REASONABLE WORST-CASE STRESS-TEST SCENARIOS FOR THE UK ENERGY SECTOR IN THE CONTEXT OF THE CHANGING CLIMATE

A synthesis report developed for the UK Climate Change Committee

Hannah Bloomfield
Hannah.bloomfield@ncl.ac.uk

Executive Summary

The UK energy system is undergoing a rapid transition to achieve the government commitment of a decarbonised power system in Great Britain (GB), as well as support the legislated economy-wide carbon budgets and the Net Zero emissions target for 2050. This transition results in the electricity system having increased weather dependence due to both increasing renewable generation and the greater electrification of energy demand (through increased need for electric heating and transport). The inherent variability of weather, as well as the possible impacts of climate change, will widen the need for balancing electricity supply and demand.

The UK Climate Change Committee (CCC) considered the potential security of supply implications of challenging weather conditions in the 2023 report *Delivering a reliable decarbonised electricity system.* The CCC aims to build on this analysis for the purposes of the Seventh Carbon Budget (CB7) and the Fourth Climate Change Risk Assessment (CCRA4) by commissioning the development of stress tests for adverse weather. These stress tests can be inputted into power system models to explore the low-carbon flexibility needed to maintain security of supply in the face of these adverse conditions.

This report synthesises research into reasonable worst-case weather conditions for GB power generation. The research will support the CCC to set out how the future power system could achieve energy security across two dimensions: power system capacity and energy availability. To assess whether power system capacity is sufficient to meet peak demand, the analysis identifies *short duration events* in the weather data – the hours of highest demand and lowest renewable generation each year, largely occurring in winter. To assess whether there is sufficient available energy, the analysis identifies single years in the weather data where there is cumulative shortfall from total renewable generation in meeting demand, termed *long duration events*. The analysis also explores the potential for consecutive challenging years which we refer to as multi-year stress events.

The research explores how requirements for non-renewables generation might evolve over time across two dimensions: the changing energy system and the changing UK climate.

- To consider the first dimension, the analysis draws on three different power system scenarios, representing the expected systems in the present-day, the mid-2030s and 2050. These different scenarios set out how the power system is expected to change given the transition to Net Zero. For the first set of results presented in this report, historical meteorological data covering the period 1940-2022 is fed into models representing these different power system scenarios, to produce a set of scenario-specific synthetic time series of electricity demand and wind and solar photovoltaic power generation. These time series are combined to create a time series of demand-net-renewables, which shows the requirements for non-renewables generation, from which stressful periods can be extracted.
- For the second dimension, future climate projections from the UK Met Office (UKCP18) are fed into the models. This analysis enables the research to explore how large the impacts of climate change are compared to the impact of energy system expansion.

The analysis takes into account energy variables for 28 European countries, which is important when thinking about the potential for power to be provided from interconnectors at times of high demand.

The implications of the analysis in this report for stress-test scenarios and design of the future energy system, plus the implications of the impacts of climate change are discussed below:

Implications for stress tests

- Across the three assessed power system scenarios short duration stress events are driven by low-wind cold snaps. When historical years of weather data (from 1940 to 2022) are fed through a model calibrated to the present-day energy system, similar events to the cold years of 1963, 1987 and 2010 would pose the greatest challenges to the power system. The weather year that would cause the greatest challenge is dependent on whether the present day, mid-2030s or 2050 power system scenario is used.
- In the present-day, the mid-2030s and 2050 power system scenarios, a 2010 weather year is the most appropriate choice for a 1-in-50 year one year stress test. The historical weather years which contain some of the most severe short-duration events are not always the same as the year which has the largest cumulative shortfall from renewable generation. This highlights the need for dimensioning the system by using multiple stress tests.
- Multi-year long-term stress events are rarely seen (defined as the cumulative shortfall from annual renewable generation exceeding the 1-in-10 year return period consecutively). Examples of these are in the present day (1940-1941) and mid 2030's (1971-1972) scenarios. Although seeing consecutive years is rare, there are multiple decades with a handful of 1-in-10 year events in them (rather than the 1 we would expect by random chance). This emphasises the importance of using multi-decadal datasets to develop stress tests.

Implications for design of the future energy system

- The energy system will become more weather-sensitive over time, due to the electrification of the economy and the rapid increases in wind and solar generation. Despite large-scale increases in wind and solar capacity, there will likely remain periods of low renewables generation, which will require low-carbon flexibility solutions to manage.
- Overall, the amount of non-renewable energy the system needs to find (the difference between demand and renewable generation) will decrease in future power systems, given the expected expansion of renewables capacity. By 2050, there could be no overall shortfall in the available *annual* electrical energy production relative to demand even in 1-in-80 adverse weather year. The challenge is then to match supply with demand as they vary across the year as a whole.
- Increasing future spatial diversity in the GB wind fleet is expected to result in reductions in the peak annual hourly demand-net-renewables and in increases in renewable generation (as annual-mean wind power capacity factors increase from 40% to 50%). This increase in wind power output means there is more potential generation to contribute at times of highest system need. Without factoring this into future stress tests energy system back-up capacity could be overbuilt.
- While GB is experiencing its most extreme short-duration stress events, it is common for interconnected countries to also be experiencing times of high need. This should be accounted for when dimensioning the system, as power imports via interconnectors may not always be available to provide the required flexibility.

Implications of the impacts of climate change

- Our results based on the UKCP18 climate projections show climate change is expected to lead to a modest reduction in the intensity of both short-duration and long-duration extremes. Although an increase in global temperatures of 1.5 or 2 °C could result in a modest decline in summer wind power generation, this is more than counteracted by the expected decreases in electricity and gas demand due to warmer winter temperatures[1]. This results in a ~4 GW (~5%) reduction in the magnitude of short-duration stress events and a ~15 TWh reduction in the size of long-duration stress events in the 2050 scenario.

- The anticipated changes in energy system composition (namely, the electrification of the economy and increases in installed renewable generation) have a much larger impact on management of the future energy system than changes in near surface temperatures and wind speed expected under a changing climate. The historical weather years analysed in this research (the 83-year period extracted from the ERA5 reanalysis dataset) therefore have a good coverage of possible climate conditions the present-day and future power systems could experience. Caution is however required in that they do not cover every possible meteorological eventuality. For example, impacts of high-impact low-likelihood events resulting from climate change that are not captured in UKCP18 could have significant further implications but were out of scope for this study.

Our rapidly changing climate means it is of key importance that climate scientists continue to work with energy system modellers to develop best practices for stress testing highly weather-sensitive future power systems and this report continues to make progress towards this goal.

Contents

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[1] This report has not focussed on possible uptake of summer cooling demand through air-conditioning, which may impact the findings.

Introduction

The UK has committed to reaching Net Zero emissions by 2050 and decarbonising the electricity system, subject to security of supply. This will require a rapid transition of the electricity system to one with lower reliance on unabated fossil fuels and greater weather-dependent renewable generation (such as wind and solar power). This increased weather dependence adds a new set of challenges for balancing supply and demand due to the inherent variability of weather, increasing the need for investment in storage and flexible technologies.

As well as substantial changes in the composition of the UK energy system, the climate is also changing. In 2023, global average temperature exceeded preindustrial levels by over 1 degree (Copernicus, 2024). Further changes in the global and UK's climate by 2050 are inevitable as the world will take several decades, at the very least, to reach Net Zero emissions (IPCC, 2021). This will have significant impacts on energy system operation. For example, global warming may reduce winter heating demand but increase summer cooling demands. Increasing temperature may alter the large-scale circulation patterns and result in changes to wind and solar power generation. Although not considered in this report, as the climate warms, we expect to see increases in the frequency, intensity, and duration of many types of extreme weather phenomena such as heatwaves, droughts, wildfires, heavy rainfall, and flooding. This could lead to increasing amounts of damage to energy system assets.

The impact of weather variability and climate change on the UK energy system is a topic of current academic interest. The UK Climate Change Committee (CCC) considered the potential security of supply implications of a weather-dependent energy system in the 2023 report *Delivering a reliable decarbonised electricity system.* The CCC aims to build on this analysis for the purposes of the Seventh Carbon Budget (CB7).

For CB7, the energy system modelling analyses the future capacity mix and network grid reinforcement associated with the transition to Net Zero. The CCC is interested in developing weather stress tests which can be used to explore the low-carbon flexibility needed to maintain security of supply in the face of these adverse conditions. They are interested in two dimensions: the required non-renewable power generation capacity and the amount of energy required to be produced from low carbon, non-weather dependent sources, extracted from energy stores or imported.

This report synthesises research commissioned by the CCC into **reasonable worst case weather events for UK power generation**. The work characterises adverse weather for the power system out to 2050, focusing on times when demand exceeds the amount of power that can be supplied by renewables. The analysis accounts for expected changes in the energy system and climate conditions, based on a thorough review of the latest evidence base. The stress tests generated by this research can be used to inform CCC energy system modelling.

2. Approach

2.1 Overview of the methodology

At a high-level, the approach involves identifying periods of system stress from synthetic weather-dependent time series of electricity demand and wind and solar photovoltaic (PV) generation. There are separate time series developed for different power system scenarios, representing the expected systems in the present-day, the mid-2030s and 2050 (accounting for factors such as the percentage of electric heating and spatial distribution of wind farms). These time series are generated by inputting spatially disaggregated historical weather data into models for electricity demand and renewables generation. These models are parameterised using assumptions about how the energy system is expected to change in the future, which are consistent with the UK decarbonising the power system. The results of these models are combined to create a time series of demand-net-renewables, from which stressful periods can be identified. The analysis also explores how electricity demand and renewables generation is expected to change because of the changing UK climate, through analysis of the UK Climate Projections (UKCP18) dataset. Full details are given in Technical Appendices A1-A4 and similar versions of these methods are described in Bloomfield et al. (2022).

2.2 Definitions of ‘stress test events’

This report sets out three types of *stress test event*. These different types of event capture how adverse weather can impact the energy system across different timescales, from a few key hours to multiple years. All three types of stress test event should be considered in future energy system design. To understand the potential stress on the energy system, all stress tests are identified through analysing demand-net-renewables, which can be expressed as:

$$Demand\ net\ renewables(t) = Demand(t) - Wind\ Power(t) - Solar\ Power(t)$$

where t is the hourly timestep of the modelled UK-aggregate data. The events are defined as follows:

1. **Short-duration events.** These types of events can be used to understand how the system responds to relatively short periods of system *stress*. These short-duration events are defined as the hours of highest demand-net-renewables within each calendar year and allow for the exploration of if there is enough power generation, storage discharge and interconnector import capacity to meet peak demand. The severity of these events is defined as the shortfall of renewable generation relative to demand in each hour. Real-world challenges to GB electricity system operation are unlikely to be driven by a single short-duration event but indicate the required size of the system.

