REPORT

A comprehensive review of peak electricity demand forecasting methodologies

Prepared for National Grid ESO

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1. Executive summary

This report presents findings from a literature review of the main drivers of electricity demand and current electricity demand forecasting methodologies.

Key conclusions drawn from the literature are summarised below. Further analysis of historical data is required to ascertain the full validity of these conclusions.

The main drivers of changes to historical electricity demand are:

- Weather has been found to correlate with electricity demand, with specific considerations such as temperature, hot and cold days and extreme weather events linked with peak demand periods
- Socioeconomic factors (e.g. population demographics, income and industrial activity) are believed to be key drivers of long-term, multi-year total electricity demand trends, even more so than typical weather variations which were found to have a greater impact on monthly or annual demand profiles
- Social behaviour has also been found to influence electricity demand patterns over time, with evolving human habits (e.g. working patterns) and the adoption of various new technologies (e.g. electronic media) significantly changing the need for and timing of electricity demand, including peak electricity demand of residential consumers

Based on this review of historical trends, it is expected that future demand drivers will affect electricity demand in Great Britain as follows:

- Socioeconomic factors will continue to drive future electricity demand in the long term – the correlations between these drivers and demand are expected to evolve over time, requiring further study to form a more accurate view on future trends
- The adoption of new technologies such as smart heat pumps, smart electric vehicles (EVs), hydrogen electrolysers, and demand-side management are expected to increase the time-shifting of demand away from demand peaks, whilst contributing to an overall increase in demand due to fuel switching, therefore potentially affecting the annual average to peak demand ratio
- Many studies point to the increasing impact of climate change on electricity demand – extreme temperatures in the warm and cold months are expected to increase demand for heating and cooling, while more frequent extreme weather events may also significantly affect electricity demand (greater transmission & distribution system losses are also expected as they become less efficient at high temperatures)
- Increases in embedded generation are also expected to impact transmission peaks while overall energy efficiency improvements are expected to have a minimising effect on demand, the magnitude of which needs to be studied in further detail

Key conclusions from reviewing literature relating to long-term peak demand modelling methodology were also drawn from the reviewed literature along with NGESO's long-term demand modelling methodology:

- Bottom-up modelling, as is NGESO's current model, is well-suited for future trends forecasting where historical data is not available – a hybrid approach can be considered as more data on emerging electricity demand drivers (e.g. EV uptake and demand-side management programmes) becomes available

- For situations with historical data, multiple linear regression analysis has been found to be well suited to long-term, multi-year peak and annual demand forecasting, with potential for considering additional methods such as autoregression and artificial neural networks if more detailed forecasting methodologies are desired
- Limitations to the ACS and 1-in-20 methodologies are raised, with further analysis needed to quantify these limitations on forecasting demand moving forward, given expected changes in weather patterns, social behaviours and technology and the impact this will have on future peak electricity demand
- Current NGESO methodology and assumptions to model the relationship between demand drivers and demand are questioned
    - Changing demand profiles with the adoption of new technologies and smart technologies due to the demand/time-shifting ability of these technologies, operation constraints and changing consumer behaviours need to be incorporated into the methodology
    - The current assumption of peak demand timing – in the winter months at 5-6pm, which increasingly needs to be considered alongside summer peak demand which is expected to grow in future years from a combination of increased air-conditioning uptake and increased occurrences of heat waves
- The expected magnitude of change of future demand trends based on the key drivers identified is required to determine how the existing NGESO methodology can be improved upon. This could be explored further in Work Package 2 :
    - Annual peak demand is made up of a combination of consumer behaviour & synchronisation, weather factors, socio-economic factors and policy
    - Over the 5-, 10- and 30-year horizon, the factors driving changes in peak demand are likely to include behavioural change, technological advancement and uptake, fuel switching in heat and transport, policy and embedded generation buildout
    - Peak demand is expected to be a combination of individual consumption components that align with the predominant synchronous factors

2. Introduction

As a central player in the GB electricity system, it is the role of National Grid ESO (NGESO) to provide the leadership and guidance for the transition to Net Zero. The regular dissemination of insights and analysis enables NGESO to facilitate a smooth transition to Net Zero by assisting stakeholders to make informed decisions on energy-related matters.

To this end, NGESO has embarked on a project to assess how electricity demand, in particular peak demand, can be forecasted over a long-term 5-, 10- and 30-year time horizon, considering the impact of uncertainties in population growth, weather events, energy efficiencies, economic conditions and calendar effects.

Overview of report sections

This report is the result of a literature review of historical demand drivers, future demand drivers and electricity demand forecasting methodologies:

- Section 3 covers the main findings of a review of historical and future demand drivers in the literature

- Section 4 covers the main findings of a review of various forecasting methodologies outlined in the literature
- Section 5 provides a review of key steps in the NGESO peak demand forecasting methodology
- Section 6 summarises areas for further study in order to improve further on the current NGESO peak demand forecasting methodology

Overview of peak electricity demand

Peak electricity demand (or peak demand) usually refers to the highest electricity demand on an electrical grid over a given time period.

In the operations and planning of electricity systems, peak and annual load forecasting can be conducted on different time horizons, depending on the intended goals. In the literature: Short-term demand forecasting typically focuses on a time horizon of several hours to less than a week (Dai, Meng, Dai, Wang, & Chen, 2021). Medium-term demand forecasting is typically weeks or months ahead. Long-term demand forecasting is associated with a time horizon of more than a year, up to several decades; this is also the time horizon that NGESO looks at for the modelling of peak demand in their Future Energy Scenarios (FES). Long-term forecasting plays an important role in informing generation, transmission, and distribution system planning (Jang, Byon, Jahani, & Cetin, 2020). In this report, the terms 'long-term' or 'long-term, multi-year' are used to refer to the time horizon relevant to NGESO's long-term forecasting.

Peak electricity demand is usually modelled from electricity demand profiles. Specifically, annual peak demand would be modelled from an annual electricity demand profile or average annual demand value. As such, the literature reviewed looks at drivers and methodologies that relate to the modelling of, both, peak demand and also overall electricity demand by end consumers.

3. Key peak demand drivers

3.1 Overview of demand drivers

It is commonly agreed upon across literature sources that electricity demand is driven by a combination of weather, socioeconomic factors, consumer behaviour, technology (uptake and improvements) and other factors such as policy and price.

Climate change, technological innovation, as well as electrification of energy services to meet carbon targets, have a significant impact on electricity demand magnitude and patterns (Cassarino, Sharp, & Barrett, 2018). Additionally, long-term electricity demand forecasts have been found to be affected more by changing socioeconomic factors than weather (Ghods & Kalantar, 2010).

Literature points out that the new digital and smart grid era calls for more attention to build flexible peak load forecasting frameworks to adapt to the rapid development of the power system. Effective peak load management would result in an estimated reduction in peak demand of 5-15%, which would bring substantial resource savings and decreasing real-time electricity tariffs (Dai, Meng, Dai, Wang, & Chen, 2021).

Overall, all drivers listed in Table 1 below are expected to correlate with peak demand and annual electricity demand, though certain factors such as hot and cold days may have a stronger correlation with peak demand.

