak demand by taking the median of 20,000 winters simulated based on 30 years of winter weather data. This study does not seek to replicate this methodology, and instead considers the effects of temperature as additional sensitivities.

7. Conclusions and topics for further consideration

The methodology and results presented in this study represent an initial look at one possible way of analysing historical peak demand trends and developing projections for future peak demand. Rather than serving as an absolute guide, it functions more as a starting point for a more detailed look at peak demand forecasting.

While developing the analytical methodology and regression model in this study, a number of limitations and areas for further work also were observed.

The main conclusions from the analysis undertaken in this study are summarised here along with a list of the assumptions and limitations of the proposed methodology, and further work needed in order to develop a forecasting methodology for peak demand.

7.1 Conclusions

Peak demand from historical drivers can be modelled to an acceptable degree of accuracy using a partial least squares linear regression model.

Further refinements to the regression model through the consideration of additional demand driver datasets and or the use of a different combination of demand drivers could yield further improvements in accuracy.

The regression analysis of historical demand drivers showed that:

1. Temperature was the most significant driver of peak demand out of all the demand drivers captured in the regression model
2. The next most significant drivers of demand were day of week and seasons, suggesting a strong behavioural contribution to peak demand historically

The study of the future peak demand contributions from new demand drivers such as battery electric vehicles, heat pumps and hydrogen electrolyers showed that:

3. In the event of no time-shifting of demand from these new technologies, the magnitude of their peak demand contributions could increase significantly over time to more than double current peak demand levels by 2050
4. In the next 5 years, peak demand will only be minimally affected by new demand drivers, causing an additional contribution to peak demand of up to 15GW in total by 2027

Overall, the modelling of peak demand cannot be purely based on a statistical approach, and will require a hybrid approach, due to:

5. The emergence of new peak demand drivers in the coming years
    - In this study, the effect of new demand drivers on peak demand had to be considered separately to historical demand drivers because the new demand drivers could not be captured in the regression model (due to little or no data on these drivers being available as of yet)
    - There are limitations of a statistical approach in capturing emerging time-shifting or reduction in peak demand as a result of the increase uptake of smart technologies
    - These peak demand contributions would need to be modelled using a non-statistical method such as bottom-up modelling

6. Gaps in historical demand driver datasets limiting the robustness of any statistical models developed
   - In this study, data had to be processed either via extrapolation or interpolation before inclusion in the regression model due to a lack of data of a consistent granularity or timescale across all demand drivers
7. Challenges in identifying and quantifying all possible behavioural demand drivers
   - In this study, we included a retail electricity price index and time dummies for day of week and seasons in order to capture some behavioural elements within the regression model
   - However unexplained drivers that contribute to the recent decline in peak demand, appear not to be captured fully in the resulting regression model, with a chance that some of these might be due to additional behavioural drivers

7.2 Key assumptions and limitations of analytical methodology

Data limitations

1. Demand profiles for residential, industrial and commercial consumer segments
   - The lack of half-hourly demand data by consumer segment (residential, commercial, industrial) makes it difficult to analyse changes in their half-hourly demand that could then be used to obtain a result for total peak demand
   - Additionally, there is no data on how these demand profiles have been changing year on year – an important consideration to be able to assess trends in peak demand over the long term
2. Gaps in demand driver datasets
   - There is a lack of half-hourly historical temperature data – in this study, the daily mean temperature was used in the regression model obtained however in order to more accurately analyse the correlation between temperature and peak demand, the temperature during the half-hour of each daily peak demand point would be needed as an input to the regression model
   - Behavioural demand drivers are difficult to measure – it was difficult to identify suitable behavioural datasets in addition to determining which behavioural drivers should be captured within the model
3. Sample size limitations
   - Certain datasets of demand drivers were only available for certain years, that did not line up with each other, resulting in incomplete datasets for the regression model which was built on data from 2009-2021
   - As a result, some datasets had to be extrapolated or interpolated to obtain additional datapoints for the regression analysis

Regression analysis limitations

The methodology explored for this study is one of many possible methodologies available – it has advantages and limitations.

