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# The increasing impact of weather on electricity supply and demand

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ABSTRACT

Wind and solar power have experienced rapid cost declines and are being deployed at scale. However, their output variability remains a key problem for managing electricity systems, and the implications of multi-day to multi-year variability are still poorly understood. As other energy-using sectors are electrified, the shape and variability of electricity demand will also change. We develop an open framework for quantifying the impacts of weather on electricity supply and demand using the Renewables.ninja and DESSTINEE models. We demonstrate this using a case study of Britain using National Grid's Two Degrees scenario forwards to 2030.

We find the British electricity system is rapidly moving into unprecedented territory, with peak demand rising above 70 GW due to electric heating, and intermittent renewable output exceeding demand as early as 2021. Hourly ramp-rates widen by 50% and year-to-year variability increases by 80%, showing why future power system studies must consider multiple years of data, and the influence of weather on both supply and demand. Our framework is globally applicable, and allows detailed scenarios of hourly electricity supply and demand to be explored using only limited input data such as annual quantities from government scenarios or broader energy systems models.



## 1. Introduction

There is wide agreement that greenhouse gas emissions from the energy sector must be reduced and eventually eliminated if climate change is to be limited to safe levels [1]. Renewable generation, in particular solar photovoltaics (PV) and wind, are now poised to take a key role in this energy system transition. Their costs have fallen substantially so that they are now competitive with fossil-fired generation in many parts of the world [2]. Global wind and solar capacity has grown from 80 to 790 GW between 2006 and 2016 [3]. This provides hope, as moving electricity generation to renewables, followed by electrification of other key sectors (notably heat and transport) is widely thought to be the most feasible way to rapidly reduce energy sector emissions [4,5]. While other options such as nuclear, carbon capture and storage (CCS) and biofuels were expected to play significant role, they are either no longer cost-competitive [3,6], or have failed to become market-ready [7]. However, wind and solar power are dependent on weather and thus variable (or intermittent), fluctuating at timescales ranging from minutes to hours to multiple days [8], as well as across years and decades [9,10]. To plan and manage the transition to high shares of renewable generation, it is imperative to better understand this variability and its impacts on the power system.

It is important to consider the range of weather conditions that affect both wind and solar power generation as well as electricity demand with a single, consistent dataset. We demonstrate a framework for quantifying these changes using open-source models and global open datasets, to maximise the ease of reproducibility. We demonstrate this using Britain as a case study, as the country is rapidly decarbonising its power system [11], has strong targets for renewables penetration, and has good availability of historic data spanning multiple decades.

The make-up of Britain's electricity has changed more in the last five years than in the 50 years from 1950 to 2000 [11,12]. This is a necessary first step in the transition to a clean energy future [13,14], but leads to many open questions on how to manage a highly-renewable power system [15]. Fig. 1 shows the supply mix simplified down to three distinct categories, and how weather-dependent renewables are anticipated to increase in importance.

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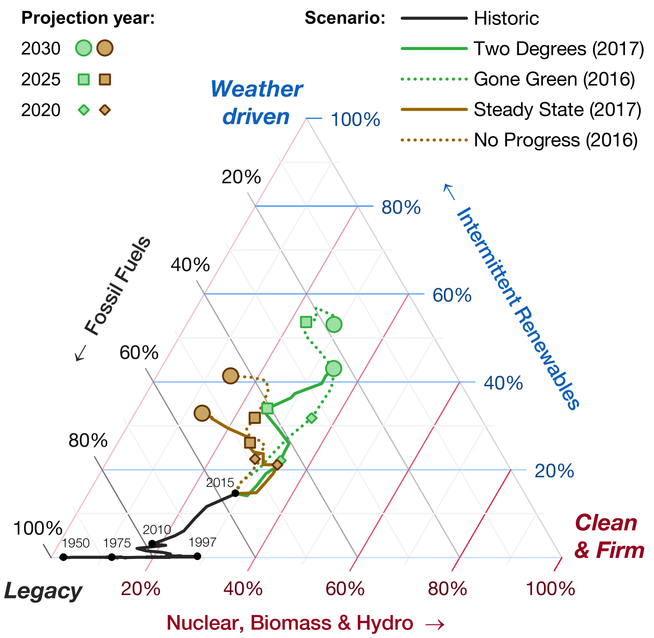


**Fig. 1.** Britain's electricity generation mix simplified to three categories. Historic data from 1950 to 2015 from BEIS[11] [18] and projections from 2015 to 2030 from National Grid's Future Energy Scenarios [16,17]. National Grid's least and most ambitious scenarios are shown; their other scenarios lie within this range. Intermittent Renewables consists of wind, solar and marine; fossil fuels include plants with carbon capture and storage (CCS).

Between 2010 and 2015, renewables more than quadrupled from 3% to 14% of the supply mix. National Grid's Future Energy Scenarios project that this share could quadruple again in the ten years to 2027, reaching 30–57% [16,17].

These recent changes have had profound impacts on demand net of renewables, as seen in Fig. 2. Electricity demand has been falling in the UK for several years, which is widely attributed to a combination of improving energy efficiency and the economic recession [19]. Net demand is now a quarter lower than its peak in 2005, bringing the amount of supply from 'conventional' generators back to levels not seen since the 1980s.

This paper considers how the future progression of these changes can be modelled at high temporal resolution using open data and models with global reproducibility. We develop a framework and use it to model the National Grid's Future Energy Scenarios forwards to 2030 to show how different and variable the British power system may become in little over a decade.

## 2. Background

The increasing deployment of both wind and PV across Europe means that power systems are becoming highly dependent on the weather. To better understand this impact, detailed modelling of wind and PV generation with high resolution in space and time is becoming increasingly important. This need is driving a convergence of the energy and meteorological research communities.

Recent work in the UK and Europe has used global reanalysis data to simulate wind power, for example, examining the correlation between generation across Europe [20] and developing validated generation time series for specific countries [21]. The Renewables.ninja platform uses a consistent method to simulate both wind [22] and PV power [23] with calibration, as does the European Commission's more recent EMHIRES project [24,25]. In the UK specifically, past studies have looked at the impact of large-scale atmospheric circulation patterns on wind farm output [26], analysed the decline in wind farm output as they age [27], and examined extreme wind power production statistics [28]. These studies are limited, however, in that they look at only one part of the power system in isolation, such as wind generation, without consideration of power demand and the technical and economic requirements of other generating technologies.

Energy and power system models, on the other hand, model an entire system and its interactions, and can thus determine the combined effect of different renewable generation options on metrics such as total system cost or on power prices. To keep pace with the growing importance of variable renewable generation, energy modellers have been moving from average annual or seasonal capacity factors to real time series data [29–31]. By doing so, models can capture correlations such as low wind output and low PV production occurring simultaneously. One common shortcoming of recent studies, however, is that they are limited to just a single year [32,33] or less than ten years [34–37]. This is primarily due to the increasing computational requirements of running what are typically complex optimisation models with ever larger datasets. However, it means that such work likely misrepresents the true extent of supply security and balancing concerns caused by longer-term weather variability, both in terms of accuracy to the 'true' long-term mean, and the range of conditions experienced.

Recent work is beginning to address this shortcoming. Bloomfield et al. [38] model a simplified British power system across several decades but only consider wind power, neglecting the increasingly important role of PV; Pfenninger [31] examines the inter-annual variability of both wind and PV over 25 years in a UK power system model. However, none of these studies consider the influence of weather on power demand. Using the British problem of the "cold calm spell" as an example [9,39], these studies would

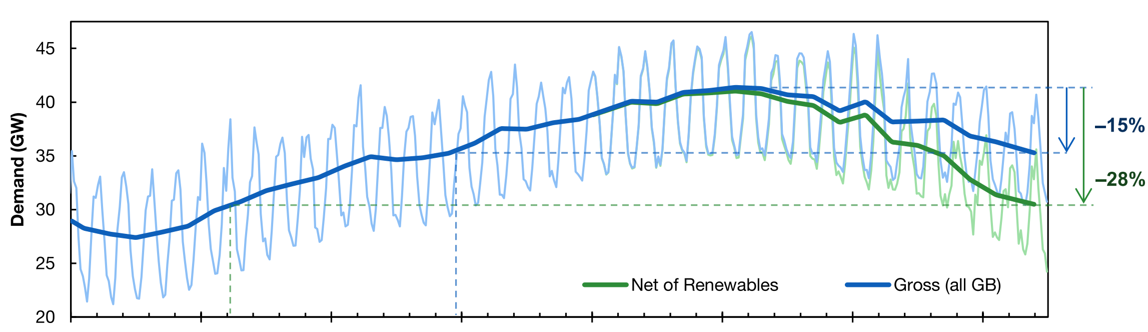


**Fig. 2.** Gross electricity demand in Britain and demand net of renewable generation (i.e. demand minus wind and solar output). Thin lines show monthly averages, thick lines show the 1-year rolling average.

identify the "calm" (due to low wind speeds), but miss the "cold" (and thus high electricity demand). While studies are now starting to analyse this in a retrospective fashion [40], power systems worldwide are undergoing a period of intense change, so it is unreasonable to expect that the future will continue to look like the past.