	Key demand drivers*	Description	Link with annual and peak demand
Weather	Temperature (h/f)	▪ Climate change causes a rise in temperatures and an increase in temperature volatility ▪ Historically, temperature found to correlate well with electricity demand	▪ Slight decrease in peak demand in the medium to long term, but greater risk of extreme weather years
Weather	Extreme weather events (f)	▪ Random weather events that result in extremely warm or extremely cold days	▪ Unpredictable in nature, but likely to significantly influence peak demand in the year of occurrence
Weather	Hot and cold days (h/f)	▪ Applies more for regions with extremes in the warmer months (e.g. tropical countries, southern Europe, southern US states)	▪ Potential to become a more significant driver in GB peak demand with increasing temperatures due to climate change
Weather	Other weather variables (h/f)	▪ Additional weather variables, such as humidity, solar radiation, wind-speed	▪ Not believed to significantly affect peak demand
Socioeconomic factors	GDP (h)	▪ For GB, correlation found to hold until 2006, beyond which there appears to be little/no correlation	▪ Potentially not an important consideration for future GB peak demand
Socioeconomic factors	Income (h/f)	▪ Higher income found to correlate with higher electricity consumption ▪ Correlates closely with GDP	▪ Given the lack of correlation between GDP and peak demand in GB, this may potentially not be an important driver
Socioeconomic factors	Population (h/f)	▪ Commonly used in predicting residential electricity demand	▪ Moderate population growth for GB (~7% growth up to 2041) – expect moderate impact on peak demand
Socioeconomic factors	Social behaviours (h/f)	▪ Changes in consumer due to changing cultural norms e.g. working hours, eating habits, media usage, etc.	▪ An increased uptake of air-conditioning may increase summer peak demand
Technology	Electrification of heat (f)	▪ In line with decarbonisation ambitions, more GB consumers are expected to switch from gas to electric heating	▪ Given the correlation between temperature and electricity demand, this is expected to be a significant driver of peak demand in the future
Technology	Electric vehicles (f)	▪ In line with decarbonisation ambitions and policy, an increase in EV ownership is expected	▪ Expected to increase demand overall, but may provide time-shifting benefits if EVs are smart
Technology	Smart technologies (including demand-side management) (f)	▪ Adoption of smart technologies such as smart EVs, smart heat pumps and other demand-side management programmes that enable time-shifting of demand	▪ Expected to reduce peak demand ▪ The extreme adoption of heat pumps may increase peak demand ▪ Extreme adoption of heat pumps may increase air-conditioning and increase demand in warm months
Technology	Smart metering (f)	▪ The use of smart meters to measure electricity consumption in households, and commercial and industrial sites	▪ Potential to use purely qualitative statistical/artificial intelligence methods to forecast demand ▪ Indicator of future ability to operate appliances smartly
Technology	Energy efficiency (h/f)	▪ Increasing energy efficiency minimises end use electricity demand	▪ Expected to have a minimising effect on peak demand
Technology	Electrolysed hydrogen production (f)	▪ Electrolysers will require electricity in order to produce hydrogen	▪ Depending on operating model, may increase annual demand and peak demand or just annual demand

Other	Shifting input prices (h/f)	▪ Prices affect consumer behaviour for electricity consumption – mostly for residential demand	▪ Unlikely to affect peak demand in the long term
	Embedded generation (f)	▪ Behind-the-metre generation such as rooftop solar (residential use) or co-located renewables (industrial use)	▪ Expected to reduce system demand, therefore potentially reducing system peak demand
	Policy (h/f)	▪ Government policy may influence a combination of drivers mentioned above and affect consumer behaviour	▪ Not widely covered in literature, but important to consider where possible moving forward e.g. with regards to EV adoption rates, electrification of heat, half-hourly retail pricing etc.

*h = historical demand driver; f = future demand driver; h/f = historical and future demand driver

Source: Aurora Energy Resources

Table 1: Summary of key demand drivers

3.2 Historical demand drivers: Literature review

3.2.1 Weather conditions

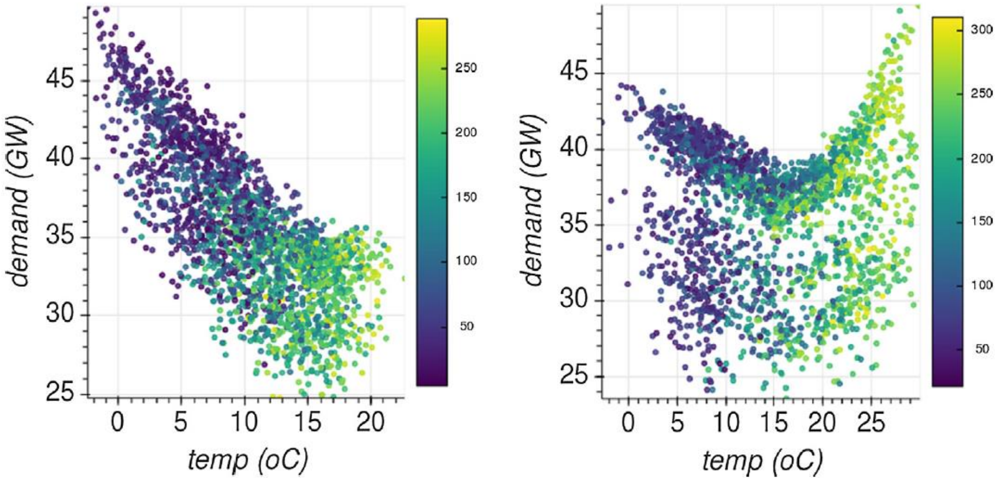
Many existing studies focus on the relationship between weather conditions and electricity demand (Chesser, O'Reilly, Lyons, & Carroll, 2021; Thornton, Hoskins, & Scaife, 2016; Ruijven, Cian, & Wing, 2019). This is because some end-use demands are strongly affected by weather conditions: space heating requirements increase as ambient temperature decreases, and the opposite trend is seen for air conditioning; hot water demand increases when water supply temperature decreases; artificial lighting requirements increase when sunlight decreases. A deep understanding of how weather conditions impact electricity consumption will make it possible to project how residential demands may change as electricity provides a greater fraction of heating, or how climate changes could increase the use of air conditioning. (Cassarino, Sharp, & Barrett, 2018)

Temperature

Temperature is the dominant weather driver of electricity demand in many developed countries, where lower temperatures result in demand for space heating whilst higher temperatures create demand for air conditioning (Thornton, Hoskins, & Scaife, 2016).

Thornton et al. (2016) finds that daily electricity demand is strongly anti-correlated with daily mean temperature, on the condition that non-temperature related variability in demand (such as socio-economic variability) has been removed. Temperature sensitivity in winter is similar or higher than that seen in spring and autumn; it is at a minimum in summer.

Cassarino et al. (2018) analyses the demand temperature sensitivity of each European country at an hourly resolution, with the aim of estimating the specific heat loss coefficients for electric space heating and air conditioning. It is observed that in colder climates such as in Sweden, energy usage in the residential and commercial sector is impacted in the short-term primarily by the outdoor temperature, as a large proportion is used for heating. The study also finds that "*The relationship between temperature and demand, however, has a different trend for each European state, with southern countries showing a parabola-like curve and northern ones generally displaying a monotonic inversely proportional trend*" potentially due to the usage of cooling technologies during the warmer temperatures in Southern European countries.



Source: Cassarino et al. (2018)

Figure 1: Temperature and daily national average electricity demand for 2011-2015 in the United Kingdom (left) and Italy (right)

Hot & cold days

Some studies use heating and cooling degree days to indicate weather conditions and long-term climate change. For example, a heating degree day (HDD) is a measurement designed to quantify the energy demand needed to heat a building. It is the number of degrees that a day's average temperature is below 18 °C, which is the "comfort threshold", the temperature below which buildings need to be heated. This approach has been criticised, as the temperature threshold is arbitrary; the 18°C threshold is also believed to be suitable to temperate regions, but not to tropical countries.

Ruijven et al. (2019) use cold and hot days as an alternative indicator to heating and cooling degree days. "*The cutoff values for defining hot and cold days are based on the distribution of daily average temperature across all world regions in temperate and tropical countries and meet the need to capture low and high extremes while guaranteeing a sufficient number of observations.*" They then determine the climatic shocks by combining temperature elasticities with the change in the number of hot and cold days between 2019 and 2050 from 21 Earth System Models and two emission scenarios. Some research thinks that the longer-scale temperature variability, presumed to be predominantly associated with anthropogenic climate change, makes the likelihood of cold winter days lower today (Thornton, Hoskins, & Scaife, 2016).

Extreme weather events

Temperate climates experience mild to warm summers and cool to cold winters with distinct seasonal changes. Studies show that countries with temperate climates such as the UK and Ireland there is demand for space heating and domestic hot water heating in the residential sector and little to no demand for space cooling (Chesser, O'Reilly, Lyons, & Carroll, 2021).

Prolonged cold periods due to a blocking high-pressure system is generally paired with low wind speeds which will result in low wind energy generation and could have serious impacts on supply. Chesser et al. (2021) emphasise the importance of understanding extreme weather events in Ireland – Ireland rarely experiences extreme winters or major snowstorms; and because of their rarity, when they do occur, they cause serious disruption. “Occasionally a significant snowfall occurs with blocking high pressure to the north of Ireland pushing the North Atlantic jet stream and associated storm systems south, bringing an easterly Polar Continental airflow. This type of pattern can follow a phenomenon called a ‘Sudden Stratospheric Warming (SSW)’” (Met Eireann, 2019).There have been 25 SWWs between 1958 and 2013.

Chesser et al. (2021) explore the impact of an extreme cold weather event on peak electricity demand of homes heated by air source heat pump (ASHPs), when compared to a typical winter day in a temperate climate. They estimate the after diversity maximum demand (ADMD) during a period of extreme weather, comparing it to a typical winter day in the UK, and find that there was a 65% increase in peak average electricity demand from 3.839 kW on the day of the extreme cold weather event compared to 2.331 kW on a typical winter day.

