Weather and Climate Related Sensitivities and Risks in a Highly Renewable UK Energy System: A Literature Review

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1 Introduction

The National Infrastructure Commission (the Commission) recently published their first National Infrastructure Assessment (the Assessment), in which they recommend targeting a transition to a highly renewable electricity generation mix, incorporating increasing wind and solar power capacities (National Infrastructure Commission, 2018). Following this publication, the Commission are looking to further build on this work by identifying and addressing gaps in the current understanding of the weather and climate implications for a highly renewable energy system in the UK. In particular, wind and solar power are highly dependent on meteorological conditions. The Commission therefore aim to contribute to better understanding how a system based on a high level of variable wind and solar renewables could perform during extreme stress events associated with adverse weather conditions and a changing climate.

In recent years, the increased deployment of wind and solar power has driven the convergence of the energy and meteorological research communities and the publication of a number of relevant studies. This literature review aims to provide the Commission with a comprehensive summary of the current scientific understanding of this topic. In particular, this review will identify which gaps in current research need further scientific analysis to address, and which can simply be filled by existing results from the literature.

Four key themes within this topic have been identified and will be addressed in turn:

- What is an Extreme Stress Event? (Section 3);
- The role of prediction in mitigating stress events (Section 4);
- Possible techniques and data sets for quantifying rare stress events (Section 5);
- Sensitivity of the energy system to climate variability and change (Section 6).

Energy system extreme stress events and sensitivity depend on both energy supply and demand. The Commission recommend an energy system in which a much larger proportion of electricity is supplied by renewable technologies, and in which gas supply (primarily for heating homes) is replaced by either hydrogen or electrified space-heating. Due to this move away from using gas, and the lack of UK focused gas consumption studies (Thornton, 2018), this literature review will primarily focus on addressing the above topics in relation to electricity demand and supply. However, where appropriate and available, energy system stress associated with gas demand will be discussed, particularly in relation to the effect of increasing electrified heating on future electricity demand.

2 Executive Summary

This literature review provides an in-depth exploration of studies relevant for understanding weather and climate related sensitivities and risks associated with a highly renewable UK energy system. The review benefits from the depth of relevant knowledge available across the Met Office, and insights drawn from discussions with scientists directly involved in a number of the key studies.

The reviewed literature suggests that extreme stress on the energy system, resulting from adverse weather conditions, can be characterised in five ways: winter-time peak residual demand (demand net of renewable supply); winter-time wind power ramping (large fluctuations in power generation in a short time window); summer-time surplus solar PV power generation; summer-time wind drought; and solar PV ramping. These stress conditions result from extreme magnitudes and fluctuations in energy demand, shown to vary with temperature, and renewable electricity supply, shown to vary with wind speed and solar irradiance (power of the sun). The reviewed studies highlight the energy system resilience opportunities associated with utilising insights related to the spatial and temporal variability and dependence in relevant meteorological conditions. For example, the dipole in meteorological conditions in North and South Europe, the anti-correlation between wind speed and solar irradiance in the UK, particularly in summer, and the link between relevant meteorological conditions and large scale modes of climate variability (such as the North Atlantic Oscillation). Climate change studies indicate, with high confidence, that the UK climate will become increasingly warm. This may reduce heating demand, and hence the severity of winter-time peak residual demand events, but increase summer-time cooling demand, highlighting the importance of considering climate change in future energy system planning. The literature focuses predominantly on winter-time peak demand conditions and a limited number of studies explore extreme stress using a whole system energy model.

Studies quantifying the predictability of meteorological conditions associated with the energy system are predominantly focused on wind power forecasting and very few consider extreme stress conditions. These studies show how wind power forecasts are improved by using a high spatial resolution numerical weather prediction model in combination with a statistical bias correction method. Such wind forecasts are shown to provide valuable information about wind ramping events up to 12 hours ahead of time. Meteorological conditions in Europe can be characterised as being associated with one of a limited number of ‘weather regimes’. An exploration of the forecast skill in predicting weather regimes associated with extreme stress meteorological conditions identified greatest skill in predicting stable weather regimes, causing very low temperatures and wind speeds in winter. Indeed, for these regimes, non-zero forecast skill is observed out to 2 weeks ahead of time in winter. This was exemplified prior to the ‘Beast from the East’ extreme cold event (February/March 2018). The weather regime associated with this event was forecast with good skill over a week ahead of time, with a first indication identified a month prior, providing significant warning time. This highlights how the predictability of extreme stress conditions could play an important role in mitigating their impact on the energy system.