An important area that lacks attention is the potentially substantial change to the shape of future demand. Modelling future demand is a significant problem in itself: many studies which project future power demand neglect the possible changes to consumption patterns and simply scale existing profiles [41]. Past work has either projected future demand from single sectors or consumers [42–44], or has been limited to predicting individual features such as load duration curves [45,46] or peak load [16,47]. State-of-the art methods to generate more realistic future load profiles either apply trend extrapolation [48,49], model specific appliances and sectors [50–52], or focus on extreme events and the relationship between demand and temperature [53–55]. An extension is the full decomposition of demand into representative user groups within sectors, to generate new synthetic total demand profiles [41].

To summarise, past work on the influence of weather on power demand and production has either been limited by considering only part of the system over a long time period, or the system for a small sample of years. Furthermore, most studies have focussed on supply-side changes, neglecting the changing nature and shape of future demand. Here, we combine an analysis of the three key parts of the future power system affected by weather – wind generation, PV generation and demand – and do so for a period of 25 years with hourly data. This allows us to quantify the contribution of embedded generation to lowering net demand and the impact of weather on both power demand and supply over multiple decades, thus capturing a fuller range of weather events.

A final consideration that limits the enduring applicability of previous studies is their reluctance to use open-source models and provide open-access data. Transparency and reproducibility are of paramount importance for energy research given its impact on the long-term planning and design of systems that affect millions of consumers and influence the speed with which climate mitigation progresses [56–58]. In this study we explicitly use only open source tools, and our complete set of results is made available on www.renewables.ninja.

## 3. Methods

We develop a framework for modelling the impacts of weather on electricity supply and demand. This has four main requirements:

1) historic data on demand, temperatures, and output from renewable generators (for calibration);
2) a high-level scenario for the future evolution of the system (for projection);
3) modelling the hourly national demand using partial decomposition and time-series data on temperatures (holding constant societal factors such as economic activity, population, the mix of appliances and human behaviour);
4) modelling the output from wind and solar generators using contemporaneous time-series data on other weather variables (holding constant technical factors such as installed capacity, its location and vintage).

Using only historic data would mean the economic activity and technology mix of 2015 can only be studied with the weather of 2015. It is necessary to delineate the meteorological and societal factors to quantify the range of conditions that could have been experienced in 2015 if weather conditions had been different, and to explore how these conditions will evolve in future scenarios.

Demand is simulated using the DESSTINEE model [41],[2] which requires data on annual electricity consumption per sector, the mix of end-use technologies and temperatures. Wind and solar supply is modelled using the Renewables.ninja platform [22,23],[3] which requires data on the spatial distribution of installed generators, their characteristics, and historic weather data from reanalysis models. We use the Two Degrees scenario from National Grid's Future Energy Scenarios to drive our future projections [16].

Together, this framework captures four key factors influencing demand: demand for electric heating due to variation in temperature; changes in technology mix for heat and transport; other sectoral changes such as efficiency improvement; and changing weather from year to year. It also captures technological changes on the supply side: the increase of installed wind and solar capacity; the changing population of wind farms (e.g. moving further offshore); and technology improvements. The framework does not capture changing weather patterns due to climate change, treating weather of the past as being representative of weather in the future. Studies show limited or no change in either wind [59–61] or solar [10,62] resources over the coming 50 years. Similarly, we do not capture weather conditions that are outside of the near-term history (e.g. 1 in 100 year events), and would instead require synthetic weather generators, or datasets with longer historical weather record which are beginning to emerge.

Fig. 3 summarises the framework we present, with the data sources and models employed, and the links between these needed to create the results.

We use Britain as a case study, but the method and tools can equally be applied in other countries to analyse the risks and challenges that increasing the weather-dependence of electricity supply and demand will cause. The case study covers 25 years from 1991 to 2015, as that is the period for which historic half-hourly demand data exists.

Our modelling, and many of the results in the following section, was divided into three phases:

1) Historic: a retrospective study of 2005–15 using contemporaneous weather data and annual sectoral demands to validate and calibrate the models;
2) Contemporary: simulating 2015 with all years of weather data (from 1991 to 2015) to hold the economic, behavioural and technological factors constant and look at the impacts of weather on present-day supply and demand.
3) Future: using National Grid's projections for 2020, 2025 and 2030 with all years of weather data to investigate the impacts of the British electricity system becoming more weather dependent in the near- and mid-future.

### 3.1. Historic demand data

Half-hourly data from 1991 to 2015 was successively gathered over the last two decades from National Grid, most recently from Ref. [63]. The measure of national consumption (labelled as INDO and more recently ND) was used, which excludes hydro storage

[1] The UK government's Department for Business, Energy & Industrial Strategy.

[2] Demand for Energy Services, Supply and Transmission of Electricity in Europe. https://wiki.openmod-initiative.org/index.php?title=DESSTinEE.

[3] https://renewables.ninja.

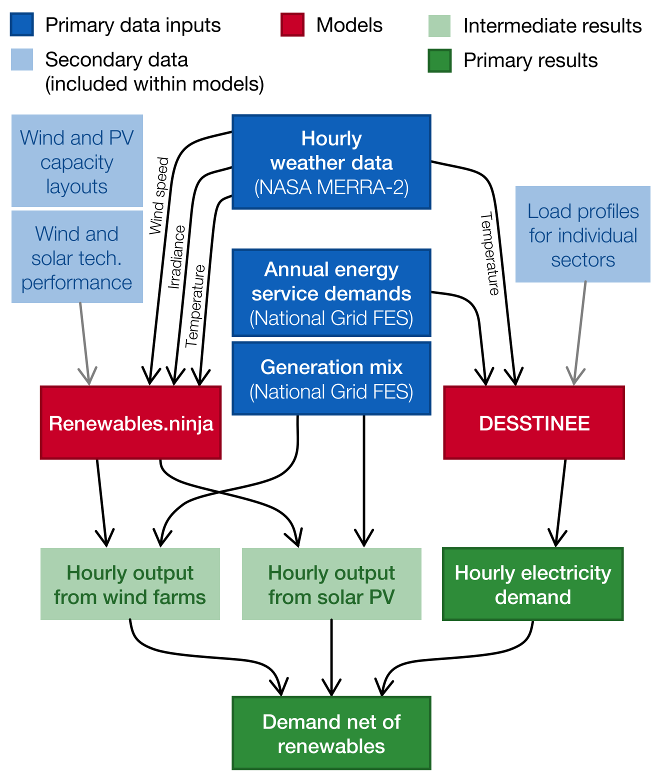


**Fig. 3.** Schematic of the framework used to assess the impact of weather variability on electricity supply and demand using free and open data and tools.

pumping and exports. Around 2 days of data were missing per year on average, and these were inferred from the other variables given by National Grid, as detailed in Ref. [11].

During this 25-year period the British electricity system has been organised as the Electricity Pool and NETA[4] which covered only England & Wales, and then BETTA[5] from 2001 which added Scotland to cover the whole of Great Britain (GB) [64]. Prior to 2001, demand for GB is not available, and so was regressed from demand in England and Wales (excluding Scotland) using data from 2001 to 12 where both England & Wales and whole-GB demand was available. Full details of this regression are given in the Supplementary Material.

### 3.2. Temperature data

An hourly time series of national average temperature was created using the T2M variable (temperature at 2 m above ground) from the MERRA-2[6] reanalysis [65]. This was extracted for all grid points within the British mainland, implying around 100 locations on a rectangular grid of 0.5° latitude by 0.625° longitude. For each hour, the temperatures at these points were averaged, weighted by the population density surrounding each point to create an appropriate measure for the influence of temperature on building energy consumption. The Gridded Population of the World (GPWv4) [66] dataset was used, and aggregated to the MERRA-2 grid using the Raster package in R.