A summary of limitations of the regression model include:

- A regression model based on historical data does not account for changing relationships between variables e.g. GDP with income, population with GDP, temperature with demand, etc.
- A regression model inherently assumes a continuation of trends between variables and demand, so the strength of the demand forecast will be dependent upon strength of the forecasted trends of the individual variables (drivers)
- A regression model without time of week and seasonal adjustment was found to underestimate the peak demand – the reason for this is potentially because the only driver dataset included in the model that varies at the daily level is temperature. The model will likely perform better with the inclusion of an additional driver that varies at a daily level e.g. some variables that represent demand habits for the residential, commercial and industrial consumers
    - For example, it was found that considering day of week (weekday/weekend) and seasonal peaks resulted in better regression model fitting to historical demand data
- The method that the regression model uses results in a mathematical best-fit of trends between demand drivers and peak demand, and provides an indication of possible correlation between drivers and demand, but not of causation
- Additionally, different combinations of drivers result in different correlations with peak demand – requiring the team conducting the analysis to form a decision on which combination of drivers to proceed with in the model

7.3 Areas to study in more depth

Areas that NGESO could consider for further study include:

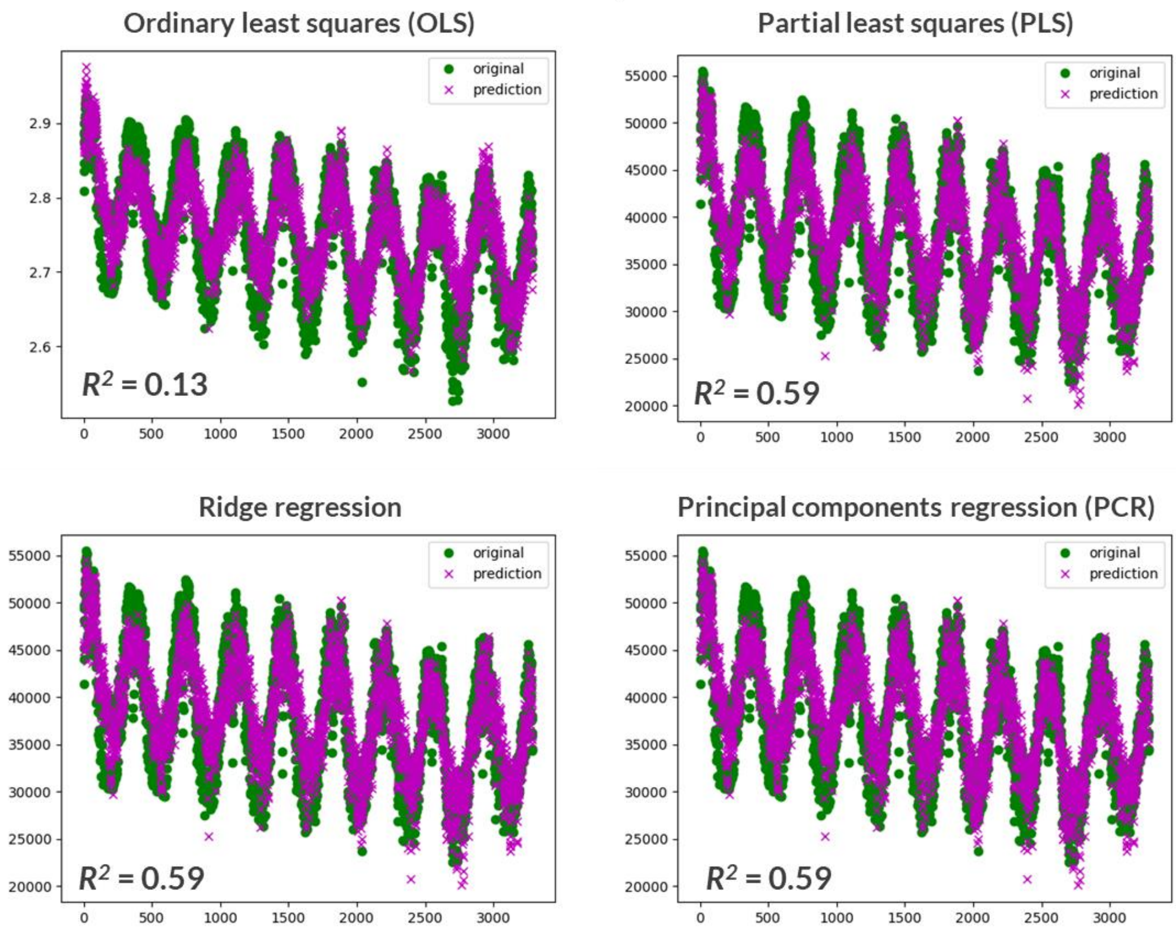
- Exploration of additional demand drivers to include in the model
- Exploration of different combinations of demand drivers and the resulting model accuracy
- Modelling of demand based on temperature from global climate model forecasts for GB for a deeper understanding of potential year-on-year changes to future peak demand
- Additional day of week time dummies (to account for different weekdays, special events, etc.)
- Bottom-up modelling of behavioural demand drivers
- The consideration of inflection points in the future demand driver trends
- The consideration of the effects of increasing uptake of air-conditioning with increasing heat pump adoption on summer peak demand
- The potential for a purely statistical demand-forecasting methodology once smart meter penetration reaches a critical value/a certain proportion of total electricity consumers