Other weather variables

Inclusion of additional weather variables, such as humidity, solar radiation, wind-speed and other derived variables, has been shown to only modestly improve demand predictability (Thornton, Hoskins, & Scaife, 2016). Jang et al. (2020) points out that besides temperature, humidity also has some impacts on electric demand, as latent loads are also addressed by heating and cooling systems in buildings. However they believe that for modelling the long-term peak density, temperature is a sufficient factor (Jang, Byon, Jahani, & Cetin, 2020).

Cassarino et al. (2018) analysed temperature, humidex, wind speed, and solar irradiation, weighted by population and aggregated nationally for each country in EU35, at hourly and daily resolution. Results show that humidex is linearly correlated with temperature at the European level, whereas wind speed and solar irradiation alone did not show a strong relationship with demand (Cassarino, Sharp, & Barrett, 2018).

3.2.2 Socio-economic factors

Along with weather conditions, electricity peak demand also largely depends on socio-economic factors, such as population and residential electricity demand patterns (Jang, Byon, Jahani, & Cetin, 2020). Some studies define socio-economic factors as “low frequency variability”, the variability with a timescale of greater than about 5 years. Low frequency variability represents the combination of different socio-economic drivers such as consumer behaviour, income, gross domestic product (GDP), manufacturing, population and building characteristics on electricity demand. The study also points out that this variability should be removed prior to comparing demand with temperature; the time varying and complex combination of socio-economic drivers of demand suggests that using an individual driver (e.g. GDP) to model and then remove the long term demand trend is not appropriate (Thornton, Hoskins, & Scaife, 2016).

GDP

Due to the paucity of data and the methodological challenges, electricity demand forecasts are sometimes derived from a simple heuristic approach: for instance using GDP-based demand-growth forecasts as proxies for the growth in demand. “GDP, or other measures of economic output are often the strongest correlators of electricity demand” (World Bank Group, 2017). The suitability of such simplified forecasts differs for developing and developed countries. GDP forecasts are available for many developing countries and therefore are often used to forecast electricity demand in developing regions. However, economic transformation, characterised by intensifying production and greater access rates among other factors, makes electricity demand growth rates go beyond growth arising from output shifts alone. For example, low-income countries experienced high electricity demand growth but having relatively low growth in real GDP. (World Bank Group, 2017) It is concluded that

GDP growth is not always strongly correlated with electricity demand; when it is, multivariate econometric time-series models more accurately estimate the GDP-energy multiplier compared to a simple 1:1 ratio.

It is worth noting that research finds that little correlation between GDP and electricity demand in the UK, from the year 2007 onwards. Prior to 2006, there was a strong positive correlation between GDP and electricity demand. The reduction in UK electricity demand since the mid-2000s is thought to be driven by the financial crisis, energy saving measures, an increase in embedded generation (demand that is not seen by the grid operator), and a move away from heavy industry. Energy saving measures, increased embedded generation and the shift from industrial to commercial demand would reduce the relationship between GDP and energy demand and could potentially explain the change in the GDP-demand relationship after 2006. (Thornton, Hoskins, & Scaife, 2016)

Population

Jang et al. (2020) use population as one of the major factors for the daily peak demand modelling. They note that in developed countries, population is a representative demand driver among many possible drivers, and that population is often positively correlated with other economic conditions. Moreover, it is relatively easier to predict the population growth or decay than other factors at a local or regional level (Jang, Byon, Jahani, & Cetin, 2020).

Income

Income is sometimes viewed as the per-capita GDP, a function of population and GDP projections, and therefore it can be key socio-economic driver of electricity demand. For example, in order to capture the socio-economic effect on future electricity demand, Ruijven et al. (2019) combine income elasticities with population and GDP projections from the Shared Socioeconomic Pathways (SSPs).

Social behaviours

Literature points out that social behaviours are increasingly recognised as a fundamental driver in energy models for both daily demand profiles but also long-term, multi-year demand trends (Pfenninger, Hawkes, & Keirstead, 2014) (Anderson & Torriti, 2018). One of the key input data for engineering energy models is human activity, which can be estimated by different means, such as through time use surveys or by metering energy usage. Energy models focused on the residential sector can estimate social behaviours by also integrating the information on building occupancy (Flett & Kelly, 2017). Social behaviour information is essential to simulate future demand upon changes in the human behaviour due to the adoption of new technologies" (Cassarino, Sharp, & Barrett, 2018).

Social behaviours can show recurring patterns in time, and are affected by the weather, cultural customs, technology and policies. Human activity has a particularly high impact over daily demand patterns, while weather conditions tend to have a stronger influence on the seasonal and annual scale.

Daily social activities represent the shortest cycle of these recurring patterns, and therefore energy models often include daily patterns to predict energy service demands (McKenna & Thomson, 2016). Daily patterns are predominantly determined by human activities at home, at work and elsewhere for leisure, shopping etc. Weekends and holidays usually cause decreased activity in non-domestic sectors, such as schools and factories, as well as increased activity in dwellings or in non-domestic sectors serving holidaying people, such as hotels (Cassarino, Sharp, & Barrett, 2018). Historically weekends and holidays have on average 15%–20% less electricity demand than weekdays in the UK (Thornton, Hoskins, & Scaife, 2016).

Research shows that there are important differences in the activity among years, seasons, and in particular, days of the week. These differences cannot be captured by calculating a single daily profile for an average day of the year, but only by determining profiles along a whole week to consider the differences between each day type. In addition, it is recommendable to extract profiles for each season, or creating a single profile that combines spring and autumn, as the demand in these periods is less influenced by space heating and air conditioning than in winter and in summer. Lastly, using a different profile for each day of the week makes it possible to design detailed scenarios that consider changes in human behaviour between working days and weekends. Interestingly, "despite being consistently separated between working days and weekends until 2015, the activity profiles for the UK showed a different trend in 2016, with a much lower difference between the two day categories" (Cassarino, Sharp, & Barrett, 2018).

"Time of use (ToU) for maximum electricity demand was found to be strongly influenced by occupant characteristics, HoH age and household composition. Younger head of households were more inclined to use electricity later in the evening than older occupants. The appliance that showed the greatest potential for shifting demand away from peak time use was the dishwasher (McLoughlin, Duffy, & Conlon, 2012)." The age structure of population might also influence peak electricity demand. Some research has shown that the presence of teenagers is one of the significant drivers of high electricity demand in UK homes (Jones & Lomas, 2015). In line with this, the ageing population in Great Britain may result in a reduction in long-term residential electricity consumption over time (and therefore lower electricity demand).

However, careful study is needed to ascertain the impact of the introduction of Time of Use tariffs on consumer behaviour as Anderson and Torriti (2018) note that a Time of Use trial in Italy resulted in only minimal changes to peak demand.

Several researchers warn against being too optimistic about the potential of time shifting households' electricity consumption by turning our attention to the temporal-spatial interconnectedness of practices and how collective temporal considerations structure everyday practices even at the household level (Friis & Christensen, 2016).

Policy

Policy is widely accepted to be a driver of electricity demand, however is not covered in detail in the literature reviewed. Selected policy considerations are commented on in other parts of this section (e.g. Time of Use tariffs). For Great Britain, we expect key policy considerations that may influence peak demand to include the potential introduction of half-hourly retail pricing and the ban on new petrol and diesel vehicles from 2030.

3.3 Additional future demand drivers: Literature review

All demand drivers mentioned above are expected to continue driving future electricity demand in GB, except for GDP. Additional future demand drivers not currently widely in use in GB and therefore not significantly present historically, are outlined in this section.

The expected timeline for the contribution of the various future demand drivers is summarised in the table below along with a view on their likelihood (high or low) of influencing demand in the given time horizon. Note: This is not an indication of the magnitude or direction of impact each of these drivers may have on peak demand.

Future demand driver	Likelihood of influencing peak demand	
	5-year horizon	10-30 year horizon
Input prices (fuel & other costs)	High	High
EV adoption	High	High

Heat pump adoption	High	High
Embedded generation	High	High
Demand-side management programmes	Low	High
Smart metering	Low	High
Electrolysed hydrogen production	Low	High

Source: Aurora Energy Resources

Table 2: Summary of future demand drivers and their likelihood of influencing peak demand

Over the next 5 years, additional demand drivers are expected to have an influence on peak demand (on top of that observed historically in the literature). In this time, the magnitude of influence of these additional drivers on peak demand is expected to be relatively small, but is expected to grow over the 10-30-year horizon.

The drivers expected to influence peak demand over the next 5 years include input prices (fuel and other electricity costs that affect electricity prices), EV adoption rates and heat pump adoption rates. Embedded generation capacity growth will influence peak demand on the transmission system but has no impact on overall end consumer demand.