This method was used in preference to local ground-based observations because of MERRA's global coverage, reducing the barrier to translating this research to other world regions. To verify the validity of this method, we compared the resulting national time-series to the daily average temperatures from the HadCET[7] dataset [67]. Our whole-GB daily averages are $0.7 \pm 0.3$ °C colder than HadCET, with a slightly larger discrepancy in winter than in summer, and no statistically significant long-term trend across the 25 years. This can be explained by the difference in scope – our data includes the colder regions of northern England and Scotland, whereas HadCET focusses on central and southern England.

Fig. 4 plots the average temperature across each day of the year, with the variability seen across the 25 weather years. The average temperature in December ranges from −0.1 to 7.6 °C ($10^{th}$–$90^{th}$ percentile), while July temperatures have a narrower range from 13.6 to 18.9 °C.

### 3.3. Future scenario

To model the future composition of electricity demand and supply we use National Grid's Two Degrees scenario, which represents a prosperous and sustainable pathway for the UK [16]. Fig. 5 charts the evolution of annual electricity demand, highlighting the electrification of heat and transport. At present, 7% of British homes (~1.8 million) are electrically heated, with 60,000 using heat pumps. The number of plug-in vehicles in the UK reached 120,000 in 2017 and these now represent 2% of new car registrations [68], as the dramatic fall in the cost of batteries has made them more affordable [69]. The scenario sees very rapid expansion in both sectors, promoted with government support schemes to kick-start the decarbonisation of heat and transport. Installed numbers are projected to more than double every year until 2030.

### 3.4. Modelling demand

We synthesise demand profiles for current and future years using DESSTINEE (Demand for Energy Services, Supply and Transmission in EuropE), a model of the European energy sector to 2050. This converts demand for energy services into hourly profiles of demand through a partial decomposition approach. It is described further in Ref. [41], and is available as a set of open-source Microsoft Excel spreadsheets.[8]

The time series of demand for a given day of year ($d$) and hour of day ($h$) is calculated for each sector ($s$) of the economy as the product of a 24-h diurnal profile for demand in that sector, a scale factor to account for weather and societal factors, and the overall energy consumption of that sector, as in equation (1):

$$demand_{d,h} = \sum_s profile_{s,d,h} \cdot scalar_{s,d} \cdot energy_s \quad (1)$$

Daily profiles of 24 periods are specified for each sector and end-use, with variants for summer/winter and weekday/weekend. The four profiles that define each sector are then assigned to each day of the year to create a 365 × 24 matrix ($profile_s$). Days of the year are classified based on whether they fall in summer or winter (defined by the use of British Summer Time or Greenwich Mean Time), and whether they are weekday or weekend. Half of electric vehicles are assumed to be charged after each drive (daytime and evening), and half use smart-charging (overnight).

The variable $scalar_{s,d}$ is a matrix of values that represents when holidays occur and the demand reduction seen during those days across each sector. In this implementation it contains values for common holidays (Easter, Christmas, New Years, and a triangular

[4] New Electricity Trading Arrangements.
[5] British Electricity Trading and Transmission Arrangements.
[6] Modern Era Retrospective-Analysis for Research and Applications.
[7] Hadley Centre Central England Temperature.
[8] https://wiki.openmod-initiative.org/index.php?title=DESSTinEE.

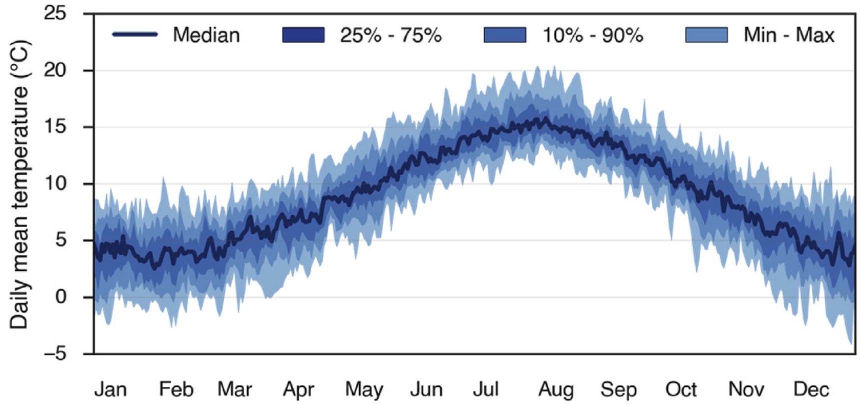


**Fig. 4.** Inter-annual variability of daily average British mainland temperature during 1991–2015.

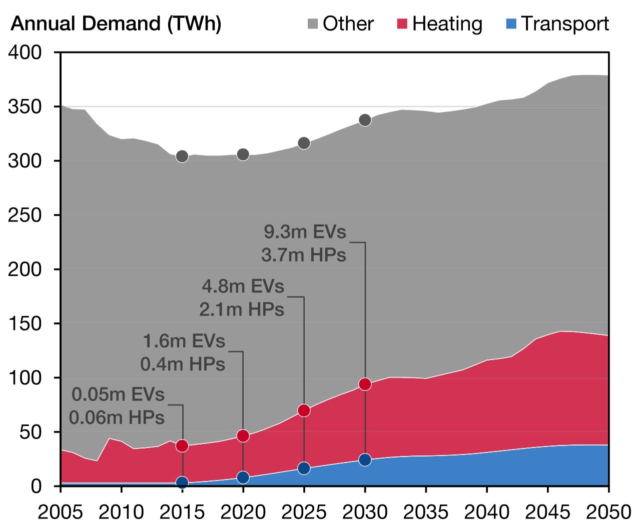


**Fig. 5.** Future annual electricity demand separated into end-uses. Projections are from National Grid's Two Degrees scenario [16]. Circles highlight the years we focus on in later results. For context, the number of pure-battery and plug-in hybrid electric vehicles (EVs) and residential heat pumps (HPs) is given for these years.

distribution through August (centred on August 16th)) to represent summer holidays. For heating and cooling end uses, $scalar_{s,d}$ also accounts for ambient temperature, using the normalised number of heating degree days, $HDD_d / \overline{HDD_d}$, or cooling degree days, $CDD_d / \overline{CDD_d}$. These are calculated with the temperature data from Section 3.2.

The variable $energy_s$ is defined by the annual demands for electricity from National Grid's Future Energy Scenarios (Section 3.3), broken down by sector (residential, commercial, agriculture, industrial, road and rail) and by end-use for building sectors (space heating, water heating, cooling, and all other appliances). The model generates annual profiles (8760 periods) for each sector, and then sums these together to give the national demand profile. To preserve the unique and anomalous features of historic load curves, the residuals between actual and simulated load from historic years are calculated, then scaled up and applied to the synthetic profiles as described in Ref. [41].

For validation, this modelling process was compared to National Grid's historic data for the years 2005–15, using our weather data for these years. Fig. 6 shows the diurnal profile in each season for three years of this sample, comparing the metered and modelled data. DESSTINEE captures the broad trends, particularly the difference in winter demand relative to other seasons, which varies between years due to temperatures. When synthesising Britain's demand for 2015, residuals were normally distributed with a standard deviation of ±1.9 GW (5.5% of the mean). These values are dominated by shape errors during spring and systematic errors on particular days (public holidays which are treated as regular weekdays, Christmas and New Year). When the residuals are added back the average error across the 11 years declines by 0.2–0.3 GW. More extensive validation can be found in the online Supplementary Material.

The results of this study are based on two sets of projections. A ‘snapshot’ scenario was created where individual weather years (1991–2015) were randomly assigned to future projection years (2016–2040) to give one potential realisation of future demand. A second ‘ensemble’ simulation was created, where selected scenario years (2015, 2020, 2025 and 2030) were simulated using each of the 25 weather years, to give an estimate of the long-run average behaviour.

### 3.5. Modelling renewable outputs

Historic wind and solar output from 2009 to 2015 was taken from Elexon's ‘FUELHH’ tables [70] and National Grid's embedded generation data [63], and are combined as in Ref. [11]. To simulate the output of the current and future installed renewable portfolio, we use the Renewables.ninja models described in Refs. [22,23]. This generates hourly time series from individual wind and solar farms, which are then aggregated up to national level. Historic weather data (specifically temperature, wind speeds and solar irradiance) are taken from the MERRA-2 reanalysis [65] for the years 1991–2015 to give a 25 year dataset of meteorological conditions.