8. Appendix

8.1 Review of regression methods

Comparison of regression methods – OLS, PLS, PCR and Ridge

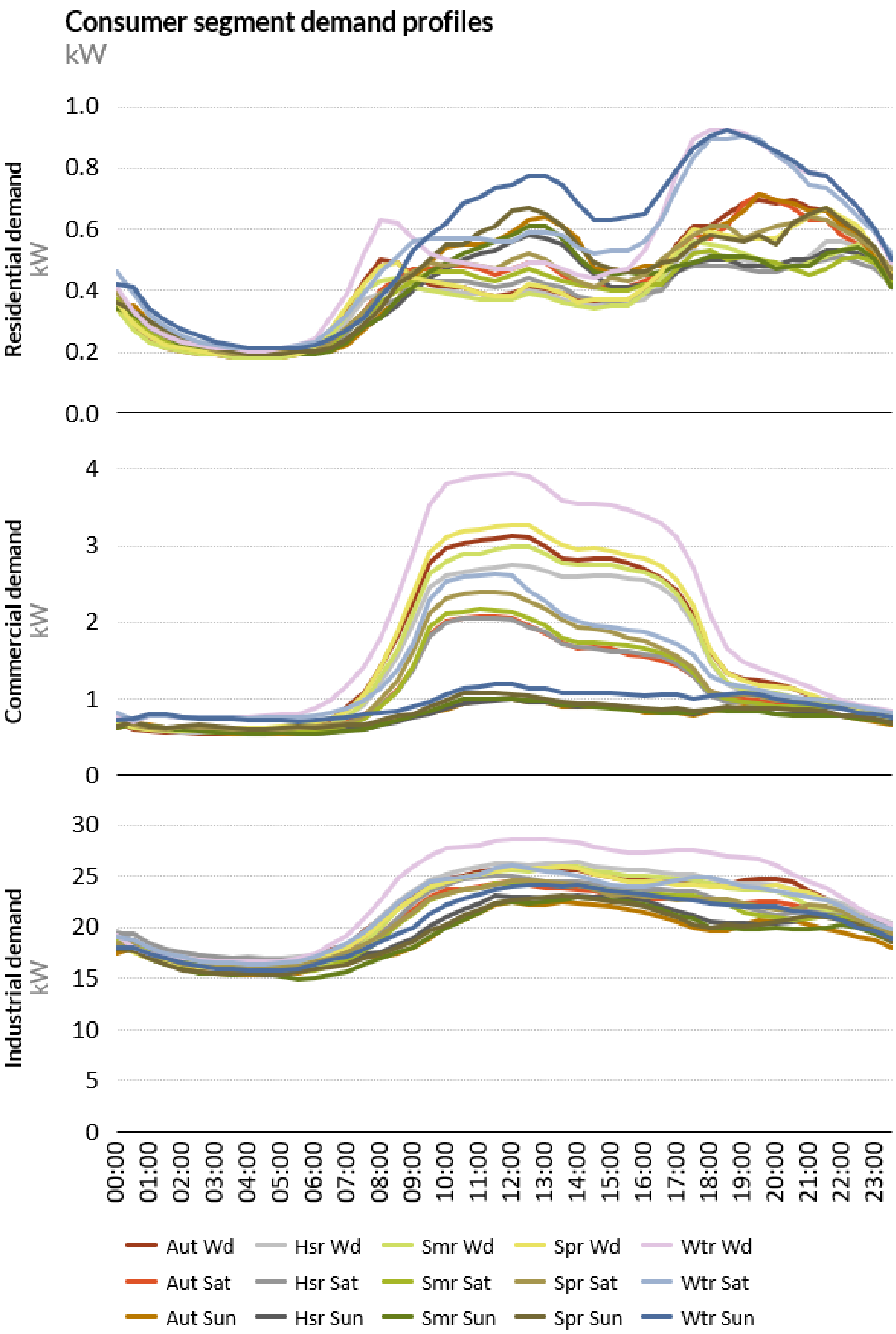
- PLS, Ridge and principal components regression are best at capturing extreme daily peak demand
- OLS regression is able to approximate peak demand, but is not as good at predicting extremes
- PLS regression is able to consider all drivers simultaneously
- Whilst OLS regression is only able to consider a small number of independent drivers (in this case 3) – a major limitation in being able to understand the interactions between all drivers for the purpose of this project
- Based on these considerations, PLS regression was selected for the correlation analysis