The reviewed literature emphasises the increasing importance of detailed models for weather dependent wind and solar PV power generation, for understanding the resilience of future highly renewable energy systems. In particular, the most advanced model of this type uses a long historical meteorological data record (25 years), accounting for year-to-year climate variability in space and time, within a whole system energy model. This model combines meteorological data with changing installed renewable capacities and demand profiles, specified within the National Grid Two Degree future energy scenario, to estimate electricity demand and renewable supply, and explore how residual demand changes throughout the future scenario to 2030. This study does not, however, incorporate flexible technologies or European interconnectivity, highlighting how these elements of the energy system are essential for resilience in a highly renewable system. In addition, the results of this study are limited to meteorological conditions experienced within the historical 25 year period. Physically plausible, more extreme meteorological conditions (now and in future climates) can be quantified and modelled using extreme value statistical methods, commonly using in applications such as natural hazards modelling and nuclear infrastructure safety.

Climate variability refers to natural fluctuations in the climate on time scales from months to decades, resulting from variation in large scale atmospheric circulation patterns such as the North Atlantic Oscillation. Conversely, climate change refers to alterations in the Earth's atmosphere that occur over much longer periods, such as multiple decades to millennia, predominantly attributed to human activity. Recent studies consider four potential future climates, or 'representative concentration pathways', characterising different trajectories of global greenhouse gas emissions. Currently the scientific community can not reliably say which scenario is most likely, hence all scenarios should be included in climate change adaptation plans. Relevant studies suggest that climate change, rather than climate variability will have the greatest impact on temperature driven demand in the future. On the other hand, climate variability is shown to have a greater impact on wind speed and solar irradiance, and hence renewable supply. As a result, the year-to-year variability in residual demand is shown to increase dramatically with increasing installed renewable capacity.

The identified gaps within the reviewed literature indicate that further research should be undertaken to test the resilience of the future highly renewable energy systems considered in the Assessment to extreme adverse weather conditions, while accounting for climate variability and change. This could be achieved by developing a spatially and temporally coherent statistical model for relevant meteorological conditions, based on a long meteorological data record, incorporating climate change. This model could be used to create a set of plausible high risk meteorological scenarios characterising different forms of stress event at different risk levels (e.g. 1 in 100 year event, 1 in 1,000 year event). These risk scenarios could be used within a whole system energy model, incorporating all important elements (such as interconnectivity and flexibility) to identify optimal future energy systems for minimising cost and carbon emissions, whilst ensuring resilience to potential meteorological and climate risks.

3 Theme 1: What is an Extreme Stress Event?

Extreme stress on the energy system is commonly characterised as periods during which energy demand is very high while supply is low, or conversely when demand is very low while supply is high. This can happen at different temporal and spatial scales, from instantaneous events at a local scale (also known as ramping), to prolonged periods at a national scale. In very extreme cases, such events can lead to power outages or large quantities of surplus, unused energy. To prepare for such events, prior to each winter National Grid publish a winter outlook report exploring potential stress events on the energy system. This includes a forecast of measures such as peak weekly demand from October to March, and the average cold spell peak demand, defined as the peak demand within a year that has a 50% chance of being exceeded as a result of weather variation (National Grid SO 2018; Thornton et al. 2016).

As part of the analysis carried out for the Assessment by Aurora, the resilience of the future energy system was tested for one potential extreme stress event in which, for a day in winter, demand was increased by 5GW while the wind capacity load factor was capped at 5%. The 40% renewable scenario was found to be resilient to this stress event, while the 90% renewable scenario incurred loss of load beyond 2030, indicating increased requirements for energy system flexibility. Balancing supply and demand in an energy system with large wind and solar capacities requires a detailed understanding of the meteorological variables (e.g. temperature, wind speed etc.) that cause extreme stress events. Therefore, to explore the resilience of the system in more detail, further physically justified stress conditions, based on meteorological literature, must be identified and tested.

3.1 Which meteorological variables are responsible for causing extreme stress events?

Temperature

A number of studies document the near-linear negative relationship between electricity demand and temperature in the UK (Hor et al. 2005; Bessec and Fouquau 2008; Psiloglou et al. 2009; Summereld et al. 2015; Leahy and Foley 2012; Thornton et al. 2016). In particular, Thornton et al. (2016) explore this relationship for each season separately, based on long historical record of temperature and demand data (1975-2013), detrended to account for low frequency variability, thought to be predominantly driven by socio-economic changes. Figure 1 presents these relationships, summarised by linear fits to the scatter points (i.e. $Demand = a \times Temperature + b$).

Thornton et al. (2016) identified that, of the four seasons, winter has the strongest demand-temperature relationship, with Pearson correlation coefficient $r = -0.81$, and the largest temperature sensitivity. They estimate that on average during this historical period, a $1°$C decrease in daily temperature in winter results in a 1% increase in daily electricity demand. Similarly, Leahy and Foley (2012) identified an