2. **One Year Challenge.** These longer events can be used to understand how large, if at all, the aggregate shortfall is between renewable generation and demand in each year. This shortfall must be supplied by non-renewable generation. In future energy systems this could include

hydrogen-fired power stations, fuelled by hydrogen generated by electrolysis during periods of surplus generation, other forms of long-duration storage and generation (e.g. nuclear, gas with carbon capture and storage), or interconnector imports. For this report, calendar years are used for the definition of the One Year Challenge, as this is commonly how power system models are run. However, this puts an artificial break in the meteorological winter. The impact of this design choice is explored in the Technical Appendix A5.

3. **Multi-year Challenge.** In future energy systems where there is a large amount of storage present, the One Year challenge events described above may become significantly easier to manage. It then becomes important to consider the ability for any large-scale storage to be charged over summer ready to respond to challenging events in winter, and the potential for sequential challenging years. The final type of stress test is therefore given as the multi-year challenge where the analysis considers years in which cumulative annual demand-net-renewables exceeds a 1-in-10 year return period for multiple years in a row, which could be periods where storage refill becomes a challenge.

For the short duration events and one year challenge, data is extracted for three return periods:

1. **1-in-10-year event**
2. **1-in-20-year event**
3. **1-in-50-year event**

These return periods were selected through considering existing security of supply regulation (where National Gas is required to meet the 1-in-20 peak aggregate daily demand), and the opinions of energy sector specialists (through a survey of 36 academic and industry experts). The uncertainty levels around these return period values of the stress tests will be quite high (particularly for the 1-in-50-year event), given the relatively limited number of years of weather data being used in this study for extreme event analysis. Future work could consider using a large climate model ensemble and techniques such as the UNSEEN approach (e.g. as demonstrated by Kay et al., 2023 for weekly wind power generation).

2.3 Identifying stress test events

The three types of stress tests described above are investigated to understand the impacts of:

1. Changing energy system composition
2. The impacts of climate variability on a chosen energy system
3. The impacts of climate change on a chosen energy system

Changing energy system composition

The stress test events are identified through analysis of weather-dependent demand, wind power and solar photovoltaic (PV) generation time series.

The UK energy system will evolve substantially by 2050 to meet the government Net Zero target. This includes substantial increases in the amount of renewable energy generation that is produced (particularly from wind power and solar PV) and the electrification of the heat and transport sectors to enable the transition from conventional fossil fuel to low carbon resources. The time series used to identify stressful periods have been developed using models which account for these expected changes in the UK energy system.

Three energy system scenarios are considered in this analysis representing the expected energy systems in present day, mid-2030s (referred to as 2035 for the remainder of the document) and

2050. The assumptions made (and links to the documentation where these are provided) are given in Table 1.

Table 1 A summary of the energy system assumptions for the project is given below with appropriate references. Throughout the report the results are colour-coded for each energy system type with present day, 2035 and 2050 in blue, purple and orange respectively.

Time period	**Present day (2021)**	**2035**	**2050**	References
Mean Demand, GW (total annual demand / TWh)	32.51 GW (285 TWh)	52 GW (458 TWh)	70 GW (612 TWh)	Fig 1.3 in Climate Change Committee. (2023). Fig 3.4.a in Climate Change Committee. (2020).
Onshore Wind Capacity (GW)	14.5	27.8	31.0	Fig 1.5 for 2035 data in Climate Change Committee. (2023) Table M5.1 in Climate Change Committee. (2020).
Offshore Wind Capacity (GW)	11.3	60.0	115.0	Fig 1.5 for 2035 data in Climate Change Committee. (2023) Table M5.1 in Climate Change Committee. (2020).
Solar Power Capacity (GW)	13.9	70.0	106.4	Fig 1.5 for 2035 data in Climate Change Committee. (2023) Table M5.1 in Climate Change Committee. (2020).

The impacts of climate variability

The impacts of weather variability are accounted for in this study through reviewing a large set of historical weather years, dating back to 1940. This data is extracted from ERA5, a reanalysis dataset,[2] which provides global hourly historical weather data (1940-present) on a ~30 km grid (Hersbach et al., 2020). Using this data allows for the assessment of multi-decadal climate variability.

The impacts of climate change

The impacts of climate change on weather-dependent stress tests are explored using data from the UKCP18 2.2 km local climate model projections. This climate model has projections for 1981-2080 with 12 ensemble members.[3] Ensembles are an important tool to explore a larger range of possible outcomes of climate variability and climate change, and to quantify uncertainty.

UKCP18 local projections are only available for a high global emissions scenario, whereas this analysis is interested in exploring a central global warming scenario. To overcome this challenge, consistent

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[2] A reanalysis is a comprehensive set of meteorological data created by combining historical observations with modern numerical weather prediction models. This provides a consistent and coherent picture of the Earth's atmosphere over a specified period, typically spanning several decades.

[3] An ensemble member refers to one of many simulations runs produced by a climate model with variations in the initial climate conditions, model parameterisations or configuration.

with the approach being taken in the Fourth Climate Change Risk Assessment CCRA4, (CCC, 2024), for each period being analysed (present day, mid-2030s, around 2050), the analysis takes 20-year time slices from each climate model ensemble member that corresponds to the expected global warming level. For the mid-2030s this relates to 1.5°C and in 2050 this is assumed to be 2°C. As there are 12 ensemble members and 20 years of data for each member, this means that for each period being analysed there are 240 weather years with which to consider climate variability.

3. Results

The results section proceeds as follows:

- Section 3.1 explains how weather contributes to system stress in the present-day UK power system;
- Section 3.2 considers how weather-related UK power system stress changes as the power system changes, without considering the additional impacts of climate change;
- Section 3.3 sets out the potential impact of climate change on weather-related UK power system stress;
- Section 3.4 highlights the challenges that can occur simultaneously in Europe during periods of high weather-related UK power system stress.

3.1: In the present day, energy system stress events are associated with low-wind cold snaps.

Figure 1 shows the distribution and severity of days that could be considered *short-duration events* [4] that would occur if the present-day electricity system experienced historical years of weather. These high demand-net-renewables days predominantly occur in winter, when the seasonal cycle of demand is highest. Short-duration events are slightly more common in the early period of the dataset (i.e. when winters were relatively colder than in recent years), but there are still a significant number of events throughout the whole period of 1940-present.

The most challenging short-duration event in the dataset is the weather the UK experienced on 27th December 1995 (see Figure 2). This was an extreme cold spell over the UK with temperatures reaching -20 Celsius in parts of Northern Scotland. This followed a storm passing on 24th December, which had resulted in high snowfall and damage to energy network infrastructure[5]. Accompanying the cold temperatures were periods of low wind. If the present-day energy system were to experience this weather, this would result in multiple days of high demand-net-renewables.

More generally, the energy system is stressed by a combination of cold temperatures and low winds in winter (a time when solar PV generation is generally low across the UK, see Figure 2). This has been noted in multiple past studies as the main meteorological driver of UK energy system stress (Sinden, 2007, Thornton et al., 2017, Bloomfield et a., 2018, Bloomfield et al., 2020).

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[4] In Figure 1 the data has been filtered to only show hours where demand-net-renewables is greater than the lowest annual-maximum demand-net renewables value from 1940-2022, indicating days where there may be system challenges.

[5] https://www.upi.com/Archives/1995/12/27/UKs-frigid-weather-continues/6882820040400/

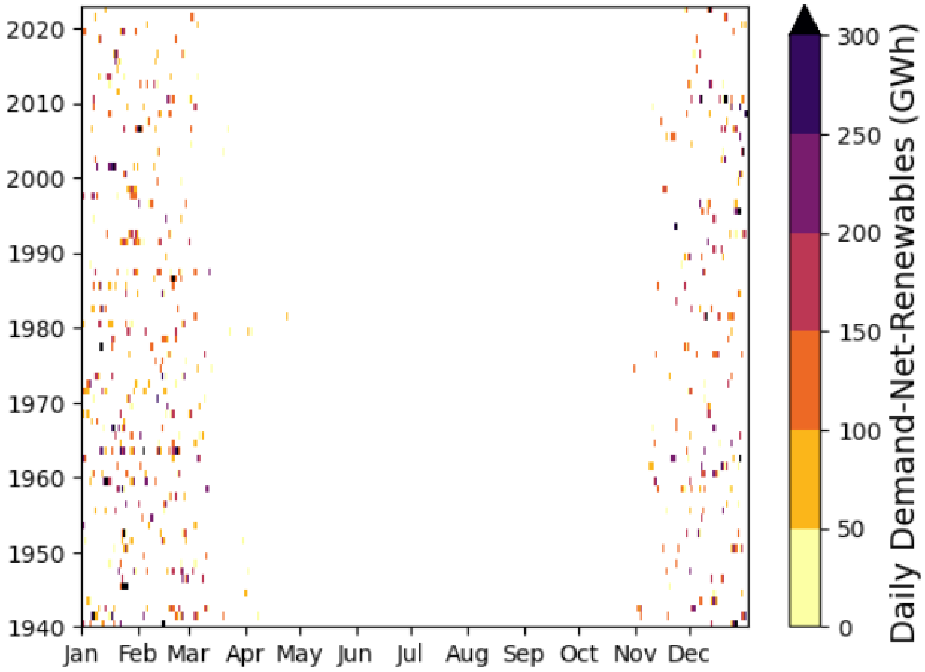

Figure 1 Occurrence of days which exceed the minimum annual short-duration stress event threshold (which occurred in 2017, see Appendix A6 for details) throughout the year (x-axis) and through time (y-axis) in the ERA5 reanalysis. The colours indicate total accumulated severity of the hourly events per day (in GWh) for days which exceed the threshold. The date marker represents the first day of each month (e.g., 'Jan' is the 1st January, 'Feb' is 1st February).

Figure 2 shows the time series of demand, renewables generation and demand-net-renewables that would occur if the present-day energy system experienced the December 1995 weather patterns which cause the largest short-duration stress event (see Appendix A6 for details of how the 1995 event compares to those from other years). It is clear from Figure 2 that these short-durations events often do not occur in isolation but may happen as sequences of hours or days over the course of a particularly cold month or season.