A crystalline silicon solar PV system was modelled at each MERRA-2 grid point due to the lack of precise data on where each of Britain's 910,000 systems is located [71]. The orientation and inclination of each panel were drawn from normal distributions derived from observed metadata from PV installations in Europe, to represent the variability in the national fleet. The underlying parameters, and a mathematical description of the conversion from irradiance to power output are given in Ref. [23].

The 590 individual wind farms operating in Britain were modelled based on their location and characteristics such as turbine model and hub height. Missing metadata were inferred using multi-variate regression as described in Ref. [22]. For example, missing hub heights were estimated using the turbine capacity and year of installation. It is expected that wind capacity factors (and

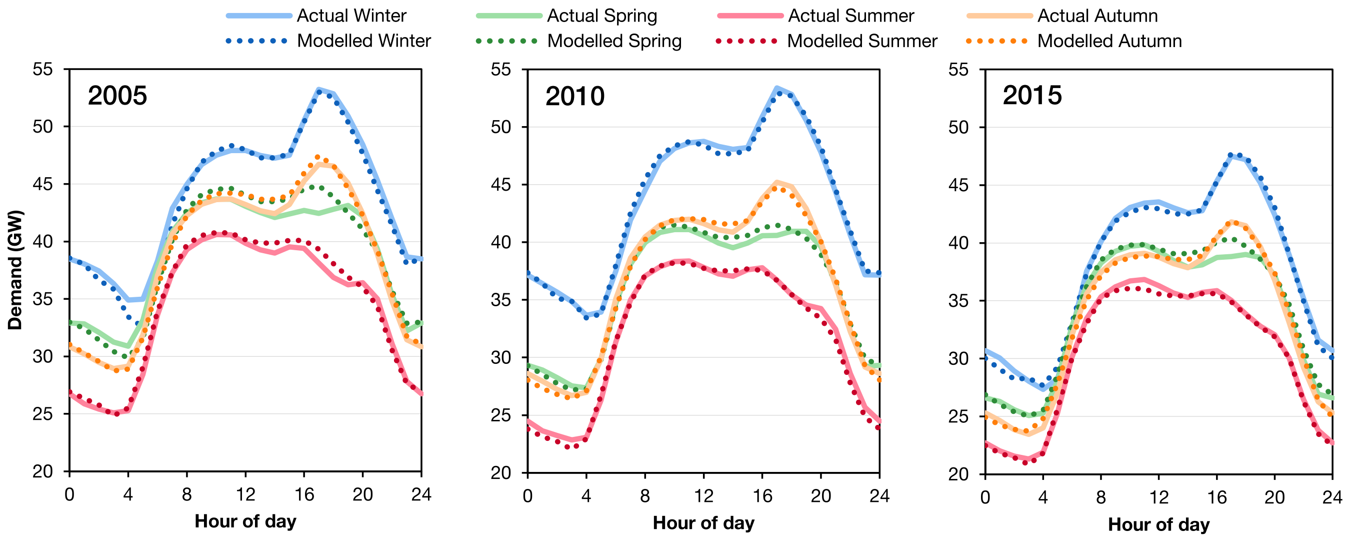


**Fig. 6.** The seasonal and diurnal profiles of demand in Britain, comparing the synthesised demand from DESSTINEE with historic data.

output patterns) will evolve over time due to the move towards larger machines predominately placed in deep offshore areas [22,72]. We model this using additional simulations of the wind farms which were under construction or in the planning pipeline as of December 2016, with onshore and offshore farms modelled separately. These fleets were called 'near-term' and 'long-term' in Ref. [22], but we use an updated dataset (running to the end of 2016 instead of 2014) which is available online.[9]

We took National Grid's projections of installed onshore and offshore capacity [16] for each year and allocated this to the three named fleets. The hourly profile of total wind output was then governed by the ratio of current, near-term and long-term capacity (both onshore and offshore). For a given future installed capacity of wind ($K$), the time-series of output ($P_{future,h}$) is determined from the simulated capacity factors ($CF$) as:

$$P_{future,t} = K_{current} \cdot CF_{current,t} + K_{near} \cdot CF_{near,t} + K_{long} \cdot CF_{long,t} \quad (2)$$

where the subscripts *current*, *near* and *long* refer to the three fleet simulations, and $t$ is time in hours (1 … 8760). Using offshore farms as an example, the capacity (in MW) associated to the current, near-term and long-term fleets was determined as:

$$K_{current} = 5100$$

$$K_{near} = max(K - K_{current}, 16000)$$

$$K_{long} = K - K_{current} - K_{near} \quad (3)$$

The capacity of the current fleet was held constant at 2016 levels (8050 MW onshore, 5100 MW offshore). Additional capacity was preferentially assigned to the near-term future fleet until reaching its capacity limit (1550 MW onshore, 16,000 MW offshore) was exhausted. Further new farms were assumed to be representative of the long-term future fleet.

A key advantage of this novel dataset is that its quality has been verified through extensive validation against historic measured power output data, so the resulting national CFs are improved through bias correction. In previous work, we find that Renewables.ninja can simulate the hourly capacity factors for the British wind fleet to an accuracy of ±4.5% (hourly root mean square error) with a correlation of $R^2 = 0.95$ [73], and hourly capacity factors for the British solar fleet to an accuracy of ±8.2% and a correlation of 0.83 [23]. Correction factors are required because of systematic bias in the input meteorological data, and the coarse spatial resolution of the MERRA-2 model preventing it from capturing local terrain effects such as airflow drag. Wind speeds were therefore reduced by 17% and solar irradiance by 2%, as detailed in Refs. [22,23].

## 4. Results

We first examine the changing level and shape of demand, followed by the variability of increasingly weather-dependent generation, before combining both to analyse demand net of wind and solar generation. Two important insights become evident. First, electrification of heating and transport causes not just the absolute level of demand to increase, but also its shape and variability to widen. Second, with the addition of PV and wind capacity, net demand will look fundamentally different by 2030, where we can expect to see net negative demand and substantial pressure on baseload nuclear generation.

### 4.1. Gross demand

Fig. 7 shows the seasonal variability in historic demand (shaded areas) and our future simulated demand for 2020, 2025 and 2030. The simulated mean demands in 2020 and 2025 remain within the historical range; however, by 2030 mean winter demand increases beyond the range of historically observed demand. The changing shape of the seasonal profile is of key importance – mean January demand increases by 9.4 GW relative to 2015 (24%), while summer demand remains effectively unchanged. This is due to the substantial projected increase in residential heat pumps (see Fig. 5). Mean peak demand increases in line with average demand, with the mean simulated January peak above 65 GW.

The increasing seasonality of gross demand is highlighted in Fig. 8. Historically, seasonal demands have changed in step with overall demand. However, our future projection shows increasingly divergent seasonal trends. Winter demand (and to a lesser extent

[9] European Wind and PV datasets v1.1: https://www.renewables.ninja/downloads/.

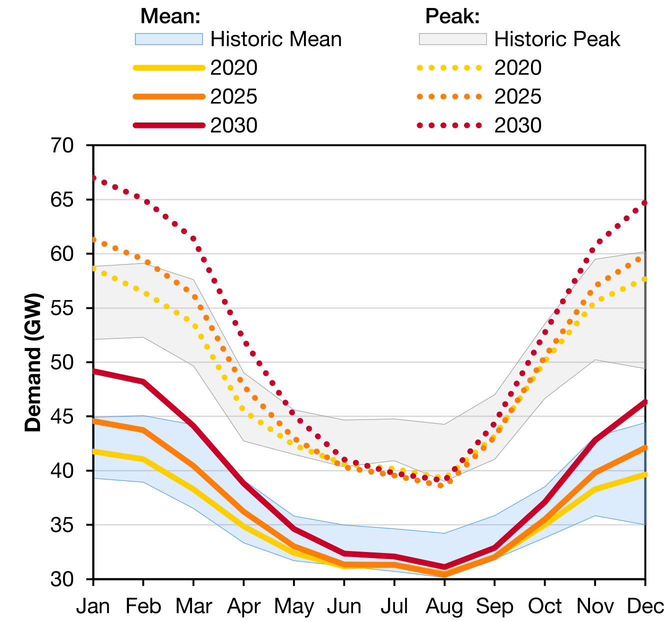


**Fig. 7.** The seasonal variation in historic and simulated future demand. Shaded areas show the historic range from 2005 to 15 while lines show simulations from three years averaged across all weather years. Dotted lines show peak demand within each month, solid lines show the mean.