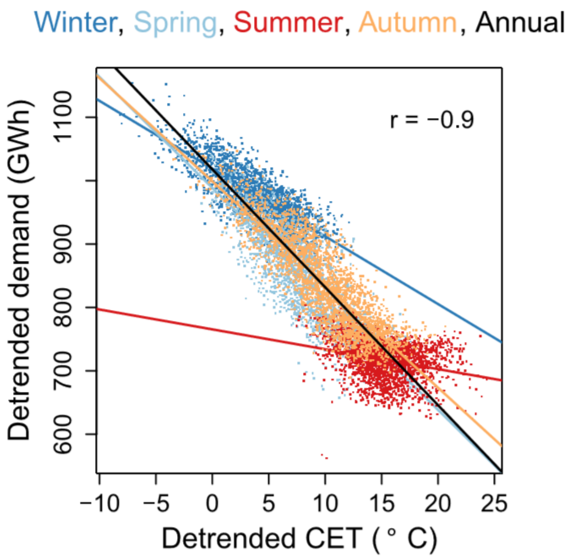


Figure 1: Taken from Thornton et al. (2016): Scatter plot of detrended daily Central England Temperature (CET) (°C) and detrended electricity demand (Gwh), January 1975-March 2013, during weekdays and non-holidays, coloured by season. Linear fits for each season and the whole year are shown. The Pearson correlation coefcient (r = -0.9) is given for the annual relationship.

increase in electricity demand of 1.6 GWh with every $1°$C drop in temperature in Ireland. These results suggest that extreme stress events associated with peak electricity demand occur during periods of extreme low temperatures.

As discussed in the Assessment (National Infrastructure Commission, 2018), to achieve a lower carbon energy system the burning of natural gas for heating and hot water could be replaced by either hydrogen or electrified using heat pumps. There are a limited number of studies focused on UK gas consumption, however, all document the high within-day variability of UK gas demand (van Goor and Scholtens 2014; Summereld et al. 2015; Wilson et al. 2013; Thornton et al. 2016), and those that explore the relationship with weather indicate a very strong negative relationship between gas demand and temperature (Wilson et al. 2013; Thornton et al. 2016). This suggests that transitioning to electrified space and water heating would increase the sensitivity of electricity demand to changes in temperature, and therefore cause more severe extreme stress events. Specifically, Wilson et al. (2013) found that during episodes of peak demand within their study period (October 2010 - January 2013), there was up to three times as much gas consumed as electricity, with gas demand being much more variable than electricity demand. As a result Wilson et al. (2013) concluded that even a partial electrification of domestic heating demand would have serious implications for the UK's electrical transmission and distribution networks, due to the increase in magnitude and variability of daily and peak energy flows. In a similar way, Thornton et al. (2016) compare temperature driven electricity and gas demand in the UK (1975-2013) and identify a stronger negative relationship between winter temperature and gas demand ($r = -0.9$), equivalent to a $1°$C reduction in daily temperature resulting in a 3-4$\%$ increase in gas demand. This further highlights how electricity demand and extreme stress will become more dependent on temperature if gas demand is to be met by electricity in the future.

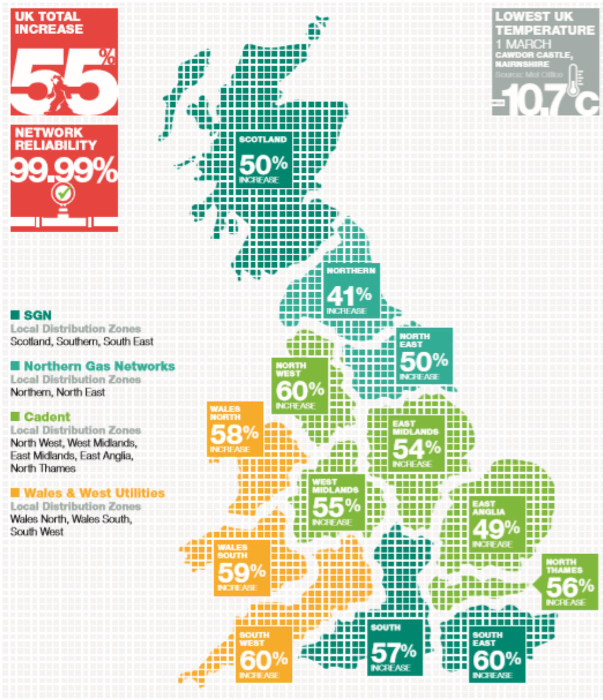


Figure 2: Difference between gas demand during the 'Best from the East' (1st March) and prior to the event (22nd February) [source: http://www.energynetworks.org/news/publications/ena-publications/].

This was exemplified during the 'Beast from the East' extreme cold weather event that occurred in the UK in early March 2018, during which national demand for gas increased by 55% (compared to demand one week prior to the event). The national variation in increase gas demand during this event is shown in Figure 2. These results indicate that the alternative, hydrogen replacement for gas, may be the more secure option for the energy system, as recommended by the Commission (National Infrastructure Commission, 2018).

These aforementioned studies predominantly focus on historical periods of demand, and do not consider the influence of wind and solar power generation. In a future energy system in which wind and solar power play an increasingly important role, extreme stress will depend more heavily than in the current system on additional meteorological variables. In particular, Leahy and Foley (2012) highlighted the important relationship between wind speed and temperature in understanding to peak demand. They discuss how, while demand sensitivity is driven by temperature, the weather related sensitivity of electricity supply is mainly due to wind variability, and hence the interplay of these two weather-driven effects is of particular concern.