Over the next 10-30 years, this list grows to include demand-side management programmes, smart metering (closely linked with demand-side management programmes) and electrolysed hydrogen production. Further discussion of these drivers are included below.

Input prices – fuel & other electricity costs

The World Bank notes that shifting prices for inputs used to produce electricity, or for intermediate products that are substitutes for or complements to electricity, also affect the electricity demand. The changes in end-use electricity prices are primarily supply-driven owing to changes in costs (regulated tariffs). An example of forecasting electricity demand in Armenia is used: the methodology is greatly facilitated by high-quality historical data, including quarterly series for aggregate income (GDP) and end-use electricity prices (World Bank Group, 2017).

Cassarino et al. (2018) find that electricity demand is influenced by available generation sources. For example, there is a high electric heat share in France, from high nuclear and hydro generation. In Norway, electricity is the choice for more than 70% of household heating, mainly because almost all Norwegian generation is hydro. (Cassarino, Sharp, & Barrett, 2018) The available generation sources and their short-run marginal cost influences the wholesale electricity prices and therefore end-use electricity prices.

Peak electricity demand in the next five years could be influenced by the volatility in commodity prices, especially gas and carbon prices, as well as the generation mix in the system. In the Office for National Statistics' Opinions and Lifestyle Survey, 32% of those surveyed said their cost of living had risen and are cutting back on their use of fuel such as gas and electricity (Office of National Statistics, 2022). They also found that energy price rises are more likely to affect lower income households, as they spend a bigger proportion of their income on utility bills. Further study into the elasticities of demand for electricity by residential, commercial and industrial consumer segments, as well as within different income brackets for residential consumers, is needed to determine the degree of influence that changing electricity prices will have on peak demand moving forward.

EVs

The deployment of electric vehicles, whilst still in its early stages currently is expected to increase significantly beyond 2030 with policy requiring all new vehicles to be electric coming into effect in GB in 2030. The (Electric vehicles and the energy sector - impacts on Europe's future emissions) estimates that the share of total electricity consumption from EVs in Europe will reach 4-5% in 2030 and 9.5% by 2050, which the share for the UK reaching approximately 14% by 2050 (EEA). Charging times for EVs will be an important consideration in terms of managing the grid, especially during peak times. In a study that looked at the impacts of charging EVs in the USA, it was found that EVs that were charged at peak time resulted in transformers being overloaded and operating at reduced efficiencies (Shao, Pipattanasomporn, & Rahman, 2009). Charging locations are also an important consideration in forecasting peak energy demand – for example, (Gilleran, et al., 2021) predict that fast charging of EVs at retail sites will be more common in the future.

The implementation of policy is also an important factor in determining the impact of EV charging on electricity demand, and specifically, peak demand. (Jones B. , et al., 2022) forecast that EVs will respond to the implementation of Time of Use tariffs in GB, with a greater decrease in peak load than if Time of Use tariffs were not implemented.

(Gnann, Klingler, & Kühnbach, 2018) find that different EV user groups have different charging profiles where the charging of commercial vehicles do not contribute to evening load peaks as much as domestic charging of EVs does. They find that demand side response reduces the system load by approximately 2.2GW (2.8%) when domestic and work charging are considered, compared to only domestic charging.

The smart charging of EVs is expected to be able to shift demand away from typical peak periods, with one study suggesting that load can be shifted from early evening hours to the early morning and midday, with 25-30% of the charge forecast to shift into a given low demand hour.

Heat pump adoption

The gas boilers currently heat around 85% of the UK's 27 million homes. Decarbonising domestic heat is a major challenge for the UK's net-zero strategy. Heat pumps (HPs) are promoted as an attractive renewable alternative to fossil fuel heating systems. Less than 200,000 heat pumps are thought to have been installed in UK homes since 2000, and around 27,000 are currently being installed each year. In 2020, the government pledged for up to 600,000 to be installed per year till 2028, a drastic ramping up of installation rates today. (Dr. Arvanitopoulos, Wilson, & Dr. Morton, 2021) Robust government policy support for heat pumps and strong user engagement in the adoption process are important drivers for the increase in HP demand (Woodfield, 2021).

Literature agrees that there is a significant challenge in understanding the impact of heat pumps on electricity demand, and especially on peak demand. The planned uptake of HPs could have a significant effect on electricity demand profiles, especially during colder winters in temperate climates like the UK and Ireland. Air Source Heat Pumps (ASHPs), for example, use electricity to transfer heat from the outside ambient air to the indoor heating system. The larger the difference between the outside and indoor temperatures, the harder the ASHP must work to achieve adequate heat comfort levels (Heinen, Turner, Cradden, McDermott, & O'Malley, 2017). As a result, the replacement of the traditional home heating (e.g. natural gas heating) with HPs will increase the electricity demand, especially during cold winters and extreme weather events (Chesser, O'Reilly, Lyons, & Carroll, 2021).

Love et al. note four potential problems associated with HP adoption: At the Transmission System Operator (TSO) level, there are problems meeting peak demand, and handling ramp rate increases; at the Distribution System Operator (DSO) level, there are problems managing excessive voltage drops, and making investment decisions on the reinforcement of low voltage feeders and transformers (Love, et al., 2017).

Love et al (2017) use a real-world dataset from HP installations to create an aggregated demand profile. They note that the total peak demand is less than the sum of the components because the daily peak in heat pump use is not concurrent with the daily peak of the rest of the home. The peak in the aggregated

HP profile occurs in the morning, while the national gird peak demand occurs in the evening. Eyre and Baruah (2015) estimate that the electrification of residential heating in the United Kingdom (UK) could increase peak electricity demand by 30% (Eyre & Baruah, 2015). Asare-Bediako, Kling, and Ribeiro (2014) employ a combination of top-down and bottom-up approaches with scaled synthetic load profiles representing base loads per household in the Netherlands. A scenario-based approach is used for the analysis of different combinations and penetration levels of renewable energy systems including different types of heat pumps. In a future scenario of base load and HPs during the winter week, they estimate there could be up to a 100% increase in peak load with the increased possibility of voltage drops (Asare-Bediako, Kling, & Ribeiro, 2014).

Embedded generation

Embedded generation and storage assets are expected to grow in deployment across GB in this period, resulting in a reduction in the magnitude of electricity demanded from the grid by users with embedded generation assets, as well as a potential reduction in peak demand by users with embedded generation and storage assets. Embedded generation in GB increased more than 100% from 14GW of installed capacity in 2011 to 31GW installed capacity in 2018 (Gordon, McGarry, & Bell, 2022). The growth in embedded generation affects the peak demand on the transmission system, but does not have an effect on end consumer (system) peak demand.

Demand-side management programmes

Demand Side Management includes building demand reduction measures such as energy efficiency (EE) and demand-side response (DSR) programmes. While EE programmes aim to reduce the electricity demand in general, DSR programs mainly focus on peak demand reduction by modifying the end-use electricity demand patterns and changing the timing and level of instantaneous demand.

According to Jang et al. (2020), a broad range of DSM programmes for residential and commercial buildings are currently implemented in the United States, typically run by utility companies and third-party aggregators. By participating in these programmes, end-use customers receive an incentive and/or other monetary or non-monetary benefits. Such incentives help utilities and power network companies maintain a predictable level of demand adjustments that can be made to support the reliable operation of the electricity system.

"Although many DSM efforts for buildings are still in the pilot stages, DSM programmes are projected to significantly increase moving forward, particularly as the electric grid is increasingly powered by more variable renewable energy sources." For example, Austin Energy, the exclusive electricity provider to the city of Austin, operates the EE/DR program titled the Custom Energy Solutions (CES) programme; the participants of this programme continue to grow. Due to the increasing interest in DSM efforts for residential and commercial buildings, the demand saving from DSM activities should be taken into account in the medium- to long-term demand forecasts (Jang, Byon, Jahani, & Cetin, 2020).

Whilst there is a current dearth of literature covering the full potential impact of smart demand on total peak demand, previous research by Aurora (In-Demand Group Meeting, Dec 2021) has suggested that peak demand could be reduced by up to 29GW through the use of smart demand technologies by 2050 (87GW compared to 58GW) in a net zero world in an average winter cold spell. This reduction primarily results from a combination of smart charging EVs, heating technologies with storage or highly insulated housing, and hydrogen electrolysis. However, the actual impact of smart demand is likely to be heavily dependent on decarbonisation pathways chosen in the heating, transport and industrial sectors and further work is needed to understand the plausibility of these pathways.