autumn and spring demand) rises substantially, while summer demand remains flat. This increasing seasonal variability poses problems for power systems. Economic cycles and technological factors such as efficiency improvements over the last 20 years have made little change to the seasonal distribution of demand. However, with an increase in weather dependency of electricity demand due to electrification of space heating, seasonal weather emerges as an important factor. The increasing influence of weather is visible in the year-to-year changes in Fig. 8. Summer demand varies little from one year to the next, except during economic recessions. Other seasons vary more strongly due to temperature, with the average absolute year-to-year change increasing from 2.0 TWh in

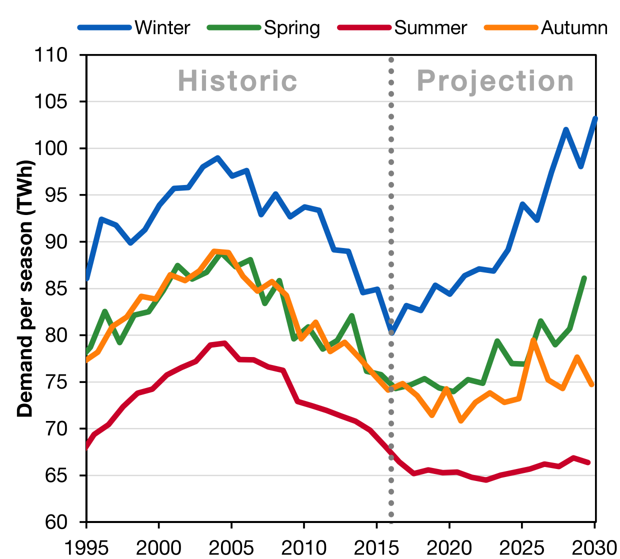


**Fig. 8.** Total electricity demand summed over each season, showing the historic evolution and projections up to 2030, using weather years randomly assigned to each projection year.

2015 to 3.6 TWh in 2030.

Fig. 9 shows mean daily demand and its variability across the 25 simulated weather years, for the current 2015 system and for 2030. Weekend demand is lower in general, so weekdays are plotted separately (along with the Christmas period of December 25th to January 1st). The seasonal trends outlined above are visible along with substantial year-to-year variability, particularly in winter when heating needs drive demand. This variability increases substantially by 2030, with demand on a January day ranging from below 40 GW to above 60 GW depending on the weather. For the same reason, the maximum expectation of daily peak demand is expected to widen from the range of 38–59 GW in 2015 to 38–72 GW in 2030.

### 4.2. Renewable output

Fig. 10 shows the daily mean capacity factor of our simulated PV and offshore wind fleets for Britain in 2030 (onshore wind is omitted as it exhibits similar variability to offshore wind). Visual comparison with Fig. 9 shows immediately obvious patterns: PV generates in summer, wind generates more equally throughout the year on average, with slightly higher output in winter. Nevertheless, the variability in both PV and wind output are substantial: a winter day can see capacity factors ranging from anywhere slightly above 0% to almost 100%. Both of these extremes are crucial for net demand: the variability of wind, with a higher installed capacity in 2030 (41 GW, versus 27 GW for PV) imposes stress on the rest of the power system, while PV generation falls short in winter, which is precisely when demand increases the most.

Fig. 11 shows the correlation between national wind and PV output for the simulated 2030 fleets, using daily mean generation across all 25 simulated weather years. To some degree, lower wind output coincides with higher PV output and vice versa. As a consequence, the combined generation from PV and wind is substantially lower than their combined capacity, reaching a peak of 40.65 GW (95th percentile of 31.83 GW) from a fleet with 68.3 GW of combined installed capacity. The scatterplot (which is summarised by hexagonal bins) shows two distinct trends. Summer is characterised by 4–6 GW of solar and 7.5–12.5 GW of wind output, whilst winter is by 0–1 GW of solar and 5–35 GW of wind.

### 4.3. Net demand

A crucial metric for the whole power system is not the individual elements considered thus far, but rather net demand – gross demand after subtracting weather-dependent PV and wind generation. The remaining net demand must be met by other generators, some of which have operational constraints that prevent them from rapidly adjusting output to fluctuations in net demand (i.e. nuclear reactors). Fig. 12 shows an overview of monthly average demand and its evolution since 1995, with our projections through to 2030. From 2005 on, we see a small fraction of total demand met by wind and solar generation, rising to 15% by 2015. This fraction becomes increasingly significant: 25% in 2020, 38% in 2025 and 44% in 2030. In 2030, the share of wind and solar averages 39% in winter and 48% in summer.

Error bars show the standard deviation across the 25 historical weather years. The monthly-average solar output does not vary from year to year. Gross demand begins to have noticeable variability in winter, but the main volatility comes from wind power. The difference between a good and bad year (defined as ±1 standard deviation) could mean an extra 8 GW of conventional generation needed over the course of January.

Net demand – the grey area in Fig. 12 – not only shrinks as renewable generation expands, but its variability also increases,

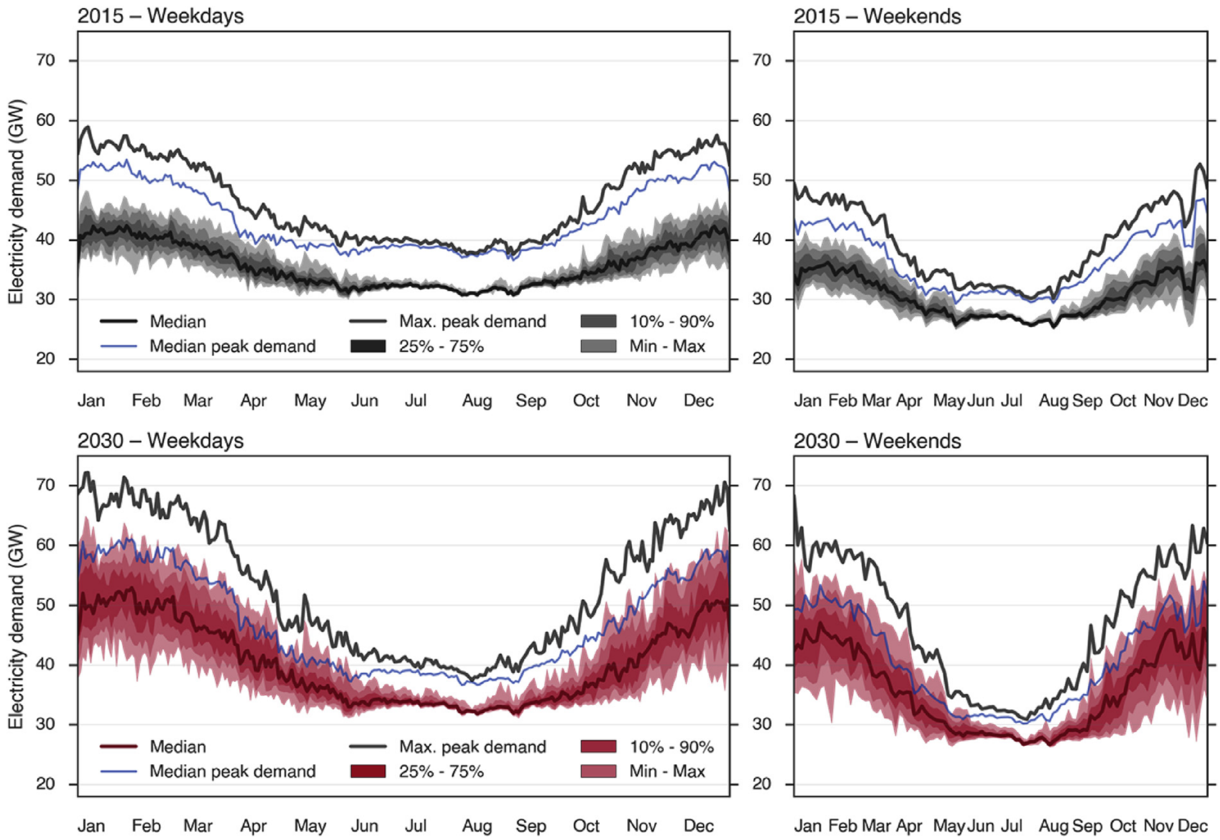


**Fig. 9.** The variability from year to year in gross electricity demand in 2015 (top) and 2030 (bottom) simulated across 25 weather years. The spread in each fan chart represents the expected frequency of occurrence based on weather from 1991 to 2015, while lines show peak demand on each day.