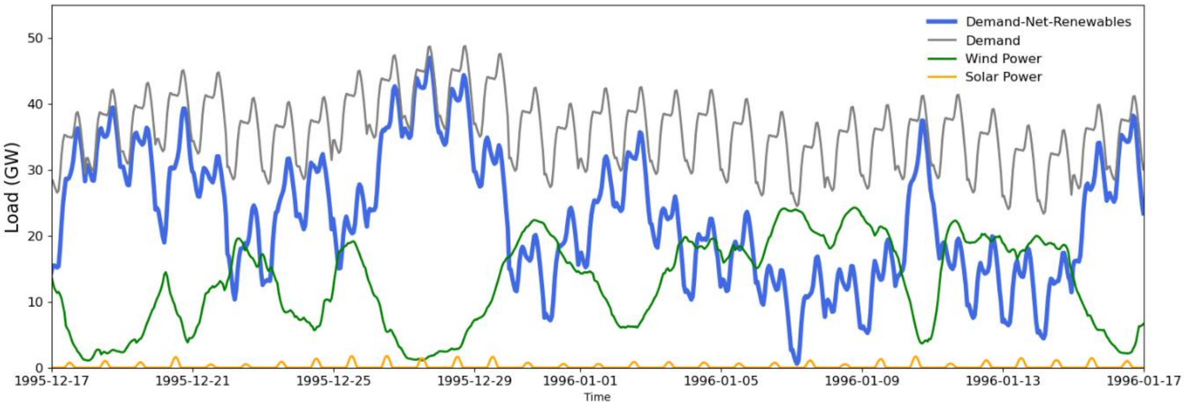

Figure 2 An example month-long period including the worst short-duration extreme event from the present-day power system scenario (27th December 1995). Demand, wind and solar PV generation during the event are provided for context as well as the Demand-Net-Renewables data.

For the One Year Challenge events, the total demand-net-renewables is aggregated over the year to give an annual total energy that is required to be met by alternative power generation, including energy storage. Figure 3 summarises these values for each of the historical weather years in the

1940-present period. Here, the years that particularly stand out in the recent period are 1987 and 2010 (with notable mentions for 1941, 1958, 1963). All these years experienced particularly cold winter periods, which in today's energy system would lead to persistently high demand, accompanied with low wind power generation.

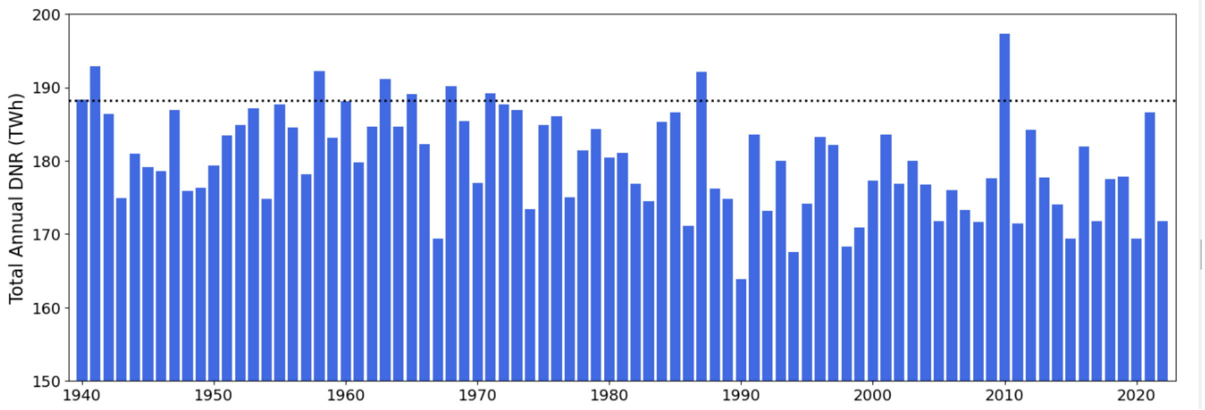

Figure 3 One year challenge values (total annual sum of demand-net-renewables) from 1940-2022 assuming a present day energy system scenario (see Table 1 for details). The black dashed line shows the 1-in-10 year return period level of the One Year Challenge metric.

As explained in Section 2, the reporting of results in calendar years was selected to make it easier to input data into energy system modelling. However, this approach splits the meteorological winter, which is where most stressful events occur. Technical Appendix A5 shows the results from Figure 3 for years running from June-May, which would be more appropriate for single year energy system simulations, particularly when considering future energy systems. Doing so changes the characterisation of the most stressful years (e.g. a relative reduction in the severity of 2010 and an increase in 1963), but this type of modelling is currently more challenging for power system model simulations conducted in the energy industry. If total annual demand-net-renewables is accumulated from June-May then other years such as 2009-10 or 1958-59 would become more appropriate (see Technical Appendix A5).

The third type of stress test event considers the risk of having multiple sequential years of relatively low renewables generation. The analysis considers whether there are any consecutive calendar years which experience high cumulative severity of adverse events (defined using the 1-in-10 year return period for the One Year Challenge, represented using the dotted line on Figure 3). This analysis shows that there is historical precedent for these events, notably the weather experienced in 1940-41. However, within decades (e.g. the 1960s) there are many years that exceed the 1-in-10 year return period, even if not consecutively.

Table 2 shows the years that would be picked to represent the three relevant return period levels from the ERA5 reanalysis period of 1940-2022. To identify these, return period curves have been calculated and the nearest year to the relevant return period level has been selected. With only 83 years of data there is uncertainty around these numbers; this is explored more in section 3.3 with UKCP18.

Table 2 Years selected to be appropriate for stress testing present day energy systems for two of the stress test metrics. Numbers in brackets represent the most relevant event from the most recent 40-year period of ERA5.

Present day energy system	**1-in-10 year**	**1-in-20 year**	**1-in-50-year**
Short duration stress test	1973 (2001)	2010	1945 (1995)
One Year Challenge	1965 (1985)	1987	1941 (2010)

3.2: Future UK energy systems will be more weather sensitive, and this will increase the duration and severity of the most extreme stress events that are faced.

This section summarises analysis on the impact of a changing energy system structure on the three types of stress events, using the same 83 years of historical weather data as in the previous section. This allows us to understand how changes to the energy system will impact the system's vulnerability to weather, before also considering the impacts of a changing UK climate.

Figure 4 summarises the impact of changing the energy system scenario for the short duration (top) and One Year Challenge stress tests (bottom). As can be seen in the top row of graphs, changes in the energy system are expected to lead to significant increases in peak hourly demand-net-renewables, with substantial volumes of non-renewables generation needed to meet peak demand. The average magnitude of the short-duration stress event increases from 42 GW in the present day scenario to 78 GW in 2035 and 106 GW in the 2050 power system scenario (see Tables 4 and 5 for details of the most challenging years at different return period thresholds).

Although there are increases in the magnitude of the short-duration events, there are decreases in the cumulative annual demand-net-renewables between the present-day and 2035 energy system scenarios. In the present-day energy system, the system operator needs to find ~200 TWh of non-renewable power generation to manage the most difficult year in the 80 year period (this is the worst One Year Challenge across the ERA5 dataset). In the energy system expected in 2035, the operator would only need to find ~90 TWh of non-renewable generation in the most challenging year, due to substantial expansion of the wind and solar generation portfolio (see Table 1). By 2050 the One Year challenge metric becomes negative, showing that renewable generation is exceeding demand on average throughout the year. However, there are still potentially periods of renewables shortfall relative to demand (as demonstrated by the increased magnitude of the short-duration events). If the excess renewable generation at times of low system stress (e.g. summer) could be stored, this could support meeting the times of peak demand. Sizing this storage is an ongoing challenge. These results highlight the need to consider these types of events in the design of future energy systems, to ensure sufficient storage and flexible generation capacity.

For the third type of stress event, the multi-year challenge is only relevant in the 2035 scenario (as in 2050 cumulative annual demand-net-renewables is negative). In the 2035 scenario the only period where consecutive years exceed the 1-in-10 year return period level for the annual challenge is 1971-72 (not shown). But again there are decades where multiple years exceed the 1-in-10 year return period threshold.

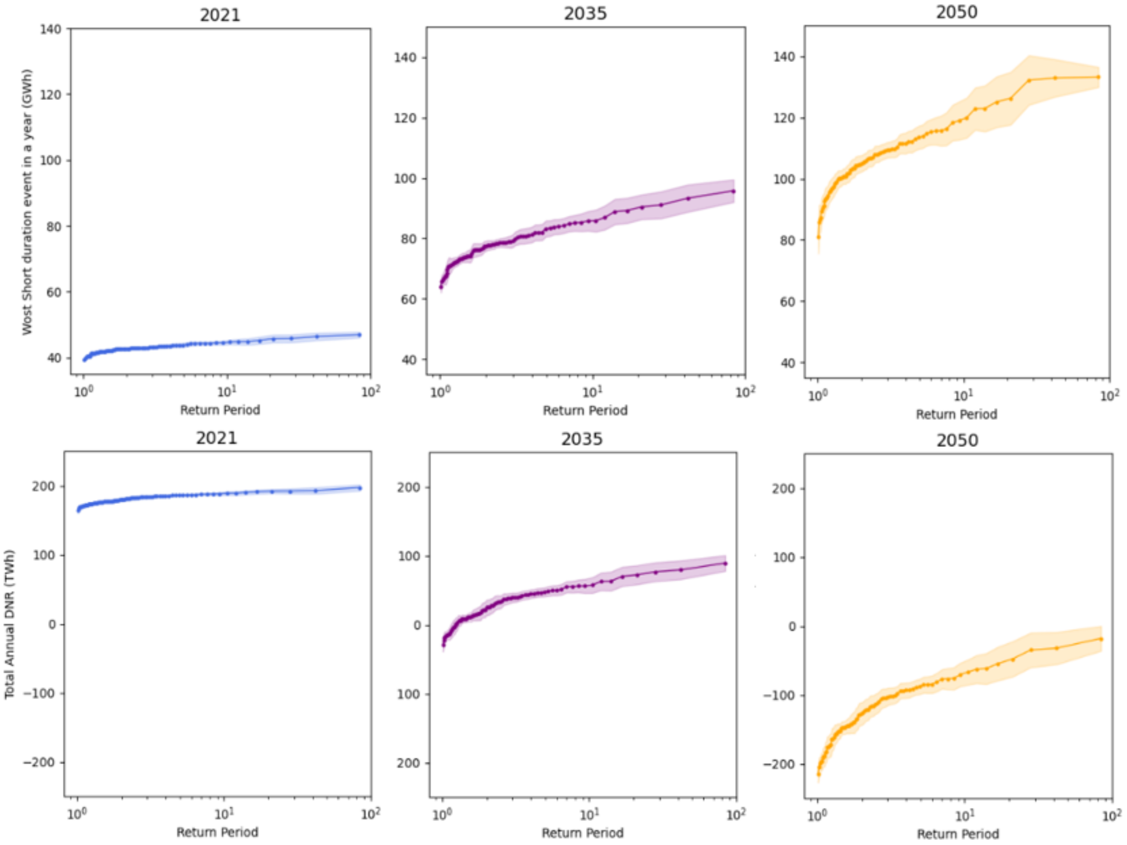

Figure 4 Return period for annual peak demand-net-renewables (short duration events, top) and Return period vs cumulative annual demand-net-renewables (The One Year Challenge, bottom for synthetic energy system data from the ERA5 reanalysis (1940-2022). Details of the 2021, 2035 and 2050 energy system scenarios are given in Table 1. Shaded areas represent the uncertainity within the 80-year sample used to create the return-period curves with 95% confidence intervals.