Smart metering

Smart metering is expected to have multiple effects on future electricity demand forecasting. Firstly, the installation of smart meters enables real-time information exchange between electricity suppliers and end-users. This increases the efficiency of the supply and encourages the rollout of different smart energy applications, such as the DSR programmes. Moreover, the high temporal resolution consumption data coupled with intermittent energy resources such as wind and solar make electricity demand present unprecedented diversity and complexity. Also, with high-resolution load data (e.g. residential smart meter data) becoming increasingly available, data privacy will become an important issue that needs to be addressed. "In the new digital era, using private encryption algorithms to protect the consumers' data has become an essential task that researchers must deal with" (Dai, Meng, Dai, Wang, & Chen, 2021).

Hydrogen

Hydrogen is produced from hydrocarbons (grey and blue hydrogen) or electrolysis of water (green hydrogen). Blue hydrogen production typically uses methane, and is the equivalent of grey production coupled with CCS.

Electrolysers produce hydrogen and oxygen. They can be grid connected, co-located with renewables (or nuclear), or a hybrid of both. Green hydrogen is expected to be the primary source of hydrogen in the net zero world, but production methods can differ and have implications on demand.

Power demand for hydrogen production could vary significantly, depending on the level of electrolyser deployment vs blue hydrogen production that sits outside the power sector. The overall impact of hydrogen on the power sector will depend on the mix between green and blue production; if all hydrogen is produced by electrolysers, it would add an additional 500 TWh to power demand.

Flexible electrolysers are expected to mostly avoid producing during the peak and instead produce during mid-day and early mornings.

Most hydrogen electrolysers in GB are expected to come online beyond 2030. The inflexible operation of electrolysers (operating at baseload capacity), which is possible if required to supply hydrogen to industry, may result in an overall increase in annual demand as well as an increase in peak demand.

4. Peak demand forecasting methodologies

4.1 Overview of peak demand forecasting methodologies: Literature review

The methods available for forecasting electricity demand can be divided into qualitative and quantitative analysis.

- Qualitative analysis involves using expert views of the expected trajectories of key drivers to predict future electricity demand, alongside conventional methods such as curve fitting and extrapolation. It is used if historical or experimental data is not available, or incomplete.
- Quantitative analysis uses historical data and assumes that the future development of demand follows the trends of the historical data within a certain range. In this case mathematical, statistical or more complex computational methods can be used to forecast electricity demand.
- Hybrid methods utilise a combination of analytical methods to produce demand forecasts.

Table 3 summarises the various analytical methods available for forecasting electricity demand.

Out of all methods, regression analysis is still widely used and efficient for long-term forecasting (Hammad et al 2020, Nti et al 2020). Hybrid models, which are commonly a combination of statistical and advanced methods, e.g. regression with artificial neural networks, have been found to perform best in terms of long-term peak demand forecasting accuracy (Dai et al 2021, Nti et al 2020) but are also more complex to implement. Machine learning methods such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), and fuzzy logic have been found to perform well for short-term forecasting in the span of days and weeks (Hammad, Jereb, Rosi, & Dragan, 2020).

Top-down modelling approaches use aggregated data, usually at a regional or national level, such as GDP, population and national or regional energy statistics to determine relationships between these drivers and electricity demand. Bottom-up approaches on the other hand use data collected at an individual unit level (be it by household, car user, etc.) to determine the relationship between these individual values and electricity demand. Regression and other statistical methods can be applied in either a top-down or bottom-up manner (McLoughlin, Duffy, & Conlon, 2012).

Other advanced modelling methods such as exponential smoothing, Kalman filtering, fuzzy logic, support vector machines, and genetic algorithms are not usually used for long-term (multi-year) peak load forecasting and are not explored further in this report .

NGESO's modelling methodology for the Future Energy Scenarios utilises a combination of bottom-up engineering and regression analysis to forecast long-term, multi-year peak electricity demand for Great Britain.

4.2 Key peak demand forecasting methodologies

Key forecasting methodologies used for long-term, multi-year demand modelling are summarised in Table 3.

Methodology	Demand type	Granularity	Pros	Cons	Prediction error
Bottom-up /engineering	Annual, peak	Days, weeks, months, years	Good for forecasts based on variables where little historical data and trends are available	Heavily assumptions-based, with the potential for mismatch with actual data (as assumptions for certain variables may not reflect reality).	N/A
Regression	Annual, peak	Days, weeks, months, years	Simple to set-up, easy to understand, with a manageable number of variables and reasonable forecasting efficiency	Assumes that trends seen in the historical data would continue to apply moving forward, which may not be the case in certain situations.	1.43% (Haida & Muto, 1994)
Stochastic time series	Annual	Years	Useful for modelling outputs where correlations with variables are based on previous results	More complex than simple regression analysis, cannot be applied to discreet (non-continuous) datasets e.g. annual peak electricity demand.	6.63% (Jain et al. 2018)
	Peak	Days, weeks, months			
Time series decomposition	Peak	Days, weeks, months			7.88% (Turner et al. 2012) – *for monthly peak loads*
Artificial neural network (ANN)	Annual, peak	Days, weeks, months, years	Found to be more accurate than simple statistical methods in certain situations (e.g. short-term modelling)	Results are heavily dependent on historical data where trends may not apply going forward. Computationally complex to set up.	4.57% (Ghods & Kalantar, 2010)
Hybrid	Annual, peak	Days, weeks, months, years	Can be more accurate than the individual methods employed.	Computationally complex to set up.	5.99% (Dai et al. 2021) - *for daily peak loads*

Source: Aurora Energy Resources

Table 3: Summary of commonly used long-term, multi-year electricity demand forecasting methodologies

4.2.1 Regression

Regression models express electricity demand as a function of demand drivers based on historical data. As a result, a relationship between the drivers and electricity demand can be obtained to forecast electricity demand. Econometric effects such as GDP, consumer price index and population have been considered in the past as drivers of peak electricity demand forecasts using multiple regression models in other countries (Mtembo, Taylor, & Ekwue, 2014), (Haida & Muto, 1994). However, Haida et al 2014 found the performance of their model on larger fluctuating load patterns to be unsatisfactory.

Regression models are simple to set-up, easy to understand, with a manageable number of variables and reasonable forecasting efficiency. However, this method does make the assumption that trends seen in the historical data would continue to apply moving forward, which may not be the case in certain situations (Dai et al 2021).

As such, regression analysis is usually combined with other techniques to improve on its accuracy in forecasting peak electricity demand.

4.2.2 Time-series forecasting

Time series forecasting can be conducted either through a stochastic time series model or a time-series decomposition model. Stochastic time series models can be generally divided into: the auto-regression (AR) model, the moving average model (MA), the autoregression moving average model (ARMA), the auto-regression integrated moving average (ARIMA) model and the seasonal auto-regression integrated moving average model (SARIMA).

The underlying principle of autoregressive models is that the present value of the series can be expressed as a linear combination of past values, thereby allowing it to predict future behaviour based on past behaviours. This method is suitable for use in situations where there is a correlation between the present value of a time series and its previous values.

A time-series decomposition model for electricity demand forecasting usually adopts the addition or multiplication model to split the original time series into four sub-parts - the continuous change of peak load demand in a long period, the regular seasonal change of peak load demand, the periodic change in peak load demand over years, and the unexpected change of the peak load demand caused by random factors. The resulting forecast is either a sum (addition) or product (multiplication) of these four parts.

When predicting peak electricity demand, each component is first calculated separately then passed through the addition model or the multiplication model to obtain the final prediction.

This method is better suited to model daily, weekly or monthly peak load demand up to a year ahead rather than forecasting multi-year annual peak load demand as NGESO seeks to do in their Future Energy Scenarios (FES).

Literature reviewed show that multiple papers have used these methods to successfully model year ahead weekly and monthly peak loads with MAPE 7.88% (Fong & Yang, 2011), (Turner, Downing, & Bogard, 2012)) and day-ahead daily peak loads (Choi, Park, Kim, & Kim, 1996). However, this method has not been used for multi-year peak load forecasting. Rehman et al (2017) found that the ARIMA method was suitable in forecasting long-term (multi-year) electricity demand for Pakistan (as opposed to specifically peak demand). Jain et al found that using the ARIMA method for multi-year demand forecasting yielded a MAPE of 6.63%.

4.2.3 Advanced forecasting methods

Advanced forecasting models that have been used to model electricity demand include modern AI and machine learning based methods such as artificial neural network (ANN) and deep learning, support vector machines (SVMs), and ensemble models.

Not all these methods are suitable or have been applied for long-term, multi-year peak electricity demand forecasting.