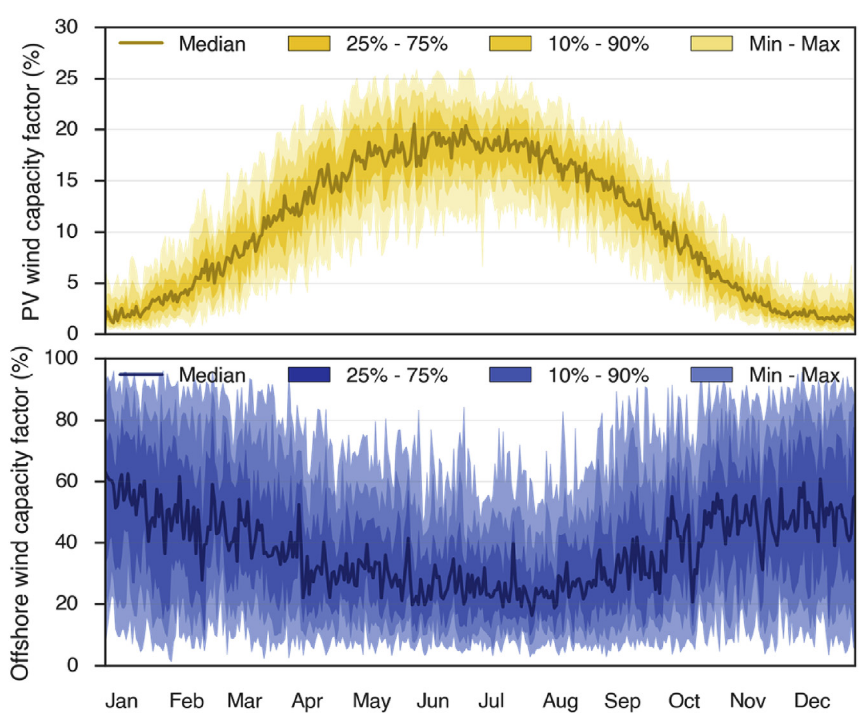


**Fig. 10.** Year-to-year variability of daily PV and offshore wind generation. The spread in each plot represents the expected frequency of occurrence over the period of 1991–2015.

even on the monthly scale shown here which smooths out the shorter-term variability. Net demand in the 2015 ensemble simulation averages 28.9 ± 1.1 GW (±4%), which changes to 26.6 ± 1.7 GW (±6%) in 2020, 22.9 ± 2.5 GW (±11%) in 2025 and

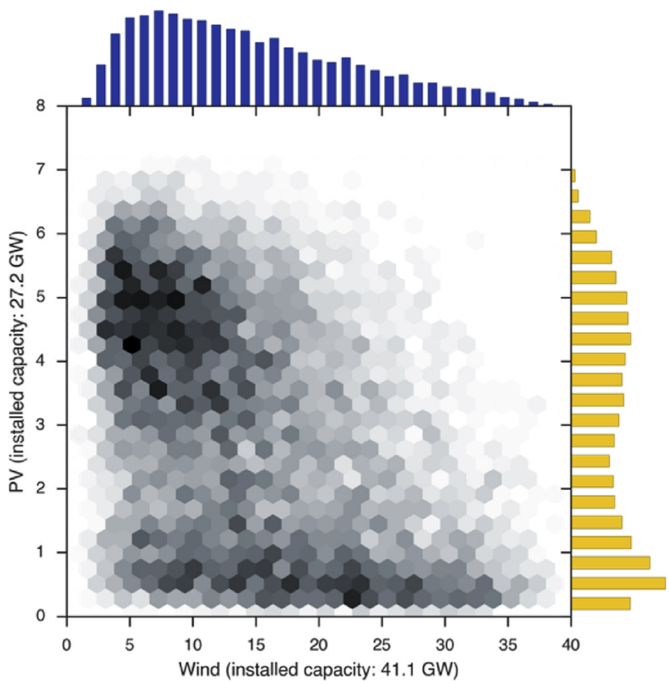


**Fig. 11.** The correlation between daily-average wind and solar output over 25 historical weather years, simulated with 2015 installed generation capacities.

22.2 ± 3.1 GW (±14%) in 2030.

Fig. 13 shows the average diurnal profile of demand in summer and winter based on historic data and future simulations with 25 years of weather conditions. The greatest changes can be seen in summer, as the coordinated output of a growing PV capacity reduces average summer daytime demand to below the levels seen overnight. Dotted lines in the figure show the profile for the 10th percentile for 2015 and 2030 (i.e. 1 in 10 days would lie below this). In 2030, overnight demand in winter and midday demand in summer would routinely fall to (or below) zero.

Fig. 14 shows the year-to-year variability of daily mean net demand, with the expected frequency of occurrence based on 25 years of historical weather conditions. The current situation (2015, top row) is eminently manageable; however, in just five years net demand on weekends in 2020 already starts to reach the region of firm nuclear generation (albeit with a low frequency of occurrence, of 1 day in 4 years). By 2025, nuclear capacity is lower as some existing reactors retire before new build is expected to be online; however, the situation worsens further with a frequency on weekends of 4.8 days/year. In addition, by 2025, weekends might see net negative demand – that is, overproduction by PV and wind generation alone, yet again with a low frequency of occurrence (1 day in 2 years).

In 2030 (bottom row of Fig. 14) we see such negative demand events both on weekdays and weekends, with higher expected frequency of occurrence – 1.1 and 3.4 days/year, respectively, and net demand hitting the baseload “floor” of nuclear becoming a regular occurrence: during the summer months, median net weekend demand is almost at the level of nuclear (24 days/year expected frequency of net demand below nuclear generation). This implies that on half of weekend days we would expect to see curtailment of either nuclear or renewable output unless there were sufficient expansion of storage, interconnection or demand-side response.

It is important to keep in mind that Fig. 14 show daily means. Hourly demand shows greater variation and will reach more challenging extremes. Fig. 14 shows the distribution of hourly net demand values for historic years, and using the 25 weather-year ensemble for the current, 2020, 2025 and 2030 scenarios. The lowest net demand observed in 2015 was 14.3 GW, and considering the range of weather conditions that Britain experiences it could be expected that 1 h per year could fall below 12.9 GW. Already by 2016 this minimum demand had fallen by 1.5 GW [11], and it is expected to continue falling to just 6.3 GW by 2020, and become negative beyond 2025, implying wind and solar output is higher than total national demand. At the other extreme, peak demand is expected increase gradually from 50.4 GW to 51.8 GW between 2015 and 2025 (across all weather-years, 2015 actual was 51.9 GW), before accelerating more rapidly after 2025 to 56 GW. Finally, the

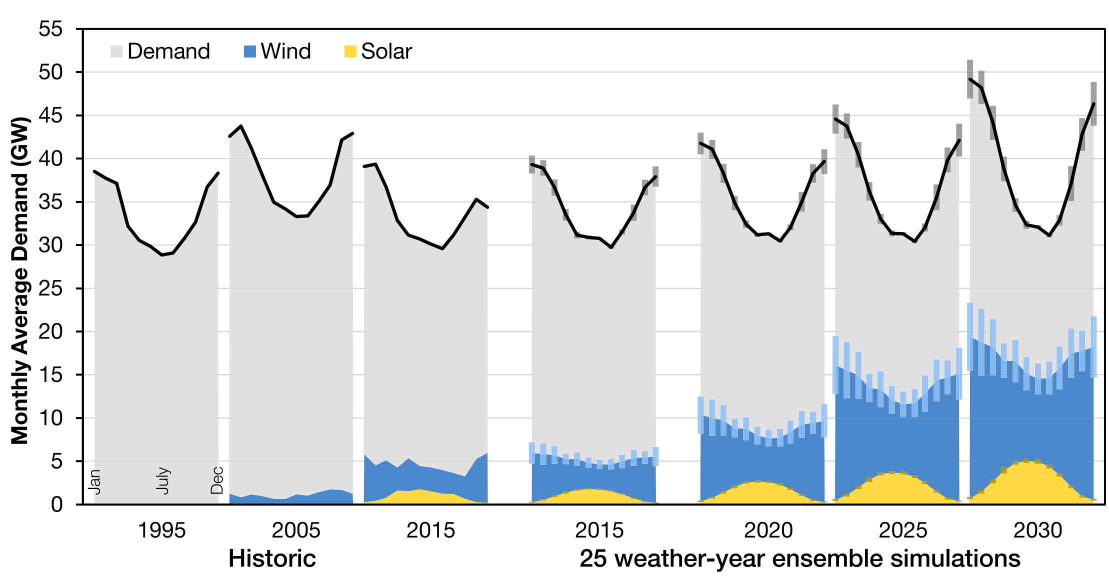


**Fig. 12.** The seasonal variation in demand and supply from wind and solar power. Each shaded area shows the monthly averages from January at the left edge through to December at the right edge. The left group shows historic data, the central bar shows 2015 simulated with the ensemble of all weather years (for comparison to 2015 historic), and right group show the future projections simulated across all weather years. For ensembles, the mean across all weather years is presented, with bars showing the standard deviation across them.