Source: Aurora Energy Research

Figure 29: Comparison of various linear regression methodologies

8.2 Residential, commercial and industrial user segment profiles



Sources: ELEXON, Aurora Energy Research

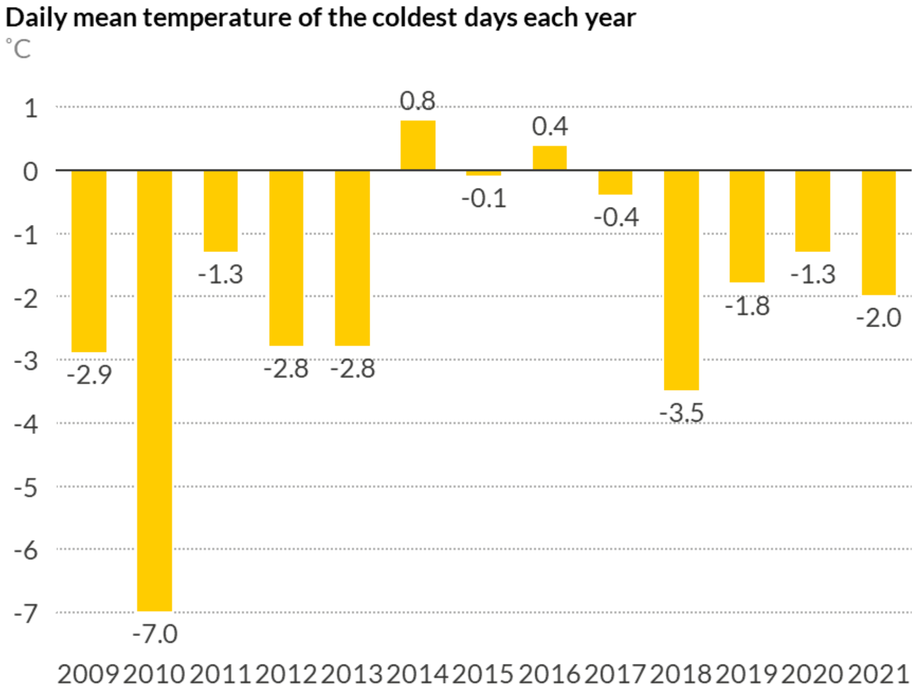
Figure 30: Residential, commercial and industrial user profiles (Aut – autumn, Hsr – high summer, Smr – summer, Spr – spring, Wtr – winter; Wd – weekday, Sat – Saturday, Sun – Sunday)

8.3 Demand driver datasets

Summary of datasets used in the daily peak demand regression analysis and the pre-processing of these datasets for input into regression model:

Demand driver	Original data		Transformation	
	Dataset years	Dataset granularity	Dataset extension	Granularity adjustment
Energy efficiency index	1990-2020	Yearly	Extrapolated 5 years	Interpolated to Daily
GDP index per capita	2007 - 2021	Monthly	-	Interpolated to Daily
Electricity price index	2004-2021	Monthly	-	Interpolated to Daily
Mean temperature	1878-2022	Daily	-	-
Number of households	1970-2022	Yearly	-	Interpolated to Daily
Cumulative floor area of commercial properties	1970-2022	Yearly	-	Interpolated to Daily