The increase in magnitude of the short duration stress events between the present-day energy systems and the energy systems expected in 2035 and 2050 is largely driven by the electrification of demand. This is demonstrated in Figure 5 which shows the demand and renewable generation for February 1963, a period where short-duration extremes are between the 1-in-10 year and the 1-in-20 year return period for all the power system scenarios. Although the diversification of the wind portfolio does lead to an increase in the average wind power generation at times of high demand the UK average wind generation can still drop below 10 GW (with capacity factors below 20%) particularly in the highest demand hours.

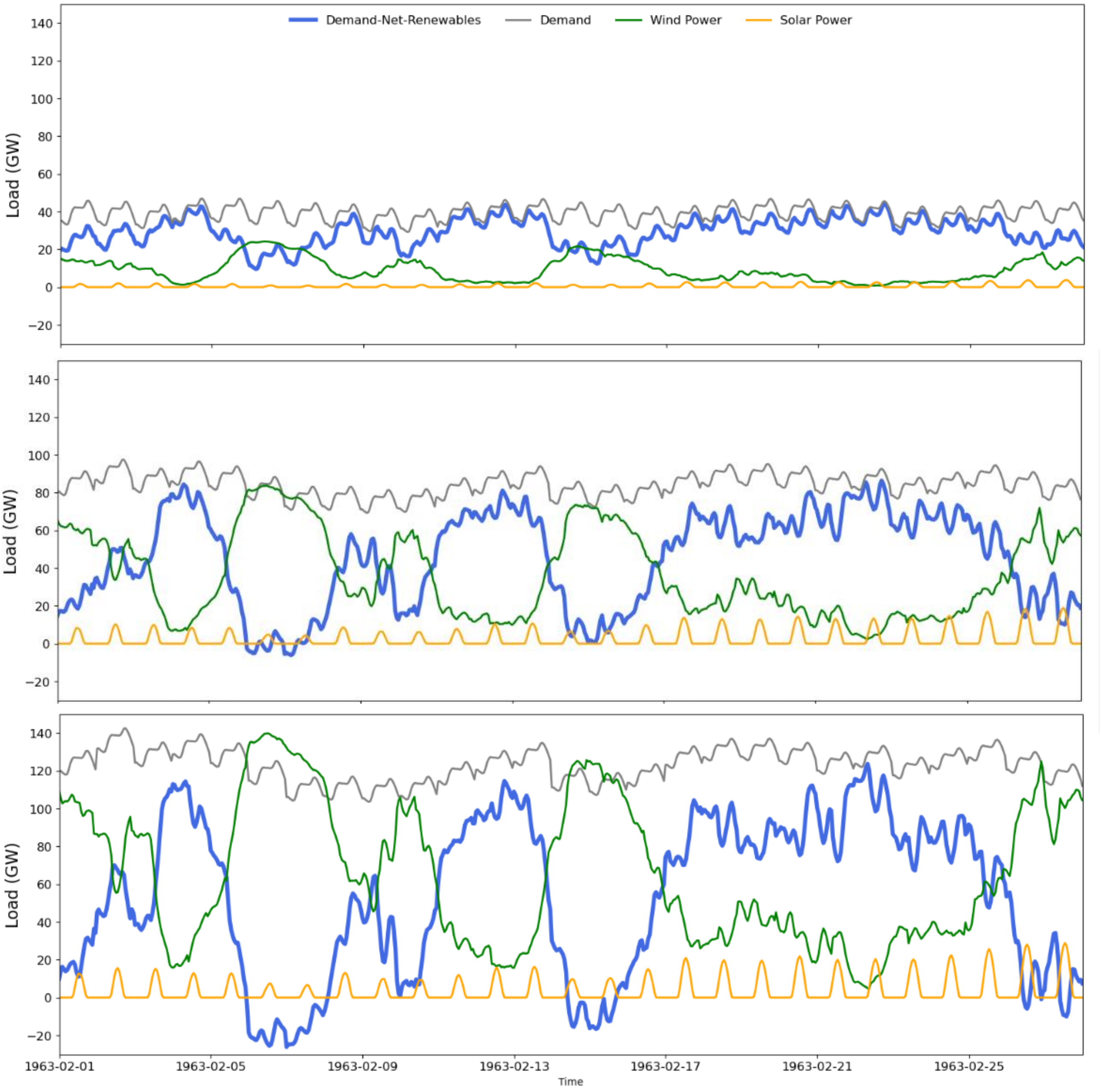

Figure 5 Demand and renewable generation for the present day (top), 2035 (middle) and 2050 (bottom) power systems for February 1963. This demonstrates the characteristics associated with low wind events even in systems with a large volume of renewable generation.

All three types of stress test events (short-duration, one year challenge and multi-year challenge) can be calculated for the 2035 and 2050 energy system scenarios from the historical weather data (see Tables 3 and 4). These energy scenarios include changing the spatial distribution of wind turbines, which has an impact on results (see Box 1). As described earlier, these events only consider how the energy system will change in the future, rather than considering the simultaneous changes in the UK climate.

Table 3 Years selected to be appropriate for stress testing the 2035 energy systems for two different stress test metrics. Numbers in brackets represent the most relevant event from the most recent 40-year period of ERA5.

2035 Energy system	**1-in-10 year**	**1-in-20 year**	**1-in-50-year**
Short duration stress test	1986	1963 (2010)	1945 (1995)
One Year Challenge	1985	1958 (1987)	1963 (2010)

Table 4 Years selected to be appropriate for stress testing the 2035 energy systems for two different stress test metrics. Numbers in brackets represent the most relevant event from the most recent 40-year period of ERA5.

2050 Energy system	**1-in-10 year**	**1-in-20 year**	**1-in-50-year**
Short duration stress test	1941 (1986)	1977 (1997)	1995 (2010)
One Year Challenge	1985	1958 (1987)	1963 (2010)

When comparing Tables 2, 3 and 4, some key points emerge:

- In all the energy system compositions, 2010 is the most appropriate stress test from the recent period for a 1-in-50-year One Year Challenge event.
- If the selection of stress tests is limited to data from the most recent 40 years, the 1987 weather year consistently is a strong contender for the 1-in-20 year return period One Year Challenge test, with 1985 or 1986 appearing for 1-in-10 years. These years were characterised by being extremely cold and having very low wind.
- The years with some of the most challenging short-duration events are not the same years as the One Year Challenge. This suggests that both short and long-duration extreme weather events should be considered in stress tests to dimension future energy systems.

Box 1 The impact of changing future wind farm locations on short-duration stress events and the One Year Challenge.

Previous studies have often analysed the impact of adverse weather on future energy systems without considering the changing spatial distribution of renewable capacity. For example, one approach has been to assume no change in the distribution of wind turbines, but to scale the capacity to anticipated future values. The analysis in this report accounts for the expected increase in spatial diversity of the UK wind fleet (see Figure 14 in Technical Appendix A3). The analysis shows that by 2050, the increased spatial diversity in wind farm locations significantly increases the chances of generation being available at times of increased demand. This increased spatial diversity results in an increase in the annual mean capacity factor over the ERA5 reanalysis period from 0.4 to 0.5[6]. If a present-day spatial distribution is used instead, annual maximum peak demand-net-renewables event is overestimated in all years except 2000 and 2010. The average overestimation is 6 GW which is around twice the size of the UK's largest nuclear power station (see top panel of Figure 6). The overestimation of short-duration events has direct consequences for the total severity of the One Year challenge stress test. Considering the 2050 energy system, on average the cumulative annual demand-net-renewables is overestimated by 125 TWh when the present-day wind farm distribution is used (see bottom panel of Figure 6, which is 20% of the 2050 total annual electricity demand, see Table 1). This overestimation of total annual demand-net-renewables through incorrect wind distributions could imply to decision makers that there is significantly less energy available to store and be used to meet times of challenging demand. Using appropriate wind farm distributions is therefore important for sizing future energy storage.

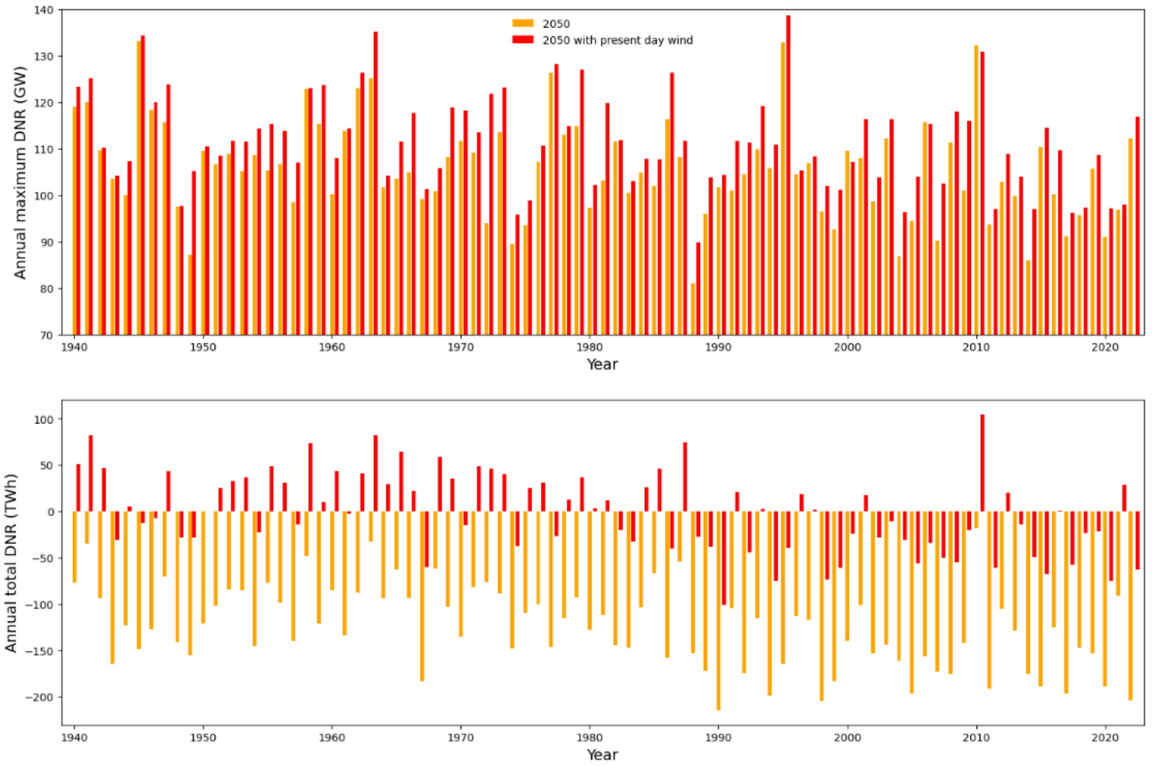

Figure 6 A comparison of the short-duration event (top) and One Year challenge (bottom) metrics for the 2050 power system scenario. Orange bars show the future wind distribution shown in the Technical Appendix whereas red bars show the impact of keeping the historical wind farm distribution for analysis of the 2050 energy system.