Wind Speed

The recent increase in wind power generation in the UK has lead a wealth of research aiming to understand the relationship between wind power capacity factor (as a function of wind speed) and electricity demand (Sinden 2007; Oswald et al. 2008; Zachary et al. 2011; Zachary and Dent 2012; Brayshaw et al. 2011; Ely et al. 2013; Brayshaw et al. 2012; Leahy and Foley 2012). In these studies, wind capacity factor is most commonly estimated using the cube of the wind speed, known to represent the work done or the power of the wind (Thornton 2018; Brayshaw et al. 2012). As a result, wind power capacity factor is very sensitive to changes in wind speed.

In particular, this literature aims to understand stress events on the energy system by quantifying the magnitude of wind power capacity factor at times of peak temperature driven electricity demand. Wind and temperature co-vary depending on the weather system effecting the UK (see the next section 'Mean Sea Level Pressure' for more detail). During high demand conditions some studies suggest the risk of lower wind speeds leading to lower power supply (Oswald et al. 2008; Zachary and Dent 2012) while others suggest moderate or higher than average winds (Sinden 2007; Zachary et al. 2011; Brayshaw et al. 2012; Thornton et al. 2017). As discussed by Thornton et al. (2017), however, most of these studies are limited by their short data periods (often less than 10 years), and the results are therefore highly uncertain (Bloomfield et al., 2016).

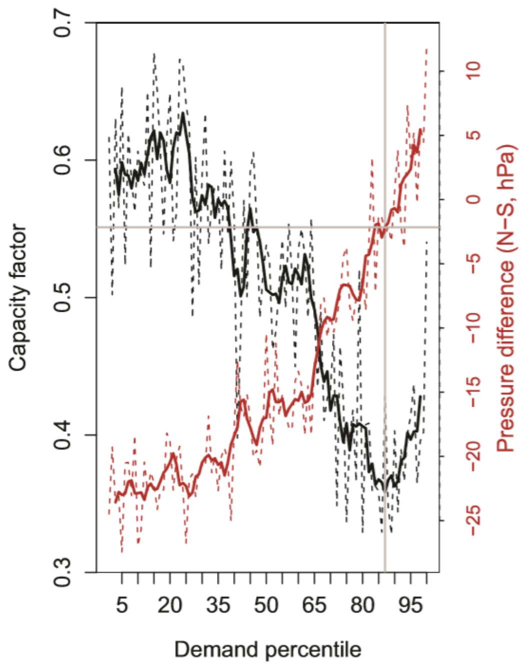


Figure 3: Taken from Thornton et al. (2017): Variation in UK average wind power capacity factor (black) and meridional pressure difference between two regions north and south of UK (hPa, red) with winter percentile of UK electricity demand, averaging over 1% bins (dashed) and 5% bins (solid) along the x axis.

To overcome this, Thornton et al. (2017) utilised a much longer data set, consisting of 34 years of wind speed and electricity demand data. This wind speed data was taken from the ERA-Interim data set[1]. Thornton et al. (2017) show that, for the majority of the year, as demand increases, average available wind power also increases. Conversely, in winter they found that average wind power reduces

[1] https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-interim

by a third between lower and higher demand, explained by a change from predominantly strong, warm westerly winds to colder, calmer easterly winds. The wind capacity factor is, however, shown to recover to an average level during very high demand conditions (above the 85$^{\mathrm{th}}$ percentile of demand). The black curve in Figure 3 shows this winter relationship between wind power capacity factor and electricity demand percentile. The increase in capacity factor during high demand conditions, in percentage terms is larger than the respective increase in demand, and is found to be due to weather conditions associated with strengthening easterly winds (i.e. blowing from the east) (Thornton et al., 2017). This upturn is also identified by Brayshaw et al. (2012).

These results indicate the important role that wind speed plays in understanding and quantifying extreme stress events on an energy system with installed wind power capacity. In particular, how wind power can contribute to the supply mix during peak temperature driven demand. Thornton et al. (2017) and similar studies are, however, limited by their consideration of historical raw demand data, fixed distributions of present or near future installed wind power capacities, and by only considering part of the energy system (just demand and wind power supply). In contrast, in a recent study, Bloomfield et al. (2018) explored how the relationship between peak hourly demand and meteorological variables, temperature and wind speed, changes when increasing wind capacity is installed within the energy system, from no wind capacity to high wind capacity (45GW). This high installed capacity value is approximately equivalent to the planned installed capacity by 2035 in the 2015 National Grid "gone green" scenario (National Grid, 2015). Indeed, rather then comparing these meteorological variables with raw demand, as in Thornton et al. (2017), Bloomfield et al. (2018) studies a more relevant measures of future energy system stress: the peak residual demand, i.e. demand after subtracting wind power supplied to the energy system.