An artificial neural network (ANN) model consists of artificial neurons in multiple layers for information communication. A typical ANN consists of the input layer, the hidden layer, and the output layer. Except for the input layer, each neuron in the ANN is connected to neurons of the former layer (i.e. the input neurons), with each connection corresponding to a weight. The sum of the product of all input and the corresponding connection weights are passed to an active function to calculate each neuron's final value.

(Zakarya, Abbas, & Belal, 2017) conducted long-term (10-year) electricity demand forecasting using ANN and ARIMA to forecast the electricity demand of Kuwait. Variables used included temperature and humidity, average salary, GDP, oil prices, population, number of households, vehicle passengers, currency exchange rates, and economic indicators such as total imports and exports. The study concluded that ANN outperformed ARIMA and weather parameters were found to be more significant than average salary, GDP and oil prices in influencing electricity demand.

(Ghods & Kalantar, 2010) used an ANN model to predict annual electricity demand in Iran for 5 years with an average error of 4.57%. Nti et al (2020) concluded that for long-term, multi-year annual demand forecasting, the ANN and autoregression models perform the best out of all tools. However, the downside of ANN models are that they are computationally complex and time-consuming to set up and run.

5. National Grid ESO's peak demand forecasting methodology

5.1 Key drivers

Summary of recommendations on key drivers (list top key drivers to consider and what we believe needs to be considered):

1. Bottom-up modelling of residential, industrial and commercial electricity demand
2. Consideration of socioeconomic factors in bottom-up model – as they have been found to be the key drivers of long-term electricity demand trends
3. Re-consideration of the Average Cold Spell (ACS) adjustment to historical electricity demand data, and in line with that, a consideration of future weather projections as a result of climate change

Table 4 shows a full list of key demand drivers identified in Section 3 alongside the NGESO FES assumptions, and a discussion of these assumptions based on the literature reviewed and other considerations.

	Key demand drivers	NGESO FES Assumption/methodology	Discussion of methodology
Weather	Temperature	▪ Indirectly accounted for since historical data is used to calculate residential demand ▪ Climate projections are explicitly considered in the heat demand model	▪ Important in considering changing effects from climate change that may not be captured in historical demand data
Weather	Average cold spell (ACS)	▪ The underlying methodology in the calculation of annual and peak demand – historical demand data is weather-corrected to reflect demand in the average cold spell (50% chance of exceedance)	▪ May not be suitable for future use as it does not capture extreme weather events associated with climate change ▪ If used, will need to consider including a forecast for extreme weather situations
Weather	Extreme weather events	▪ Extreme weather events are not accounted for in the current methodology, as the ACS method adjusts data to exclude extreme weather events	▪ Can be forecast for a set of potential extreme weather events and added to ACS demand – requires further study
Weather	Hot and cold days	▪ Not explicitly accounted for in the current methodology	▪ The likelihood of cold days is expected to decrease as a result of climate change
Weather	Other weather drivers	▪ No explicit consideration of additional weather drivers such as humidity, wind speed and solar radiation, amongst others	▪ Not believed to significantly affect peak demand
Socioeconomic factors	GDP	▪ Not factored into the model	▪ Could potentially be indicative of industrial and commercial activity and corresponding demand, however a clear decoupling of GDP from peak demand from 2007 onwards was observed in literature
Socioeconomic factors	Income	▪ Not factored into model	▪ Believed to be linked with GDP, and found to be linked with residential demand, though this correlation needs to be validated for GB
Socioeconomic factors	Population	▪ Not factored into model	▪ May not be a significant contributing factor to the population in a developed country – to be explored in WP2
Socioeconomic factors	Industrial production	▪ Not considered – currently industrial demand is calculated as the difference between total demand and residential demand	▪ To be tested in WP2 to determine correlation with historical demand data
Socioeconomic factors	Social behaviours	▪ Not considered	▪ These may be significant drivers of demand, but further study is required to determine which behaviours are more likely to influence demand moving forward and their magnitude
Technology	Electrification of heat	▪ Modelled in detail using a bottom-up heat model	▪ Lack of historical data to determine a correlation with demand suggests the current bottom-up modelling approach to be the best practice
Technology	Electric vehicles	▪ Modelled based on historical data	▪ A bottom-up approach should be explored to more accurately forecast behaviours expected from the charging of electric vehicles
Technology	Smart technologies (including demand-side management)	▪ Smart heat pumps modelled in the heat model ▪ Smart EVs modelled in the EV model, based on assumptions of expected adoption rates ▪ Demand-side management not actively modelled, but calculated as the difference between actual daily peak demand and peak demand using a normalised profile	▪ Potential to define a more robust approach to modelling time-shifting of demand as a result of the uptake of smart technologies ▪ Further study is required to develop this

Technology	Smart metering	▪ Smart meter data are not currently utilised in modelling methodology	▪ Recommend studying the accuracy of forecasting using smart meter data in more detail
	Energy efficiency	▪ Not actively accounted for	▪ To be explored as a potential driver in WP2 ▪ Believed to be a contributing factor to changing energy demand levels over time
	Electrolyser hydrogen production	▪ dispatch for electrolysers, however, can vary by the hour ▪ four dispatch profiles, ranging from hourly load without any storage, through daily fuel-cost optimised profiles. Profiles with seasonal storage and yearly fuel-cost optimisation are also considered	▪ To potentially consider inflexible electrolyser operation (but the model may decide that the more economical option is to produce blue hydrogen), however we do expect the cost of electrolysed hydrogen to decrease to below that of blue hydrogen in the long-term (30-year) horizon
Other	Shifting input prices	▪ Not considered	▪ Prices have been found to influence residential electricity user behaviour, but may become more significant if half-hourly retail pricing is introduced – a consideration for future forecasting methodology revisions
	Embedded generation	▪ Not currently considered in system peak demand forecasts (but accounted for based on limited data of existing embedded generators when looking at total gross demand)	▪ Important to consider when forecasting peak system demand as there may be a negative correlation between embedded generation and peak system demand
	Policy	▪ Accounted for in the heat model	▪ Ideally should be accounted for across all aspects of long-term forecasting, but difficult to include in the models if policy is not clearly defined in advance

Source: Aurora Energy Resources

Table 4: Discussion of NGESO's assumptions on key demand drivers

5.2 Methodology

5.2.1 Discussion of the ACS and 1-in-20 methods for modelling peak demand

The average cold spell (ACS) peak demand is defined as the level of peak demand for which there is a 50% probability of exceedance in a given winter. It is the approach used by NGESO to model peak demand considering what is connected to the system but discounting extreme weather effects.

"The estimation process involves simulating 20,000 synthetic weather winters, each constructed from week-long blocks of temperature data sampled from around 30 historic winters" (Wheatcroft et al 2022). This is mapped to a demand series using a set formula that relates demand with what is connected to the system (basic demand less unmetered generation) and weather, including randomly sampled residuals. The ACS peak demand is the median winter peak demand across these 20,000 synthetic peak seasons.

"1-in-20 peak day demand is the level of daily demand that, in a long series of winters, with connected load held at the levels appropriate to the winter in question, would be exceeded in one out of 20 winters, with each winter counted only once" (Wheatcroft et al, 2022).

Limitations of the ACS methodology:

- The ACS method is not able to account for peak demand due to extreme weather events, that are expected to occur with greater frequency and magnitude in the coming years due to climate change
- In its current form, it is unable to capture the effects of future drivers and technologies that historically have not had a significant influence on peak demand, but are expected to become significant drivers of peak demand in future years
    - Literature reviewed reveals that historically, there has been a moderate correlation between temperature and electricity demand for Great Britain (0.5 < R^2 < 0.8; R^2 is the regression coefficient) (Thornton et al 2016). This could be attributed to the fact that only a small proportion of heating in the country is electrified currently
    - It is expected that a stronger correlation between temperature and electricity demand will develop as the proportion of electric heating increases and social behaviours change to incorporate more use of air-conditioning during summer months
    - In line with this, heat waves are expected to become more prevalent moving forward (Intergovernmental Panel on Climate Change (IPCC). Climate Change 2013: The Physical Science Basis, 2013), raising the need to review and forecast peak summer demand in addition to the standard ACS peak demand, for better visibility of period of potential maximum system constraint
- With increasing demand from electric vehicles, the applicability of the ACS method to forecast peak demand should be studied further as this demand may not have a correlation with the ACS as demand, leading to potentially inaccurate forecasts of peak demand if the ACS method continues to be used
    - In this case, a hybrid approach to consider the ACS methodology in combination with a statistical approach to forecast electricity demand from EVs may yield better accuracy

Limitations of the 1-in-20 peak day demand methodology:

- 1-in-20 peak day demand is not able to account for extreme weather events due to it being a relatively new weather phenomenon not present to the same magnitude and intensity in historical weather data
    - This is something to be examined in more detail using historical data
- Similar to the ACS methodology, the 1-in-20 methodology is not able to capture the changing effects of future technologies and efficiencies along with social behaviours – the effects of which need to be studied in more detail to determine how material these drivers are in influencing peak demand
    - (Anderson & Torriti, 2018), in their study of UK electricity demand from 1974 to 2014, highlight how changing social behaviours (patterns in labour market participation, travel, personal/home care, food-related activities, etc.) influence the time-shifting of demand, indicating that this is an important trend to study and incorporate into future peak demand forecasting methods on top of the time-shifting effects of smart heating, smart EVs and demand-side management programmes

Overall, it appears that one methodology on its own presents shortcomings in forecasting peak demand for the long term. This suggest that a hybrid approach, incorporating a combination of statistical methods to predict the effects of future drivers on peak electricity demand, alongside the ACS method may yield more promising results.