Table 4: Summary of datasets used in the daily peak demand regression analysis



Sources: ELEXON, Aurora Energy Research

Figure 31: Temperatures of the coldest winter day each year

8.4 PLS regression model code (Python)

```
 import pandas as pd
from sklearn.cross_decomposition import PLSRegression
import matplotlib.pyplot as plt
from sklearn.model_selection import cross_validate
import numpy as np
from sklearn.metrics import mean_absolute_percentage_error

if __name__ == '__main__':
    # Read in data
    data = pd.read_excel("regressors_final.xlsx", index_col=0, header=0, engine='openpyxl')
    X = data.loc[:, data.columns != 'Demand']
    Y = data[['Demand']]

    # Fit the data - PLS with 5 components
    pls = PLSRegression(n_components=5)
    pls.fit(X, Y)

    # Output backcast predicted values
    pd.DataFrame(pls.predict(X)).to_csv('predicted values.csv')

    # Validation

    # General metrics
    print('Model has an R2 of: ' + str(pls.score(X, Y)))
    print('Model has an MAPE of: ' + str(mean_absolute_percentage_error(Y, pls.predict(X))))

    # Stratified cross validation
    scores = cross_validate(pls, X, Y, cv=3, scoring=['r2', 'neg_mean_absolute_percentage_error'])
    scores_df = pd.DataFrame(
```

```
    [scores['test_r2'], scores['test_neg_mean_absolute_percentage_error']]
  ).T
  scores_df.columns = ['R2', 'MAPE']
  scores_df['MAPE'] *= -1
  scores_df.to_csv('cross_validation_performance.csv')

  # Plot backcast against original data
  plt.plot(np.array(Y), 'go', label='original')
  plt.plot(pls.predict(X), 'mx', label='prediction')
  plt.legend()
  plt.savefig('orig vs pred daily mean.png')
  plt.close()

  # Read in sensitivity/forecast data to predict against
  Z = pd.read_excel("Forecast_final_plateau - average winter.xlsx", index_col=0, header=0,
engine='openpyxl')

  # Predict using PLS model
  Z['output'] = pls.predict(Z)

  # Output to csv
  Z.to_csv('Forecast_final_plateau_results - average winter.csv')
```

[1] https://www.gov.uk/government/statistical-data-sets/historical-electricity-data

[2] https://www.bmreports.com/bmrs/?q=demand/initialdemandoutturn; https://data.nationalgrideso.com/demand/historic-demand-data?from=10#resources

[3] https://www.macrotrends.net/countries/GBR/united-kingdom/population

[4] https://www.ons.gov.uk/economy/grossdomesticproductgdp/bulletins/gdpmonthlyestimateuk/latest

[5] https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/bulletins/averageweeklyearningsingreatbritain/latest

[6] https://data.oecd.org/industry/industrial-production.htm

[7] https://www.metoffice.gov.uk/hadobs/hadcet/index.html

[8] https://www.eea.europa.eu/data-and-maps/daviz/energy-efficiency-index-in-households-3#tab-chart_1

[9] https://www.gov.uk/government/statistical-data-sets/monthly-domestic-energy-price-stastics

[10] https://www.gov.uk/government/statistical-data-sets/industrial-energy-price-indices

[11] https://www.gov.uk/government/statistical-data-sets/gas-and-electricity-prices-in-the-non-domestic-sector

[12] https://data.ukedc.rl.ac.uk/browse/edc/other/demographics/UK

[13] https://www.gov.uk/government/statistical-data-sets/live-tables-on-house-building

[14] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1007402/non-domestic-need-2021.pdf

[15] https://www.eea.europa.eu/data-and-maps/daviz/energy-consumption-for-electric-appliances-2#tab-chart_1

[16] https://trl.co.uk/uploads/trl/documents/CVEI-D5.3---Consumer-Charging-Trials-Report_1.pdf

[17] https://www.theccc.org.uk/wp-content/uploads/2020/12/The-Sixth-Carbon-Budget-Methodology-Report.pdf

[18] https://www.theccc.org.uk/wp-content/uploads/2020/12/The-Sixth-Carbon-Budget-Methodology-Report.pdf

[19] https://www.theccc.org.uk/wp-content/uploads/2020/12/Sector-summary-Fuel-supply.pdf

[20] https://www.theccc.org.uk/wp-content/uploads/2020/12/Sector-summary-Buildings.pdf

[21] https://data.ukedc.rl.ac.uk/browse/edc

[22] https://octoenergy-production-media.s3.amazonaws.com/documents/OE-NGESO_Domestic_Scarcity_Reserve_Trial_Results_vSEND_v2.pdf

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