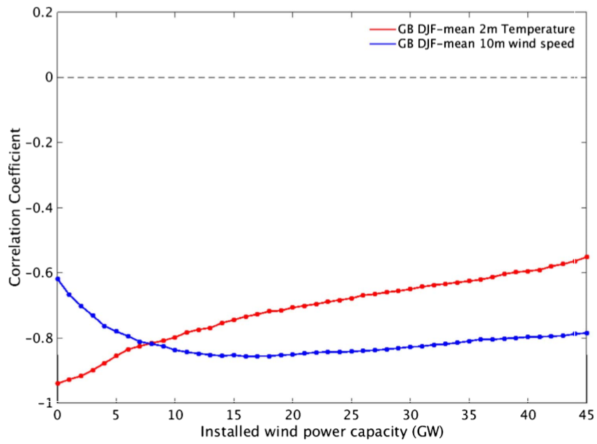


Figure 4: Taken from Bloomfield et al. (2018): Correlation coefficient between winter-mean 2m temperature and the top 10% of residual demand events (red) and winter-mean 10m wind speed and the top 10% of residual demand events (blue) with varying levels of installed wind power generation from 045GW.

As shown in Figure 4, when no wind power is installed there is a strong negative correlation ($r = 0.94$) between winter-mean temperatures and residual demand during the top 10% of residual demand events, similar to the relationship identified by Thornton et al. (2016), shown in Figure 1. The corresponding negative correlation with winter-mean 10m wind speed is weaker ($r = -0.61$). As installed wind capacity increases, the strength of the negative relationship between peak residual demand and winter-mean temperature monotonically decreases, while the strength of the negative relationship between peak residual demand and winter-mean wind speed rapidly increases, plateauing once 15GW of wind power is installed. As described by Bloomfield et al. (2018), this plot shows that, as increasing wind capacity is installed, there is a clear transition in the meteorological conditions associated with peak residual demand events: from situations in which temperatures are very low but wind speed is near average, to those when wind speed is very low but it is less cold. As noted by Bloomfield et al. (2018), this suggests the need for generation adequacy analysis to shift from focusing on wind power availability during peak load (as in Thornton et al. (2017) and similar), towards a more integrated measure of peak residual demand which will depend increasingly on wind speed as more wind capacity is installed.

Cannon et al. (2015) explore an alternative energy system stress event known as ramping, in which energy supply experiences a rapid change. Wind power has the potential to experience ramping stress events characterised by rapid fluctuations in wind power over short time windows. Cannon et al. (2015) find that wind speed can be effectively used to explore the frequency and severity of such events. Further, Bloomfield et al. (2018) investigate the meteorological conditions associated with wind power curtailment, defined by Bloomfield et al. (2018) as an event in which wind generation instantaneously exceeds 70% of total demand, requiring wind turbines to be shut down to reduce supply. They find that such events do not happen until at least 30GW of wind power is installed in the energy system. These events are found to be most common in September and October, when wind speed and hence wind power generation approaches its winter maximum level, while demand remains moderate (Bloomfield et al., 2018). Again, representing such events requires an understanding of the relationship between temperature (driving demand) and wind speed (driving wind power ramping).

Mean Sea Level Pressure

The relationship between temperature and wind speed (as well as other meteorological variables) can be effectively summarised using weather regimes, characterised by Mean Sea Level Pressure (MSLP) fields. A short description of atmospheric pressure is presented in the Appendix (Section 7). In zones of high pressure, descending air suppresses weather development often leading to calm, clear conditions, while in zones of low pressure, winds circulate rapidly inward and upward (due to the Coriolis force of the spinning Earth), cooling the air to form clouds and precipitation. In winter, high pressure often leads to cold, dry days with light winds in the UK, whereas low pressure often signals stormy, windy but warmer conditions.

As noted by Bloomfield et al. (2018) and others (Thornton et al. 2017; Oswald et al. 2008; Leahy and Foley 2012), in the UK peak electricity demand in the winter is associated with a large area of high pressure in the vicinity of the UK. This is because this pattern of MSLP causes lower than average temperatures. Thornton et al. (2017) compare average MSLP fields during the lower and upper 5% of electricity demand days in winter in the historic period 1975-2013. They identify that on average, during high demand days, high pressure extends from Russia and Scandinavia across GB, with anomalously (i.e. different from average) high pressure in northern Europe and anomalously low pressure in southern Europe. This results in anomalously cold conditions, often below freezing, and below average wind speeds across all of the UK. In addition, Thornton et al. (2017) find that the average MSLP pattern associated with peak demand days (the top 1% of days) is similar to that during high demand, but with more intense high and low pressure regions. This results in strengthened easterly winds, and hence greater wind power capacity factor (as seen in Figure 3). These MSLP patterns are shown in Figure 5.