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[6] This analysis does not account for improvement in wind turbine technology which may independently impact capacity factors.

3.3: The events we have seen in the past are a good proxy for what we might see in the near future, but under climate change the energy system may need to operate quite differently.

The impacts of global warming on UK electricity demand[7], wind and solar power generation under various levels of global warming can be seen in Figure 7. When comparing the historical (1981-2000) and future, warmer periods, reductions are seen in demand throughout the year, with the largest impacts found in winter (the time where demand is most sensitive to fluctuations in temperature). Climate change results in a small reduction in annual mean wind power capacity factors when modelled using UKCP18. This is in general agreement with the results seen over Europe for current state-of-the-art global and regional climate models (Carvalho et al., 2021), although it is noted that the year-to-year variability in wind speed is much more uncertain than the climate change signal (Carvalho et al., 2021, Bloomfield et al., 2021). These changes in wind speed are largest in the summer, so may inhibit future storage refill strategies. Moderate increases in solar power generation are seen across the whole year, with largest increases present in summer.

The bottom panels of Figure 7 show that overall, there is a relatively small impact of climate change on demand-net-renewables. Under a 1.5 degree warming world, the average magnitude of a short-duration event reduces by 7% and 11% under the 2035 and 2050 power system scenarios respectively. These results suggest that stress tests based on historical weather patterns (i.e. using the ERA5 dataset) are a valid, if conservative, approach when dimensioning the system. However, future research should continue to leverage climate models to understand the expected changes in large scale circulation and the associated impacts for the energy system.

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[7] In this modelling only the temperature-dependent impacts of climate change on energy demand are captured (see Technical Appendix A2)

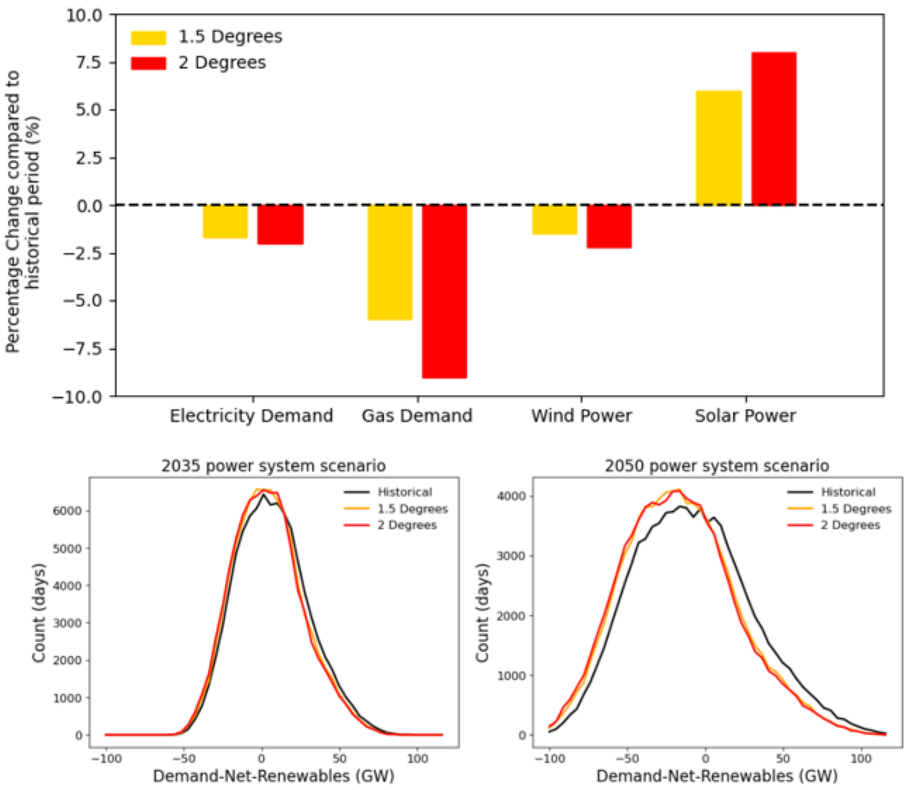

Figure 7 Annual-mean percentage change in energy variables between the warming levels (represented by colours) and the historical period (1981-2000) of the UKCP18 dataset. Probability distributions of the resultant demand-net-renewables field are given in the bottom panels.

The UKCP18 ensemble allows us to question whether ERA5 has enough years of data to accurately capture the extreme events discussed in the previous sections. UKCP18 provides 240 years of data (20 years per ensemble member) for each of the historical, 1.5 degrees warming, and 2 degrees warming levels which can be compared to previous results.

Figure 8 shows an equivalent analysis to that shown for Figure 3 for the One-Year challenge events but using the UKCP18 dataset[8]. When using UKCP18, multiple years exceeding the 1-in-10-year return period line are seen within a five-year period.

Figure 9 shows the return periods of the short duration stress tests from the UKCP18 time slices. The historical weather period (simulating an approximate 1981-2000 period) is also overlayed in the future energy scenarios to directly see the impacts of climate change. It shows similar results to those from the ERA5 reanalysis, showing that overall using the 83 years of ERA5 data has provided a reasonable approximation of the short-duration stress test return levels found in a larger ensemble for the present-day climate. The black lines show the results of maintaining the historical weather period (1981-2000 in UKCP18) rather than the relative warming levels. In terms of the peak demand-net-renewables there is a reasonably consistent reduction of 3.5 GW and 4 GW in the 2035 and 2050 energy system scenarios respectively due to global warming. This small positive contribution is, however, dwarfed by increases in demand due to electrification (as peak demands increase from ~40 GW in the present day to ~100 GW in 2050). The 4 GW reduction in demand-net-renewables due to

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[8] These graphs only include demand-net-wind due to limitations in hourly solar radiation availability from UKCP18. But this is believed to not strongly influence the results due to the extremely low solar generation in winter compared to wind power generation and demand.

climate change is therefore only ~5% of the total annual energy required by 2050. Similar results are seen for the one-year challenges return periods in UKCP18 (not shown) where there is a reduction in total annual demand-net-renewables of 15 TWh and 30 TWh in the 2035 and 2050 energy systems respectively due to global warming. For context, 30 TWh is ~15% of the present day total annual demand-net-renewables value of 180 TWh (see Figure 3).

Future work should continue to explore much larger climate model ensembles and a range of climate model projections to confirm the importance of climate variability, climate change and climate model calibration in influencing the uncertainty of the results. The 80-year period from the ERA5 reanalysis is shown to have a good coverage of possible climate years the present day power system could experience. However, these results should be read with caution given wider uncertainty in the UKCP18 data.

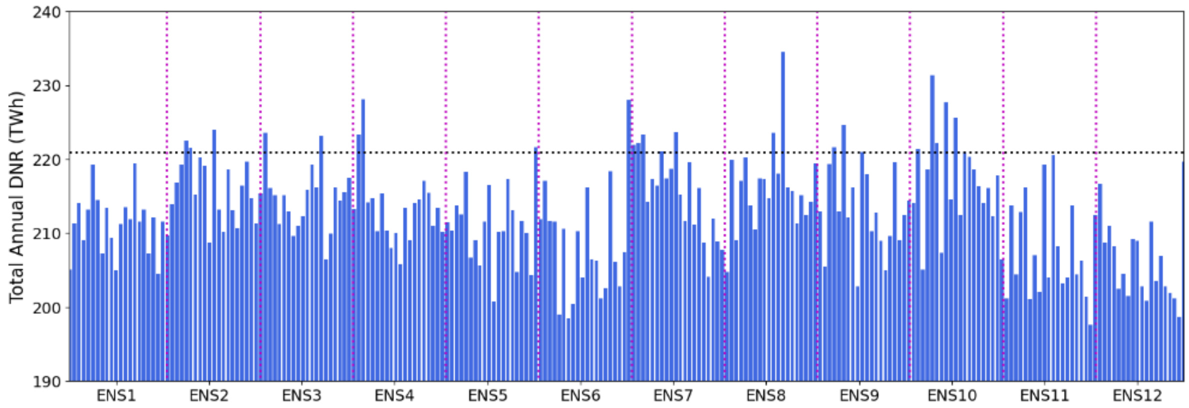

Figure 4 One year challenge values (total demand-net-renewables for each simulation years) from 1981-2000 over all 12 ensemble members assuming a present-day energy system scenario (see Table 1 for details of energy system scenarios). The black dashed line shows the 1-in-10 year return period. Pink horizontal lines distinguish the 12 different ensemble members.

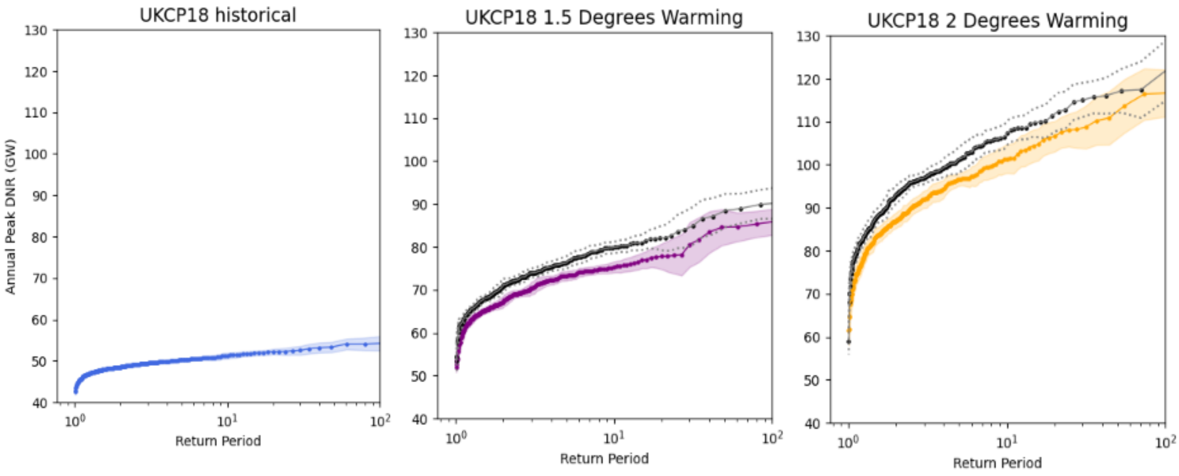

Figure 5 Return period for short duration event (annual maximum hourly peak demand-net-renewables) for synthetic energy system data from the UKPC18 climate projections. Details of the 2021, 2035 and 2050 energy system scenarios and appropriate climate data taken from UKCP18 are given in Table 1. Shaded areas represent the uncertainty within the 240-year sample used to create the return-period curves with 95% confidence intervals. Black data are if the historical UKCP18 weather years are used with the future energy scenarios (showing the impact of energy system change in isolation).

3.4: While the UK is experiencing times of potential stress it is common for interconnected regions to also be experiencing challenges.