5.2.2 Main model

Further to the overarching methodology, this section dives into key steps within the modelling of system peak demand in the AEDAS model by NGESO, alongside a discussion of how these assumptions could be explored in more detail to improve overall forecasting accuracy.

Calculation step	Description	Discussion
ACS peak demand for residential, commercial and industrial demand	▪ Weather-adjusted historical demand data for all of GB	▪ Normalised to exclude extreme weather conditions – but increasingly will need to consider this as extreme weather conditions become more prevalent with climate change ▪ "Single extreme weather events are less likely to pose a risk for the power production sector and energy security than are compound extreme events" (Anel et al 2017)
Annual to peak demand ratio	▪ Calculated from 2,000 home metres from ELEXON	▪ Sample size and location ▪ Validity of ratio methodology ▪ Will also need to review summer peak demand – as heat waves are expected to become more prevalent (Intergovernmental Panel on Climate Change (IPCC). Climate Change 2013: The Physical Science Basis, 2013)
Synchronisation of peak demand components	▪ The total peak demand is obtained by summing up peak demand from the various sectors	▪ Timing of contribution of electricity demand with key demand drivers should be explored in more detail – can be explored at a preliminary level in WP2, but may require more in-depth study beyond this
Transmission losses	▪ Estimate these losses at the system level to average around 8%	▪ Impact on losses in the case of extreme hot days (transmission & distribution systems become less efficient at high temperatures), indicating that more robust estimation of losses is needed (Anel et al 2017)
Industrial and commercial demand forecasting	▪ Calculated as the balance in peak demand after subtracting forecast peak residential demand (approximately 50%)	▪ Literature reviewed reveals many types of bottom-up models to forecast industrial energy consumption (FORECAST, Save), and should be looked into to determine if NGESO's forecasting accuracy can be improved this way (Daniels & Van Dril, 2007)
Residential demand	▪ Annual residential demand is projected forward using historical trends	▪ Inherently assumes similar trends as history – in reality, consumer behaviour is found to change in the long term with socioeconomic factors and cultural norms (Anderson & Torriti, 2018)
Determination of demand sector ratios	▪ Sector components such as heat, microgen & storage, losses, transport and appliances are distributed and proportioned to each sector	▪ This was not covered by the literature reviewed, but is potentially an area requiring further analysis by NGESO
Seasonal variations	▪ Indirectly accounted for by using historical data, and in the demand profiles for heat and transport	▪ Influences the value for annual demand rather than peak demand, but important to be considered in further detail
Summer peak	▪ The current peak demand forecasting method assumes a winter peak	▪ Recent weather trends have shown the increasing occurrence and magnitude of summer peak demand in GB

Daily peak – 5-6pm	▪ Currently assumed to be the hour during which peak demand occurs	▪ This is expected to change with the emergence of more smart technologies

Source: Aurora Energy Resources

Table 5: Discussion of key steps in NGESO's main long-term demand forecasting model

5.2.3 Heat

NGESO's modelling of electricity demand for heating involves the use of a bottom-up engineering model that considers the most common building archetypes alongside heating technologies to solve for the most cost-effective heating solution for each archetype. This model also takes into account consumer willingness to pay and policy support in the technology lifetime costs.

Calculation step	Description	Discussion
Hourly and annual heat demand	▪ The model calculates the heat loss rates for each building archetype and from this determines the hourly and annual heat demand	▪ Profile applied based on a 1 in 20 demand or weather year (from historical data), which may not be representative of future years due to changing weather trends from climate change
Heating technology costs	▪ The CAPEX and OPEX of gas, electrified, hydrogen and district heating production and distribution are modelled	▪ It would be important to ensure that these costs account for improvements in heating efficiencies as newer technologies mature, and input costs e.g. hydrogen production decrease over time
Determination of proportion of electrified heat demand	▪ The final technology pathways are chosen by the model based on consumer willingness to pay, accounting for technology costs and policy incentives	▪ Accounting for policy incentives and consumer behaviour is good practice and should be considered across demand sectors
Industrial space heating	▪ The model does not account for industrial space heating needs	▪ This amount may be small enough compared to residential and commercial heating demand to be excluded without any material consequences on the accuracy of the annual and peak demand forecasts
Demand profile for each technology type	▪ The overall heat demand profile does not differ by type of heating (electric or gas)	▪ Literature shows that the dominant driver for heating demand is temperature ▪ However moving forward, with increasing heat pump adoption, we expect the demand profiles from electrified heating to change – requires further in-depth study to assess the behavioural changes expected with heat pump adoption, and how heat pump operating principles may affect the electrified heating demand profile ▪ We expect that with the adoption of heat pumps, that residential consumers would be more likely to employ it for cooling during summer months, and may result in summer peaks close in magnitude to winter peaks, as well as an overall increase in annual electricity demand from more constant use of air-conditioning in the summer months

Demand profile for each building archetype	▪ Same hourly profile is applied for all building archetypes	▪ Residential should be different from commercial and industrial space heating profiles ▪ Potential source of discrepancy in a post-Covid world where there have been behaviour changes (e.g. more people now working from home)
Interpolation of 5-year results to obtain yearly values	▪ Calculations are made for each 5-year time step with intermediary values calculated as a straight line between the calculated points	▪ Interpolation risks missing out on important inflection points in trends e.g. when new policies come into play, fuel price trends, and weather events

Source: Aurora Energy Resources

Table 6: Discussion of key steps in NGESO's long-term heat demand forecasting methodology

5.2.4 Transport

Overall, there is a need to better account for the uptake and usage of smart EVs in forecasting annual and peak demand. What proportion of electricity demand from EVs occurs at a fixed time due to practical daily routines, and what proportion of demand can practically be catered to by smart charging?

There is also a need to study the timing of the peak for smart EV charging profiles, and determine how this fits in with other demand sector peaks. A final key consideration is how temperature affects EV electricity requirement, with lower battery efficiencies in colder months and greater need for engine and cabin heating/cooling in the winter and summer months. This may affect peak demand in colder months, even with some time-shifting of demand from smart charging.

Methodology	Description	Discussion
Uptake rate for electrified transport	▪ Calculated by considering the number of vehicles on the road, miles, efficiency of doing those miles, the associated costs and policy effects	▪ Can be assessed against historical uptake rates to determine whether model is under or overestimating uptake
Charging profiles	▪ Demand is split by charging type – 5 types: residential, work, rapid, public, HGV depot ▪ Profiles for each charging type developed based on real charging data from 2017-18 (private & public data)	▪ Applicability of the profiles from 2017-18 for future EV charging behaviours needs to be studied in further detail, especially with the increasing uptake of smart EVs ▪ Further investigation required to better model smart charging profiles – this will become increasingly important as the proportion of smart vehicles increases ▪ Further investigation needed to determine effect of temperature on EV electricity demand
Contribution of each profile to total EV charging demand	▪ Proportions change each year as behaviours/trends change	▪ There is the opportunity to explore a bottom-up approach to forecast the expected combination of EV charging profiles

Source: Aurora Energy Resources

Table 7: Discussion of key steps in NGESO's long-term transport demand forecasting methodology

5.2.5 DSR (excluding heat and EV)

Overall, there is potential for the DSR modelling methodology to be further improved through a bottom-up approach that needs to be informed by a deeper investigation of future DSR trends. Common methodologies to inform bottom-up modelling include conducting pilot programmes to determine user demand profiles in response to demand-side management, or obtaining results from similar programmes in other countries with comparable electricity usage patterns. Studies reviewed suggest that DSR profiles are likely to be driven by user behaviour and electricity prices – further study will be needed to determine in more detail the components and weightings of these drivers in influencing DSR.

Ultimately, local government support and policies will define the success of the implementation of demand-side management programmes. Study of policies and programmes in other countries may inform best practices for such policies and programmes in GB.