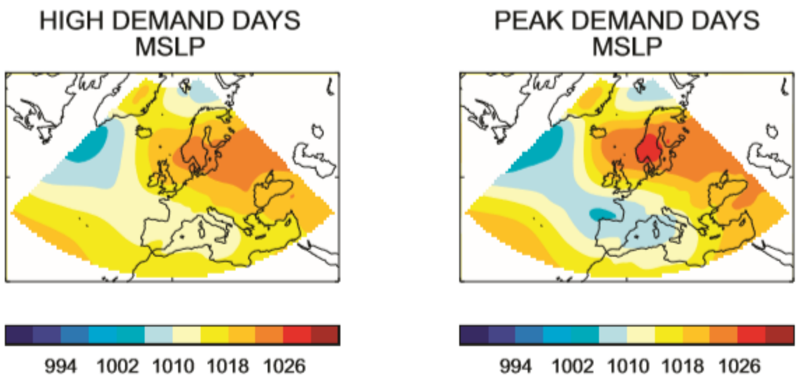


Figure 5: Taken from Thornton et al. (2017): Mean of MSLP during high (top 5%) and peak (top 1%) UK electricity demand days between 01/01/1979 and 31/03/2013.

Thornton et al. (2017), however, base this insight on just 18 days within the 34 year study period (i.e. the top 1%), and hence acknowledge the associated uncertainties in their findings. They suggest that an improved estimation could be made by assessing a longer historical record or using large ensembles of climate model simulations. Alternatively, extreme value statistical approaches could also be utilised, discussed further in Theme 5.

Within the literature, there is an apparent debate over the exact location of the zone of high pressure responsible for causing very extreme demand stress on the energy system. Brayshaw et al. (2012) explore the relationship between MSLP patterns and UK winter electricity demand, and identify three distinct situations that are important for understanding peak demand. Firstly, the high-over-Britain, causing very low wind speeds and moderately cold conditions; secondly, blocking highs with north/easterly winds into the UK, causing extreme cold conditions but moderate winds; and thirdly, extended north-south low pressure troughs over western Europe, causing similar conditions to the blocking MSLP patterns. Brayshaw et al. (2012) argue that the high-over-Britain is likely to result in lower demand compared to the other two regimes since temperatures are slightly higher. Similarly, Grams et al. (2017) explore the impact of seven distinct MSLP patterns, often used to categorise European weather, on European wind power production and energy demand. In particular, they identify that during Greenland Blocking regime conditions (characterised by a region of high pressure over Greenland) the UK experiences extremely cold temperatures and reduced winds. However, they also identify that during the European Blocking regime (characterised by a strong zone of high pressure over the UK and Scandinavia) wind speeds in the UK are extremely low, having the most effect on wind power production.

Again, these studies focus on historic or current levels of installed wind power capacity, and therefore underestimate the effect of wind speed on peak demand, or more importantly peak *residual* demand. Bloomfield et al. (2018) explore how the location of high pressure, causing very extreme peak residual demand, changes as increasing wind power capacity is installed, from NO-wind, LOW-wind (15GW), MEDIUM-wind (30GW), to HIGH-wind (45GW), shown in Figure 6.