A key component for security of supply considerations is the potential availability of energy from interconnectors. In this study, the potential for interconnectors to alleviate capacity constraints is assessed by calculating the frequency at which connected European countries experience short-duration events at the same time as the UK. This gives an indication of the spatial extent of these events for the present-day energy system.

The first panel of Figure 10 shows for each country the percentage of hours where the UK power system is "stressed" (defined using the 95th percentile for demand-net-renewables, to represent times when system operation may begin to become challenging), where that country's power system simultaneously experiences stress ("agreement"). This is calculated for the whole ERA5 dataset, for the present-day energy system. For central European countries this value is ~40%. Among countries the UK currently has an interconnector with, maximum values are seen in the Netherlands and Belgium (43% and 47% respectively) and minimum values in Norway 23%. [9]

The sub-panels of Figure 10 show that if the percentile threshold is increased for the UK energy system stress[10], the number of hours in common across central European countries increases up to 80%. This suggests that at times of highest short duration system stress there may be competition for power through the interconnectors.

The reason for this high agreement has been explored in previous studies, and is due to the presence of very large scale blocking high pressure centres, located with their centre over the North Sea. These result in very low wind generation and relatively cold weather (Bloomfield et al., 2018, Grochowicz et al., 2024).

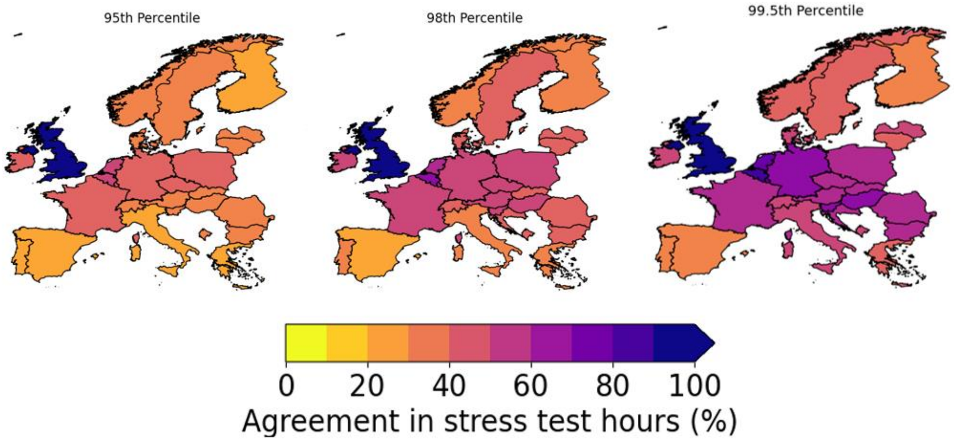

Figure 6 Comparison of the percentage of time that each European country spends exceeding the 95th percentile stress test threshold while the UK is experiencing various degrees of stress for the present day power system scenario. The percentiles used to define a stressful event increase from left (95th percentile) to right (99.5th percentile) to give a sense of how the results are dependent on the severity of the event.

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[9] In this analysis only wind power and solar power are included as renewables and in countries with a large share of hydropower this may be able to contribute during the stressful periods outlined in Figure 10.

[10] E.g., The hours in which UK demand-net-renewables is above the hourly 9Xth percentile value, but the level of stress in the other European countries is above the 95th percentile value.

4. Conclusions

This report identifies key years of weather data that can be used to stress test the resilience of the present-day and future UK energy system to weather and climate variability. The analysis presented in this report has been based on a large, processed weather dataset that can be used as an input for stress testing the UK energy system. The dataset consists of 83 years of hourly historical near-surface temperature, wind speed and surface shortwave radiation data from the ERA5 reanalysis. These weather variables have been converted into national demand, wind power and solar power time series for 28 European countries.

Three types of potential stress events are explored, all of which focus on times where demand exceeds the amount of energy available from renewables:

- Short-duration events: which can be used to understand the extent of non-renewable generation, storage discharge or interconnector import capacity needed to respond to peak periods of high demand-net-renewables.
- The One Year Challenge: which can be used to understand if enough renewable energy is available to meet demand over longer periods. If there is a gap between renewable generation and demand this must be filled by non-renewable generation, stored energy or imported energy.
- Multi-year challenge: which can be used to explore the potential for future long-duration storage to support the energy system.

For the first two types of events, the report presents return periods of extreme events for 1-in-10 year, 1-in-20 year and 1-in-50 year return levels. These stress tests can be used to model whether greater investment may be needed in the future energy scenarios to maintain security of supply in challenging meteorological conditions.

In the present-day energy system, the main meteorological driver of short-duration extremes is low-wind cold snaps during winter. Short-duration events often do not occur in isolation, but multiple periods of high demand-net-renewables are often seen in particularly cold years (e.g. 1963 and 2010). The energy systems of 2035, and 2050 are more weather sensitive, due to the electrification of the economy, and the rapid increases in wind and solar generation.

When looking across the three power system scenarios, a present-day 1-in-80 short duration stress event year value is of ~50 GW (the non-renewable generation needed to manage the highest demand-net-renewables hour in the year). This level of peak demand-net-renewables is an everyday occurrence by 2035, with 1-in-80 year events of nearly 100 GW increasing to ~130 GW by 2050. When considering the one-year challenge events, in the present-day energy system, the system operator needs to find ~200 TWh of non-renewable power generation to manage the most difficult year in the 80 year period. By 2035 this is expected to reduce to 100 TWh and becomes negative by 2050 due to substantial expansion of the wind and solar generation portfolio. Utilising this excess renewable generation through energy storage will be critical to meet short duration high demand-net-renewables events.

Across all power system scenarios 2010 is the most appropriate choice for a 1-in-50 year stress test event for the One Year Challenge. If the stress testing period is limited to the last 40 years of meteorological data, then 1987 appears consistently as a 1-in-20 year event. The years with some of the most challenging short-duration events are not the same years as the One Year Challenge, which highlights the need to consider the requirements of the stress test carefully.

The future spatial diversity in the UK wind fleet is expected to result in ~5 GW reduction in peak demand-net-renewables. Modelling the power system with an incorrect wind farm distribution could result in the volume of excess renewables being substantially underestimated, and power generation or storage discharge power capacity would be incorrectly sized. It is therefore important that the correct spatial distribution of wind farms is accounted for in energy system stress tests so that future systems are not over-built.

The UKCP18 climate model projections have been used to understand the possible impacts of climate change on the stress test metrics described above. The impacts of climate change on the weather-dependent power system components leads to a ~5% reduction in annual-maximum demand-net-renewables. The changes in energy system composition (including the electrification of heating and increases in installed renewable generation) have a much larger impact on management of the future energy system than changes in wind speed and solar irradiation expected under a changing climate. Climate change alone could result in a ~5 GW reduction in short-duration stress events and a ~15 TWh reduction in the One Year challenge events in a 2 degree warmer world.

While the UK is experiencing its most extreme short-duration stress events, it is common for its interconnectors to also be experiencing times of high need. This suggests that interconnectors may not always be available to provide power at times of highest need. This is expected to continue to be the case in the future, as European energy systems transition to higher penetrations of renewables. Infrastructure damage from extreme weather is beyond the scope of this work, but should be considered in weather-dependent stress testing exercises.

Building on this report, our rapidly changing climate means it is of critical importance that climate scientists continue to work with energy system modellers to develop best practices for stress testing highly weather-sensitive future power systems.

Technical Appendix

This section provides a detailed description of the methodology, assumptions and data sources used in this project.

A1 Modelling overview

Similar versions of the demand, wind power and solar photovoltaic models have been created and verified for more than 25 European countries and are comparable to other models available in the academic literature (see Bloomfield et al., 2020, 2022). Previous versions of these models have been used in the Met Office Adverse Weather Scenarios analysis (Dawkins et al., 2021), and numerous academic papers have been published using these models to understand meteorological drivers of European power system stress events and their predictability.

For this project the models described in sections A2 to A4 are run at hourly resolution over the ERA5 reanalysis (Hersbach et al., 2020) from 1940-2022 and the UKCP18 local 2.2km[11] domain from 1981-2080. The models are also run at daily resolution over the regional (12km European domain) UKCP18 dataset from 1981 to 2080. Both the UKCP18 local and regional model simulations include 12 ensemble members, so a possible 1200 years of data for analysis. This is useful when considering the return periods of the power system stress events.

A2 Demand model

In this project, demand is modelled in two steps. Firstly, for each country, a multiple linear regression is established linking weather properties from gridded meteorological observations (ERA5, Hersbach, 2018) to observed national-aggregate daily “total load” (ENTSO 2019).

The regression takes the form:

$$Demand\ (t) = \alpha_0 + \alpha_1(t) + \alpha_2 HDD(t) + \alpha_3 CDD(t) + \sum_{i=4}^{10} \alpha_i WDi(t)$$

Equation 1

Here t is the daily time step, and α_i are the regression co-efficients. The first two terms (α_0 and α_1) correspond to a constant “background” level of demand which permits slow changes over time due to social, economic and technological factors. α_2 and α_3 describe how the heating degree days (HDD) and cooling degree days (CDD) relate to the total national demand. α_4 to α_{10} describe how demand is modulated by the day of the week. The WD terms represent each day of the week of binary indices of 1 when it is the appropriate day, and zero otherwise. The weather sensitivity of demand is expressed (HDD and CDD as follows:

$$\begin{aligned} &if\ T(t) < 15.5: \\ &\quad HDD = 15.5 - T(t) \end{aligned}$$

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[11] We note that only daily surface shortwave radiation was available from the 2.2 km UKCP18 dataset so monthly mean diurnal cycles were inferred from this to match the total daily surface shortwave radiation accumulation.

$$
\begin{aligned}
&else: \\
&\quad HDD(t) = 0
\end{aligned}
$$

Equation 2

$$
\begin{aligned}
&if\ T(t) > 22: \\
&\quad CDD = T(t) - 22 \\
&else: \\
&\quad CDD(t) = 0
\end{aligned}
$$

Equation 3

Here T(t) is the daily-mean national-average temperature. In Equation 2 and Equation 3 the thresholds match those used by the European Environment Agency (see, e.g., Spinoni et al., 2018). A country's HDD or CDD time series is zero if T(t) is between 15.5°C and 22°C, as this is the temperature range in which demand is assumed to not be weather-sensitive. Each country has a unique regression model, where any combination of terms can be chosen, such that the Akaike Information Criterion (Wilks, 2011) is minimised. Verification of this model can be found in the supplement of Bloomfield et al., (2020).

The daily-mean demand data is downscaled to hourly resolution using a prescribed diurnal cycle. A different diurnal cycle is determined for each meteorological season based on the recorded 2023 hourly demand data (Figure 11, similar results are seen if any combination of years from 2020-2023 are used to create the diurnal cycles). Each daily demand value is downscaled to hourly resolution using a linear combination of relevant diurnal curves (e.g., the daily-mean demand for 1st December is downscaled using a 50%–50% weighting of the diurnal curves derived from the autumn and winter hourly data). This means that there are smooth transitions between each monthly diurnal cycle without large step changes.