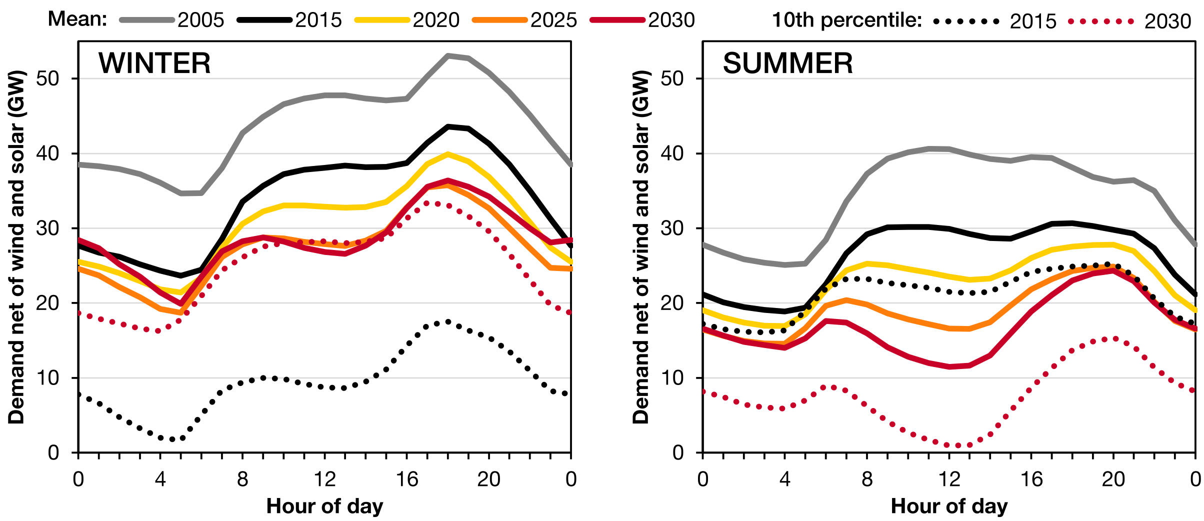


**Fig. 13.** Evolution of the average diurnal profile in January (left) and July (right) for demand net of renewables. Solid lines show the mean across all days in the month (and across all weather years for future ensemble simulations), while dotted lines show the tenth percentiles.

red lines in Fig. 14 show the extremes that occurred once in the 25 years of weather data. These are currently 4 GW lower and 7 GW higher than the expected values for any given year, and grow wider to 9 GW below and 12 GW above by 2030.

Ramping at hourly scales is an issue for the stable operation of Britain's future power system. Fig. 16 shows the distribution of one-hourly ramps in net demand in the current system, and for the 2020, 2025 and 2030 scenarios. The width of the frequency distribution increases – by 2030, ramps on the order of ±15 GW are possible, while ramps of lower magnitudes become more frequent. However, given that wind and PV generation are mostly uncorrelated (see Fig. 11), the widening of the spread is less severe than one might expect. Nevertheless, the increasing magnitude of ramps expected to occur once a year on average (top part of Fig. 16) must be considered in planning backup and storage capacity for the 2030 power system.

## 5. Discussion

The results shown in Figs. 14 and 15 suggest that perhaps the shorter one-hourly time scale is not as serious a problem, whereas the encroachment of daily mean net demand onto nuclear baseload – and eventually to the zero demand mark (Fig. 13) – foreshadow more difficult planning choices for the power systems in the years to come.

A naïve argument would be that Britain should therefore not aggressively decarbonise with renewable electricity and the electrification of other sectors. However, it is important to note that this paper represents the starting point of how a 'dumb' electricity system would respond: a 20th century system in which supply unthinkingly follows load, with no 'smart' system elements enabling demand to adapt to changes in supply. Our results therefore add to the body of evidence that justifies the need for new flexibility options to help balance and harness this output [74–76].

Interconnection, storage and load-shifting form the 'foundations of clean energy' proposed by King et al. [77]. Demand-side management from consumer appliances up to heavy industry, fleets of electric vehicles with coordinated charging, electricity and thermal storage could form a substantial resource for shifting demand, balancing renewables and reducing peak demand [78–80]. In their Two Degrees scenario, National Grid propose that by 2030, Britain could host 19 GW of interconnection, 9 GW of storage and 3 GW of demand-side response; a total of 30 GW of flexibility, up from 9 GW at present [16]. Similarly, the increasing deployment of heat pumps forms a critical component of projected demand changes; however, several factors influence their effect on demand. First, through combination with heat storage, heat pumps themselves could provide balancing by shifting their electric load to aid grid stability [81]. Second, their impact on demand is critically dependent on future improvements to both building thermal efficiency and heat pump efficiency. Best-in-class models deliver a coefficient of performance (COP) of 5.6, but the average across currently available pumps is a COP of just 3.25 [82]. Future research improving on our framework could focus on the untapped potential of a more coordinated deployment of better heat pump systems, and their use as flexibility providers.

Future work could further explore the instantaneous shares of flexible and inflexible demand across time, which may substantially change as electric heating and transportation allow flexibility through heat storage and optimised electric car charging patterns. In addition, our time series of demand is a static point-estimate. However, an understanding of how much demand could be shed for a given price, i.e., a dynamic price-dependent demand curve, is likely to become increasingly important with an increasing share of flexibility sources in the system. This would allow an economically realistic assessment of the potential for demand shifting to balance variable renewable generation in future work.

## 6. Conclusions

We build a framework to quantify the impacts of weather on electricity supply and demand, using the Renewables.ninja and DESSTINEE models, and demonstrate its application with a case study of Britain's power system through to 2030. This quantifies changes to shape and variability of electricity demand driven by electrification of heat and transportation; and to demand net of renewable output (which must be met by 'conventional' generators on the system) because of increasing generation from weather-dependent PV and wind generation. The framework explicitly accounts for correlations in space and time, for example the coincidences of cold and calm weather during winter and the anti-correlation between wind and solar output at seasonal and daily