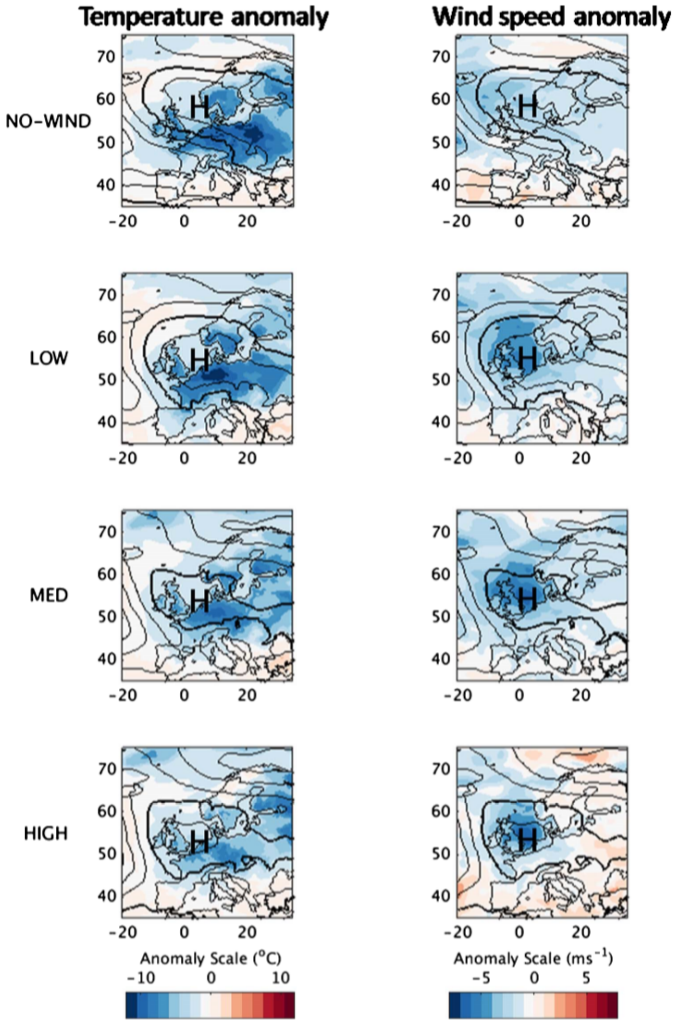


Figure 6: Taken from Bloomfield et al. (2018): Mean temperature anomaly and wind anomaly maps (i.e. difference from average), for the ten most extreme residual demand days in 1980-2015 for the NO-WIND, LOW, MED and HIGH scenarios. Mean-sea-level-pressure contours for the events are overlaid in black with a 4hPa interval. The thick contour represents 1016hPa. The H represents the location of the centre of the region of high pressure.

In line with the previously discussed literature, Figure 6 shows how, when no or low wind power capacity is installed, peak demand is associated with high pressure not centred over the UK (as seen in Figure 5) resulting in extremely low temperatures and moderate winds. However, as increasing wind capacity is installed, weather conditions associated with high pressure located directly over the UK (very low winds and moderately low temperatures) become increasingly responsible for causing extreme peak residual demand (bottom row in Figure 6).

On a larger scale these MSLP patterns can be broadly characterised as positive or negative phases of the North Atlantic Oscillation (NAO), a meteorological index measuring the pressure difference between Iceland and the Azores (Hurrell et al., 2003). As discussed in Ely et al. (2013), NAO variability is strongest in the winter (December to March) and is associated with shifts in the path of weather systems, such as storms, travelling across the North Atlantic. The positive phase of the NAO, characterised by a zone of lower than average pressure over Iceland and higher than average pressure over the Azores, is generally associated with anomalously warm, wet and windy conditions in northern Europe, while the negative phase, characterised by higher than average pressure over Iceland and lower than average pressure over the Azores, causes cold and calm conditions. For further information about how the NAO affects UK weather, see the Met office website[2]. In the UK, there is known to be a strong positive correlation between NAO and meteorological variables: temperature, precipitation and wind speed (Ely et al., 2013). In relation to the energy system, Ely et al. (2013) showed how the cold, calm conditions associated with the negative phase of the NAO caused increased electricity demand and decreased wind-power production when compared with other NAO states, and Brayshaw et al. (2011) showed that the distribution of wind power output over the UK is dependent on the phase of the NAO.

Furthermore, Bloomfield et al. (2018) showed that this well established relationship is consistent for all installed wind capacity scenarios (NO-wind to HIGH-wind). However, they also found that the amount of wind power capacity installed in the system has a large influence on the relative magnitude of the impact of an extreme NAO year. Bloomfield et al. (2018) go on to suggest that this indicates the growing significance of large scale modes of climatic variability (such as the NAO) on future UK and European power systems. As a result, an accurate seasonal NAO forecast could be of increased importance in the future.

As discussed in Thornton (2018), Zubiate et al. (2017) extend this analysis to investigate the influence of the next two most important atmospheric circulation patterns in the UK, the East Atlantic (EA) and Scandinavian (SC) patterns. They find that in certain locations, the phase of the EA and SC patterns can modify the relationship between NAO and wind speed. For example, when the NAO phase is positive and the EA phase negative, enhanced wind speeds are found over much of north-western Europe, leading to increased wind power capacity factors.

[2] `https://www.metoffice.gov.uk/research/climate/seasonal-to-decadal/gpc-outlooks/ens-mean/nao-description`

Bloomfield et al. (2018) also investigate the MSLP pattern responsible for causing extreme wind power generation at times of low demand, described as wind curtailment events. They find that such events occur when a zone of low pressure is located to the north of the UK causing strong horizontal pressure gradients and hence high wind speeds. In a similar way Cannon et al. (2015) indicate that extreme wind power ramping events are associated with low pressure weather systems moving across the UK.

Solar Irradiance

As noted by Bloomfield (2017), research into the modelling and understanding of the solar power resource and its impacts on the UK power system is in its relative infancy, with only a handful of studies focussed on the UK specifically. Indeed, most of the literature previously introduced focuses on the relationship between meteorological variables and wind power supply. This is most likely since electricity generated from solar photovoltaic (PV) panels is much lower compared to wind, both in the UK (National Grid SO, 2018) and Europe (Grams et al., 2017). In addition this may be due to the UK's unique position next to the Atlantic Ocean and at the end of the North Atlantic storm track, making it a prime location for wind power resource (Thornton, 2018). It is, however, important to also consider the meteorological variables responsible for influencing solar PV generation in a system with increasing installed PV capacity.