Calculation step	Description	Discussion
Summer demand-side response	▪ No demand side response is currently assumed due to little information on summer behaviour, particularly demand turn-up	▪ Potential to explore this further given expectations of increasing summer peak demand
DSR profile	▪ The real historical daily demand profile is subtracted from the short-term daily demand profile. This difference is attributed to DSR and embedded generation.	▪ Important to investigate further the actual and expected DSR profiles based on a bottom-up approach as it may be different to the regular demand profile that is currently assumed
DSR value	▪ DSR is assumed to be 50% of the difference between historical daily demand at peak (5-6pm) and the forecast short-term daily demand at peak (5-6pm) ▪ This is assumed to be industrial and commercial DSR (but mostly industrial)	▪ In line with a review of methodologies to determine a representative DSR profile, it would be also important to test the validity of this assumption ▪ Further study is needed to identify a suitable method to ascertain contribution of DSR to a flattening of peak demand
Residential DSR	▪ Residential DSR starts coming in as time of use tariffs come in, and smart EV and heat pumps increase.	▪ Careful study is needed to ascertain the impact of the introduction of Time of Use tariffs on consumer behaviour as previous studies found this to not significantly influence peak demand ▪ Several researchers warn against being too optimistic about the potential of time shifting households' electricity consumption by turning our attention to the temporal-spatial interconnectedness of practices and how collective temporalities structure everyday practices even at the household level (Friis & Christensen, 2016)
Appliances	▪ Assume 10-15% of peak residential demand from whitegoods, people only willing to shift this at most. Based on study 10 years ago	▪ Given the changing social behaviours and work-patterns, this assumption may need to be revised ▪ Further investigation is needed to ascertain what adjustments are needed to be made to this assumption to better apply to post-Covid behaviours, on top of forming a view on longer-term trends

Source: Aurora Energy Resources

Table 8: Discussion of key steps in NGESO's long-term DSR forecasting methodology

5.2.6 Hydrogen

As with heat, the hydrogen model is a bottom-up engineering model based on expectations of uptake of various types of hydrogen technologies and the costs of the different types of hydrogen manufactured (blue, electrolysed).

While not explored in detail for this particular review, it would be important to ensure that the full range of operating assumptions of hydrogen electrolysers, including inflexibly operating electrolysers, is considered. This may have significant implications of the forecasting of system peak demand moving forward in the next 10+ years, as more green or electrolysed hydrogen is produced for industrial use and the costs of producing green hydrogen are expected to drop significantly, potentially below that of blue hydrogen.

Flexibly operated hydrogen electrolysers may be able to adjust their operation timing to avoid peak demand periods, effectively avoiding adding to peak demand, and conversely would be able to operate during times of excess electricity supply to avoid the need for the curtailment of intermittent generation assets during times of low demand. However inflexibly operating electrolysers (that might be required to do so for industrial hydrogen production) may add to peak demand. Further study into the expected trajectory of growth for flexible and inflexible hydrogen electrolysers in GB is required to be able to forecast their contribution to peak demand.

6. Discussion – areas for further study

Based on a review of literature and NGESO's current long-term peak demand forecasting methodology, as well as Aurora's own red flags and suggestions for consideration, the following areas for additional, in-depth, consideration are proposed.

6.1 Drivers

- **Weather** – To fully understand the impact of weather on future peak demand, Aurora considers further investigation is needed to fully understand the potential implications extreme climate change could have on temperatures in Great Britain, including both on maximum summer temperatures and minimum winter temperatures as well as the probability, frequency and magnitude of extreme weather events in the long term. Consideration would then need to be given to the extent to which these temperatures maximum and minimums could be expected to influence peak electricity demand in the country, considering the likely uptake of the electrification of heating and the potential for increases in air-conditioning to usage to drive summer demand peaks. However, the impact of weather on other electricity demand, such as EV demand also needs further study, as literature reviewed suggest significant fluctuations in the amount of electricity required by an EV in the winter months as opposed to the summer months due to the operating efficiency of EV batteries at different temperatures, and heating/cooling requirements (of both the cabin, but also the battery itself) in the cooler/warmer months (Koncar & Bayram 2021).
- **Decarbonisation policy** – In order to meet the CCC's targets of reducing emissions by 78% compared to 1990 levels across all sections of the economy by 2035, significant electrification of the transport, heating and industrial sectors will be required. This is recognised across the literature and by NGESO as a major driver of future electricity demand. However, Aurora considers the actual uptake of EV's and heat pumps is also likely to be policy driven. When considering other electricity usage, other factors such as future energy efficiency targets and housing policies, may also be important factors to consider.
- **Socioeconomic factors** – many papers reviewed highlighted the link between socioeconomic factors (population, income, industrial productivity) and long-term electricity demand, which is a

dimension currently not modelled in detail in NGESO's existing demand forecasting methodology. It may therefore be necessary to study in more detail the extent of the correlation of socioeconomic factors with electricity demand, particularly where this may impact the uptake of new technologies, to determine which socioeconomic factors could be usefully incorporated into long-term peak electricity forecasting for GB moving forward.

- **Demand shifting**– these are currently modelled by NGESO only to the extent of economic decision-making in certain models that feed data into the AEDAS model (e.g. the heat model). However, the literature review conducted reveals that changing social behaviours do have the potential to materially impact electricity demand, suggesting the need for further study to determine the magnitude of impact they have on electricity demand alongside a determination of how these behaviours are projected to change moving forward in terms of appliance usage, transport usage, and times of use as a result of an increasing rate of adoption of smart appliances, heat pumps and vehicles. A final consideration is of how the introduction of half-hourly retail pricing could impact consumers' electricity use, something which would need further study and modelling in order to understand how prices may potentially affect residential user behaviour. The adoption of heat pumps in residential space heating has the potential to change user behaviour to also consume electricity in large amounts during summer months (when currently this is not a contributing factor to demand due to the low penetration of air-conditioning in GB homes).
- **Other demand considerations** – the current review has focused on demand drivers that are linked to transmission or end-user electricity demand in Great Britain. On top of this, it is important to also consider the potential impact of other sources of demand on peak electricity demand within the GB transmission system, and how this might impact network management needs going forward. Aurora believes some overlooked considerations here are:
    - The compounding effect of interconnector export demand on top of peak demand in GB, and how this may affect generation requirements within GB.
    - The potential increase in embedded/BTM generation and storage and its impact on peak transmission system demand.
    - The full potential impact of a future hydrogen economy, where significant proportions of demand could feasibly be shifted away from peak demand periods/high power price periods.
    - The impact of hydrogen deployment in heating could result in lower than predicted electrification of heating and therefore lower than expected temperature driven demand.
    - Major system shocks such as the impact of COVID-19 on electricity demand. Whilst the cause of a system shock may be difficult to predict, thought should be given as to whether major, mass, near-simultaneous, changes of behaviour ought to be considered.

6.2 Methodology

Whilst NGESO has relied on an ACS methodology to determine peak demand, given expected changes in weather due to climate change, alongside changing user behaviours, a detailed review of alternative modelling methodologies could facilitate the integration of suitable alternative methodologies with NGESO's existing methodology to ensure a more robust forecast moving forward. Additionally, alternative statistical methods could also be explored for better accuracy. Further study into the use of smart meter data for forecasting is also justified given the expected increase in smart meter usage in GB moving forward (across the residential, commercial and industrial sectors), which could enable purely statistical forecasting of peak electricity demand.

While the current methodology utilised by NGESO is robust in its bottom-up modelling, a number of assumptions require further review to determine whether improvements need to be made for better forecasting accuracy.

- Assumptions – current assumptions that could be challenged are:
    - The peak demand time assumption of 5-6pm
    - That peak demand occurs in the winter triad days
    - The trends for summer peak demand (and whether there is a point of intersection with peak winter demand in the long term)
    - The assumed value for transmission losses of 8% of residential, commercial and industrial demand – literature reviewed indicates a variation in losses by temperature and demand, which should be studied in further detail to ensure it is better capture in the current modelling methodology

The expected magnitude of change of future demand trends based on the key drivers identified is required to determine how the existing NGESO methodology can be improved upon. This will be explored further in Work Package 2 :

- Annual peak demand is made up of a combination of consumer behaviour & synchronisation, weather factors, socio-economic factors and policy
- Over the 5-, 10- and 30-year horizon, the factors driving changes in peak demand are likely to include behavioural change, technological advancement and uptake, fuel switching in heat and transport, policy and embedded generation buildout
- Peak demand is expected to be a combination of individual consumption components that align with the predominant synchronous factors

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