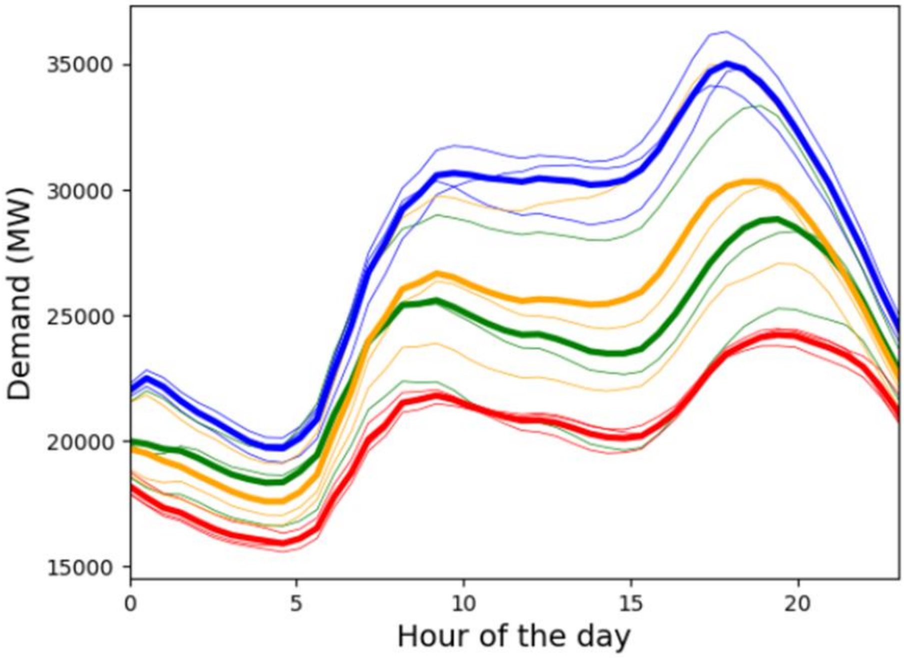

Figure 7: Mean seasonal diurnal cycles from 2023 observed National demand data for Winter (Dec-Feb, blue) Spring (March-May, green), Summer (June-August, red) and Autumn (September-November, Orange). Individual months are shown as thin lines and the full seasonal mean is shown in thick lines.

To account for the future uptake of electric heating technologies across the UK a similar model has been developed for present daily UK gas demand, from the non-daily metered (NDM) gas data from 2020-2023. This model is designed in the same way as the electricity model (i.e. allowing the selection of the parameters from Equation 1, although more sophisticated methods are possible using composite weather variables, National Grid Gas 2016). For our future time-period of 2035 and 2050 demand is calculated in a similar way to Deakin et al., (2021), using the following equation:

$$Demand(t) = ED(t) + elec_{perc} * COP * GD(t)$$

Equation 4

Here ED and GD are the present day daily electricity and gas demands respectively. COP is the heat pump coefficient of performance (taken as 2.83). Changes in the intraday time profile of heat demand have not been included in this modelling. Here the electrification percentage is optimised so that the 83-year mean demands values match those from Table 1 (52 GW and 72 GW in 2035 and 2050 respectively). This method of electrification has the impact of increasing the temperature sensitivity of demand significantly compared to in the present-day scenario. An example of this electrification can be seen in Figure 12. This model does not assume any changes in the seasonal or diurnal cycles of demand in the future, which are highly uncertain (Deakin et al, 2021). Potential increases in the uptake of air conditioning are also not including in the modelling.

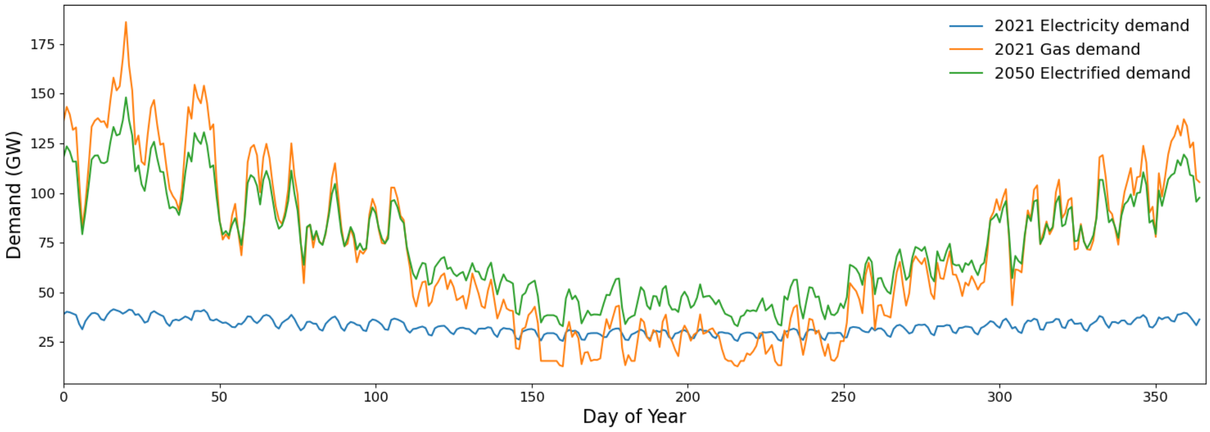

Figure 8 Example synthetic daily demand time series from 1940 for present day electricity demand (blue) gas demand (orange) and our electrified demand for the 2050 scenario (green).

A3 Wind power Model

A physical model is used to produce estimates of national and regional wind power capacity factor. Gridded hourly 100 m wind speeds are extracted from the ERA5 reanalysis for each ~30km grid box and are converted into wind power capacity factors using either an onshore or offshore power curve extracted from a National Grid report (National Grid, 2019, shown in Figure 13). These curves represent total power available at a wind farm level. Before passing the gridded 100 m wind speeds through the appropriate power curve, they are first corrected to the Global Wind Atlas (2019) to account for uncertainties in the ERA5 data over complex terrain (see Bloomfield et al., 2020). These corrected 100m wind speeds are then scaled to the UK average onshore or offshore hub height using a wind profile power law. The onshore and offshore hub heights were 71 and 92m, respectively[12]. These were calculated as the weighted average of operational wind farms in April 2021 taken from TheWindPower.net database.

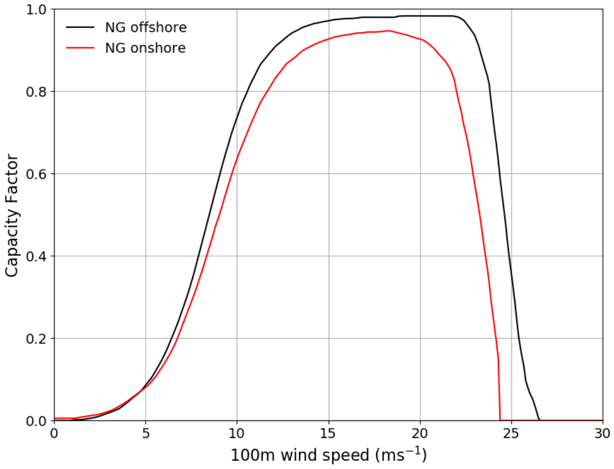

Figure 9 The onshore (red) and offshore (black) wind power curves used in this study, taken from National Grid (2019).

Information regarding the spatial distribution, hub heights, and installed capacity of wind turbines is taken from the https://www.thewindpower.net/ database (see Figure 14). The present-day distribution includes all farms that are operational at the time of writing the report (March 2024). The 2035 scenario includes all operational and 'approved' farms in the database and all of those listed by The Crown Estate as future developments, giving a total of 77.4 GW installed capacity. The 2050 scenario includes all operational and planned farms from thewindpower.net database (114 GW). The diversification of the UK future wind fleet locations is clear from Figure 12, and this is critical to capture in future power system stress tests as it directly impacts periods of prolonged high and low wind power generation (Giddings et al., 2024). In this study the wind farm characteristics (turbine type and hub-height) are kept constant through time, but this is an interesting topic for future work.

The national or regional capacity factors are created by weighting the capacity values from the ERA5 reanalysis by the installed capacity in each grid box (taken from Figure 14) and aggregated to the required level. When creating the national data, the capacity factors are then multiplied by the total scenario installed capacity (from Table 1) to give the national wind power generation value.

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[12] Reanalysis data products contain biases that are dependent on the terrain type, and elevation (see Bloomfield et al., 2020 supplementary material for examples of the biases in ERA5 compared to the Global Wind Atlas).

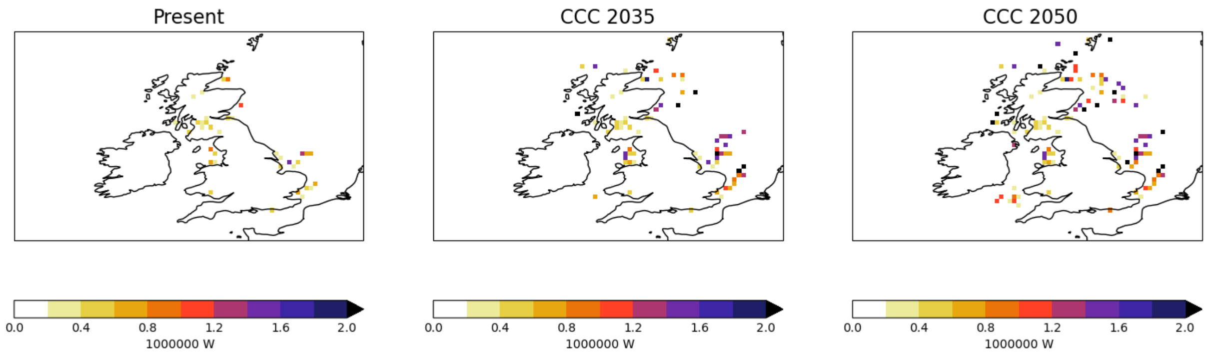

Figure 10 Locations of the Onshore and Offshore wind farms present day (operational in January 2023) approved for construction (2035) and planned (2050) from thewindpower.net database

A very similar method is followed for modelling wind power using the UKCP18 local or regional models. The only difference being that only 10m wind speeds are available (rather than the 100m winds available from ERA5). These 10m wind speeds are first bias corrected to HadUK-Grid (Hollis et al., 2019) and following this are extrapolated up to the onshore and offshore hub-height values. Following this the same methodology is followed.