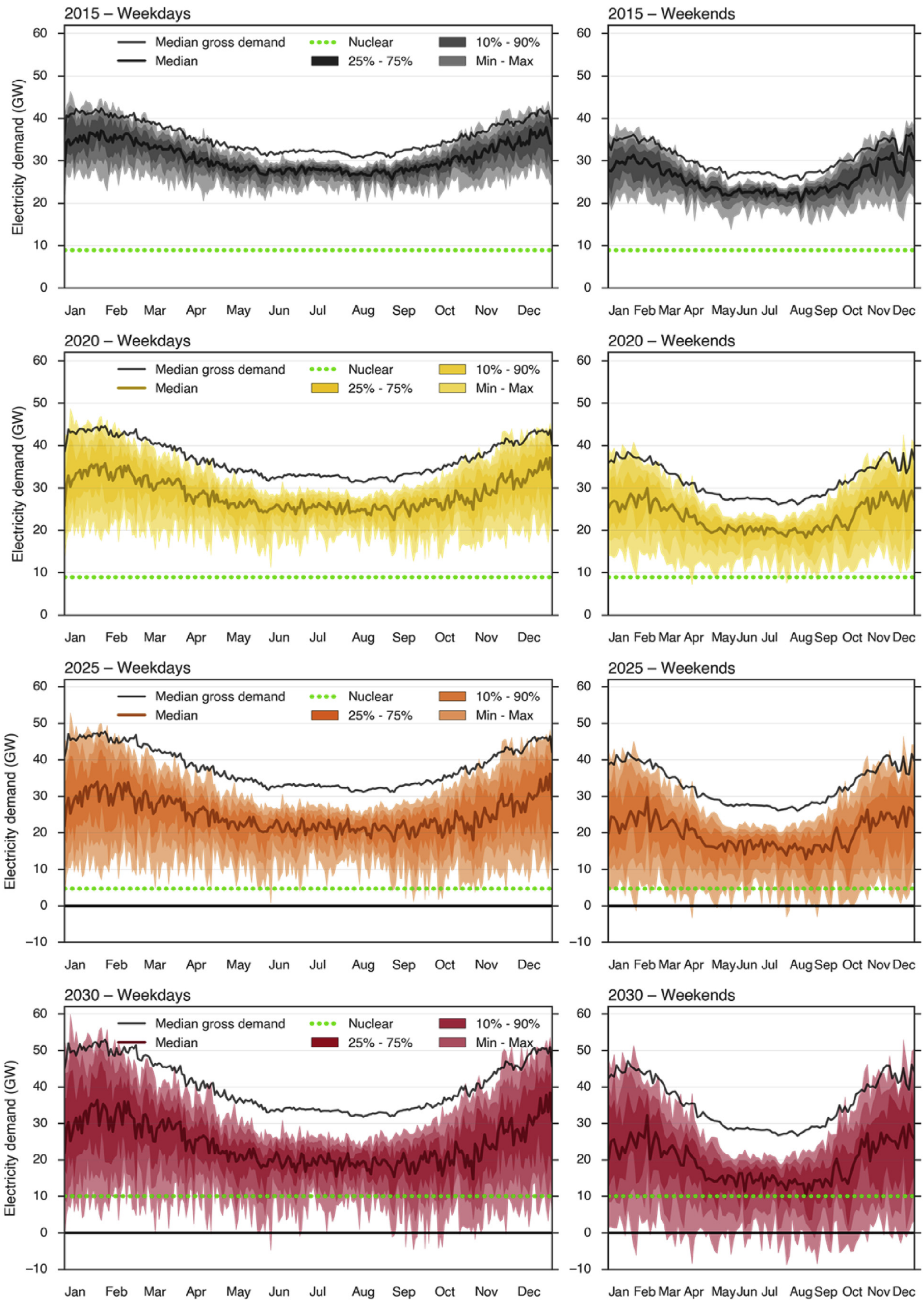


**Fig. 14.** Year-to-year variability of hourly average net demand across 25 historical weather years for the current (2015) system and the 2020, 2025 and 2030 scenarios. The green hatched area shows the capacity (and expected firm output) from nuclear generation based on National Grid's projection [16]. The spread in each plot represents the expected frequency of occurrence over the period of 1991–2015. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

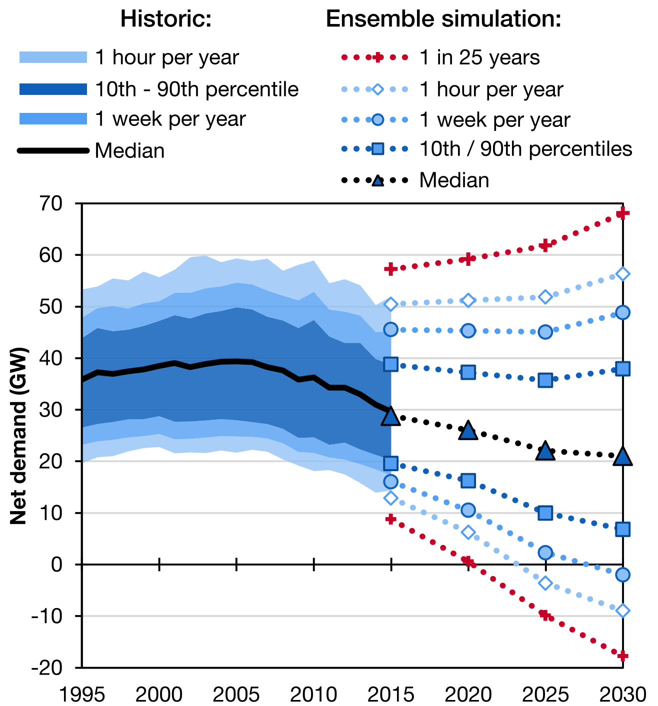


**Fig. 15.** The distribution and extremes of hourly demand net of wind and solar, historically and for the future ensemble simulations.

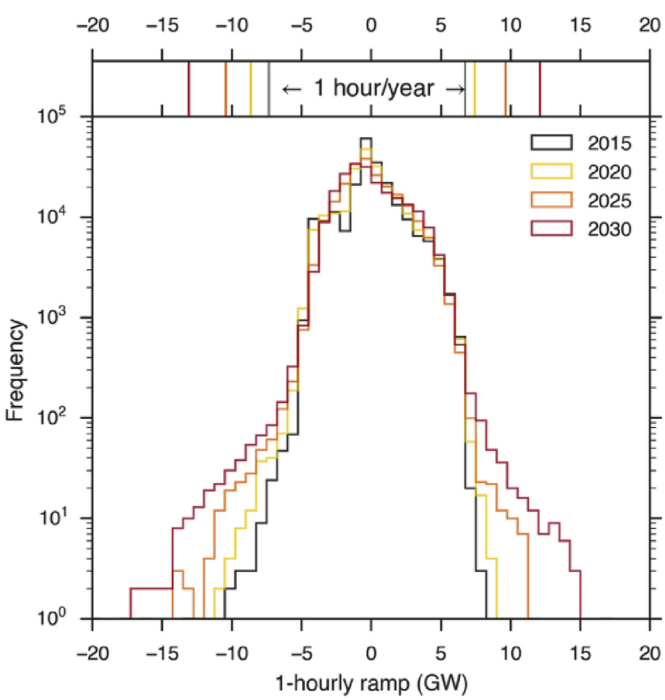


**Fig. 16.** The distribution of 1-hourly ramps in net demand across all 25 simulated weather years, for 2015, and for the 2020, 2025 and 2030 scenarios (bottom part), and the magnitude of 1-hourly ramps with an expected frequency of once per year (top part).

timescales [8].

We show that Britain's power system could swiftly move into unprecedented territory if it follows the rapid decarbonisation 'Two Degrees' pathway from National Grid. In this under-explored territory, net zero demand may occur on individual days as early as 2021, and become a common occurrence by 2030, with net demand reaching levels below the available firm nuclear generation capacity on most weekends. Peak demand will rise above 70 GW and hourly ramping rates will increase in both magnitude and their probability of occurrence.

We show that year-to-year variability of net electricity demand increases by 80% by 2030. This casts strong doubt on past energy scenario studies using a single or a small number of weather years. Using just one historical year is tantamount to drawing a single sample from a large population of widely-distributed weather years. If we had selected a single year rather than 25 historical years, we could expect metrics such as peak demand to be ±3% from the 'true' mean; minimum demand net of renewables to be ±13% away; and the number of hours per year with negative net demand ±23%.

An alternative is to use a mean weather year or typical meteorological year (TMY) in scenario and modelling studies, but this clearly removes extremes. Successfully dealing with extremes — such as steep ramps, peak and minimum demands, storage and balancing requirements over different time scales — is crucially important for the reliable operation of power systems. Our findings strongly suggest that other work must consider multiple years of data to cover this year-by-year variability and the influence of weather on both supply and demand, or be of limited significance and validity.

The exact numbers we present in this analysis are arguably of secondary interest. They are specific to the choice of scenario, assumptions made for the deployment of renewable generation, electric heating and transport, and the profiles for individual sectoral consumption. In other words, they are an exploration of just one of many possible futures. More relevant are the broad structural changes to the shape and scale of demand, which contain an important message to research and industry alike: demand changes cannot be ignored, and scaling up historic load profiles will yield potentially unacceptable errors. An important contribution of this paper is the intellectual framework for quantifying these changes, using freely and openly available models and datasets which future work can build on and further refine, both for Britain and any country or region undergoing rapid energy system transformation.

The framework we present here is globally applicable through our choice of models and data. The weather variability data come from the Renewables.ninja platform, which is based on global reanalysis data. The demand is modelled with DESTINEE, which is openly available and can easily be parametrised for use in any country using high-level energy scenarios and projections of future demand. By allowing the construction of synthetic scenarios of hourly electricity supply and demand, our approach enables new research applications to help ensure a reliable power supply as countries worldwide increasingly rely on weather-dependent wind and PV generation.

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## Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.energy.2017.12.051.

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