A4 Solar Photovoltaic model

This analysis uses a national-aggregate capacity factor estimate, based upon the model from Evans and Florschuetz (1977). This model depends only on near surface air temperature and incoming surface solar radiation rather than needing information about solar panel characteristics. The solar power model calculates the capacity factor in each reanalysis or climate model grid box at each time step using Equation 5:

$$CF(t) = \frac{Power}{Power_{STC}} = \eta(G,T,t)\frac{G(t)}{G_{STC}(t)}$$

Equation 5

where G is the incoming surface solar radiation and T is the grid box 2m temperature, and t is the time step (hours). STC stands for standard test conditions (T=25°C, G=1000 Wm^{-2}) and η is the relative efficiency of the panel following equation:

$$\eta(G,T,t) = \eta_r\,(1 - \beta_r(T_c(t) - T_r)$$

Equation 6

where η_r is the photovoltaic cell efficiency evaluated at the reference temperature T_r, β_r is the fractional decrease of cell efficiency per unit temperature increase and T_c is the cell temperature (assumed to be identical to the grid box temperature, i.e., T=Tc).

This model was originally designed for the calculation of solar power yield from a specific panel, rather than over a large grid-box area as in this setup. Following Bett and Thornton (2016), η_r is set to a constant value of 0.90. and β_r is set to constant 0.00042 to reflect more modern setups. Using this model, capacity factors are calculated at each grid box and then aggregated to national or regional level as required, assuming a uniform capacity distribution over all grid boxes in the country. Future exercises could explore the impact of including more detailed information about solar panel locations.

However, this was not of critical importance to this project as the stress events of interest occur during winter, when solar generation is often very low.

A5 The impact of the starting point of the year on results

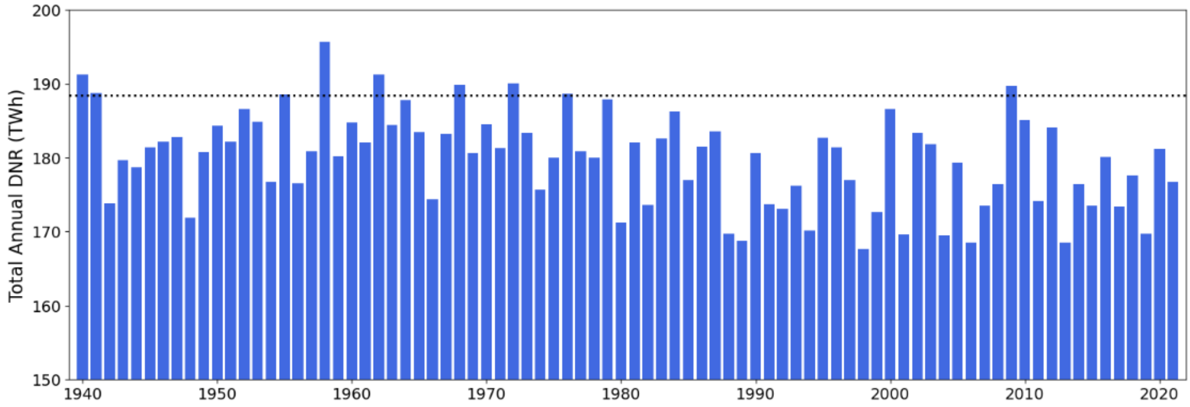

Figure 15 One year challenge values (total of the demand-net-renewables for each year from 1940-2022 assuming a present day power system scenario (see Table 1 for details of power system scenarios). The black dashed line shows the 1-in-10 year return period level of the One year challenge metric. Here a year starts from June and ends in May, preserving the meteorological winter. So 1940 would be June 1940 – May 1941 inclusive.

Figure 15 shows how the present-day system one-year-challenge stress test statistics is impacted by the starting point of the 'year'. In the results section of this report a calendar year running from January to December is used. However, this includes two separate truncated winter periods within it. If the models are instead run from June to May, there is a different characterisation of the most stressful periods, and therefore the multi-year stress events. A key example of this is 2010, where to total annual severity is reduce by ~12 TWh when the meteorological winter (where the majority of stressful periods are present) is preserved and 2009 is increased by 12 TWh. This is because there is very little meteorological link between the weather in January-February and the December of a calendar year, and in 2010 both were the coldest parts of the 2009-10 and 2010-11 winter.

Running power system models from June to May would be an important capability to work towards, particularly in systems that will include large volumes of storage.

A6 Exploring the short duration stress test metric.

The top panel of Figure 16 shows the annual values of the short-duration stress test metric (the annual maximum hourly peak demand-net renewables). There are notable variations in this metric, with 1945, 1977, 1995 and 2010 standing out as high values. However, relatively low values are seen in years such as 2017, 1988 and 1945.

Within a year, low wind cold-spells (which result in the peak demand-net-renewables events) are rarely isolated hours. The bottom panel of Figure 17 shows that in extremely cold and low wind years such as 1941, 1963 and 2010 there can be over 80 individual hours when demand-net-renewables exceeds the hourly annual maximum value from 2017 (the year with the lowest peak demand-net-renewables value). This shows that if these extended periods are important for a particular stress test, then a duration-severity framework could be used (as in Dawkins and Rushby, 2021).

If a power system was conditioned only on one of these high or low years, there may be significant over or under build of technologies. This therefore emphasises that multiple years should be used for stress testing experiments.

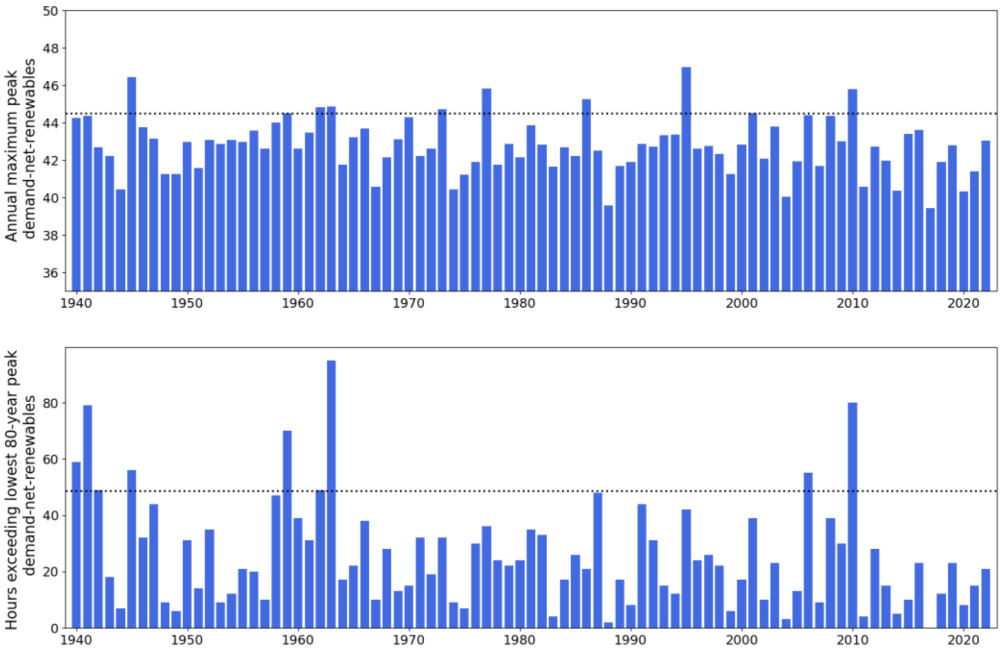

Figure 116 Top: Annual maximum hourly peak demand-net-renewables (the short-duration stress test metric) where the black line shows the 1-in-10 year return period. Bottom: The number of hours that each year exceeds the 2017 value of the annual maximum hourly demand-net-renewables (from the top panel we can see 2017 is the year with lowest hourly maximum demand-net-renewables). Black dashed- line represents the 1-in-10 year return period..

A7: Exploring the potential for storing excess renewables in the 2035 scenario.

Large-scale storage is a known solution to the variability of renewable generation (Llewellyn Smith et al., 2023). We have therefore constructed a simple bucket model to capture *excess renewables* and then allow these to be used to meet demand at times when demand exceeds renewable generation.

This experiment considers the idea of the cumulative difference between supply and demand, expressed as a deviation from the long-term average. Here, the 10-year running mean is first removed from the demand-net-renewables time series (to remove the impacts of long-term trends in the demand and renewable energy data) and following this the cumulative sum of demand-net-renewables is taken through time. There are large year-to-year deviations in the cumulative surplus demand-net-renewables (Figure 17). We see a maximum of 195 TWh of non-renewable requirements in the 2035 power system scenario. Key points of rapid multi-year changes are 1940-1943 (large storage requirements), 1986-1990 (large storage requirements), 1989-1993 (large storage discharge), 2008-2010 (large storage discharge) and 2010-2013 (large storage requirement). This highlights the importance of considering multi-decadal variability for accurately sizing future storage requirements, as throughout the 83-year period we see several multi-year challenges of 3-4 years duration.

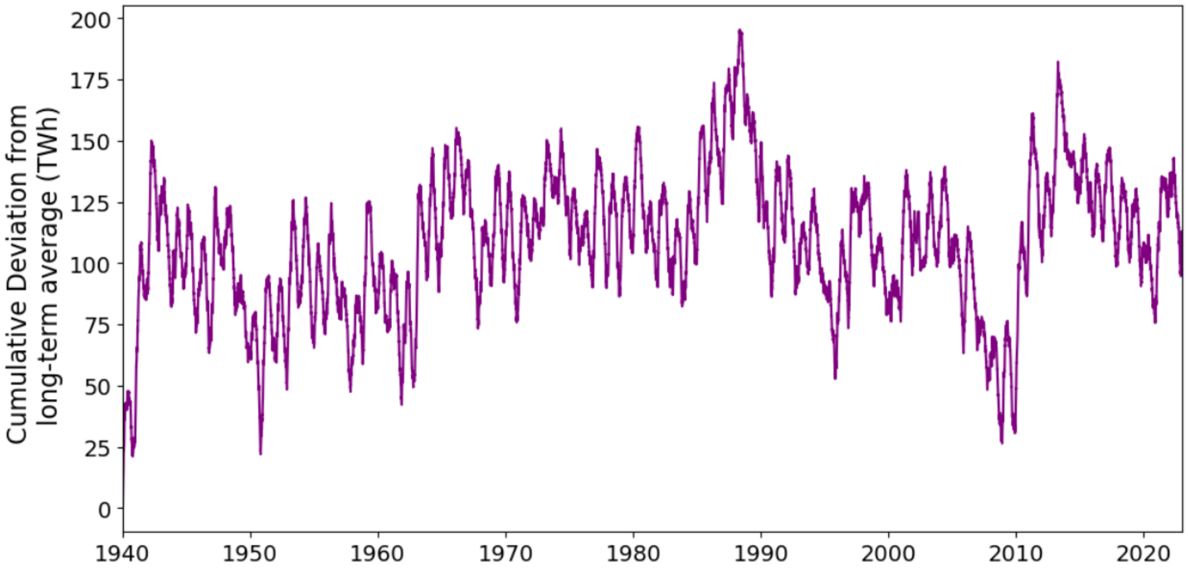

Figure 17 A demonstration of the simple bucket model storage values (i.e., the cumulative deviation from 10-year running average demand-net-renewables) from 1940 to 2022.

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