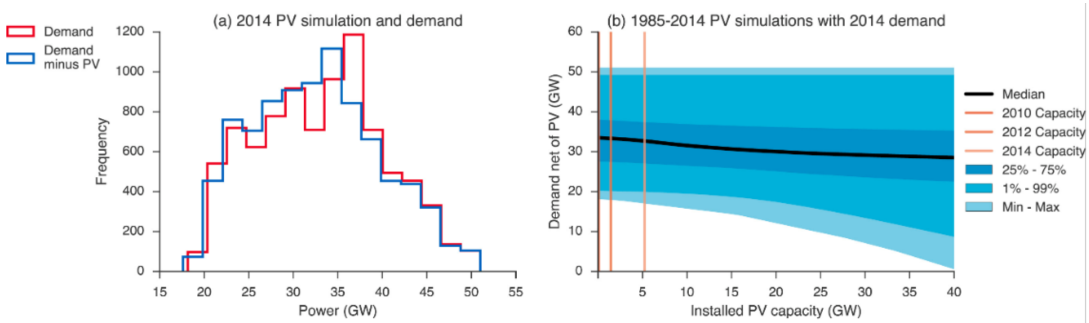


Figure 7: Taken from Pfenninger and Staffell (2016): (a) Comparison of 2014 hourly demand and hourly residual demand (demand - PV production). (b) 2014 demand net of PV, from hourly PV simulations for 30 years (1985-2014).

Pfenninger and Staffell (2016) investigate long-term patterns in European PV over the 30 year period 1985-2014. Within this analysis PV is estimated as a function of solar irradiance, defined as the power per unit area received from the sun in the form of shortwave electromagnetic radiation. In addition, the efficiency of solar PV panels is known to depend on ground level air temperature and wind speed (most efficient in cold and windy conditions), and hence these meteorological variables are also included in the PV generation model. They show that, based on demand and PV installation as at 2014, PV generation occurs at times of both high and low demand, but contributes nothing towards the highest peak demand events. This is shown in Figure 7 (a), in which the frequency of different levels of 2014 hourly demand and hourly residual demand (demand minus PV) are compared. The frequency of medium and low demand hours is greater in the residual demand distribution while the frequency of moderately high demand hours is reduced, indicating that PV generation occurs during low to high demand hours. The frequency of very extreme demand (45-55GW) is unchanged when PV generation is subtracted from demand (Figure 7 (b)), indicating that PV generation does not help to off-set these extreme stress, high-demand events. This indicates that solar irradiance may have less of an influence on extreme high-demand stress events on the energy system compared to temperature and wind speed.

Nevertheless, recent literature has aimed to incorporate both wind power and solar PV within their analysis of the energy system. For example, Pfenninger (2017) examine the inter-annual variability of wind power and PV over 25 years in a UK power system model, Grams et al. (2017) and Bett and Thornton (2016) explore the relationship and potential co-deployment of wind and solar power for reducing energy system volatility in Europe and Britain respectively, and Staffell and Pfenninger (2018) develop a framework for quantifying the impact of weather on electricity demand and supply, including the generation of weather-dependent PV and wind generation. In all cases these analyses are based on meteorological data sets of temperature, wind speed and solar irradiance. These studies further indicate the smaller influence of PV and hence solar irradiance in the current system, identifying that PV could balance low-wind regimes locally, but only by expanding current capacity tenfold (Grams et al., 2017).

Pfenninger and Staffell (2016), however, show how increasing solar PV in the energy system, from 0 to 40GW changes the distribution of minimum hourly residual demand (demand minus PV generation), presented in Figure 7 (b). This figure shows how, when 40GW of PV capacity is installed, the UK starts to experience negative residual demand from PV generation alone (ignoring the additional contribution of wind power generation).

In addition, in relation to mean sea level pressure (MSLP) patterns, Pozo-Vázquez et al. (2004) show how solar radiation is anomalously high in the UK during periods of negative NAO phase (i.e. when temperature driven demand is high and wind speed and therefore wind power generation is low), identifying another important meteorological relationship that must be accurately represented when investigating extreme stress on the energy system. In winter, however, PV potential is low and therefore the effect on production is low. This is discussed in more detail in Section 3.4.

These finding emphasis the importance of using a complete power system model, incorporating the influence of temperature, wind speed and solar irradiance (resulting from MSLP patterns) on power supply, as well as the importance of considering residual demand (after accounting for wind and PV generation), similar to the framework presented in Staffell and Pfenninger (2018).

Other meteorological variables

Alternative parameters, used to model electricity demand in the literature include: relative humidity, clearness index, cloudiness and rainfall (Psiloglou et al., 2009), effective temperature (an average of current temperature and the previous days elective temperatures), the cooling power of the wind (a non-linear function of wind speed and average temperature) and effective illumination (a complex function of visibility, number and type of cloud, and amount and type of precipitation) (Taylor and Buizza, 2003). Within these studies the relationships between these meteorological variables and extreme energy system stress events are not investigated. Further, in some studies solar PV power generation is modelled as a function of surface wind speed (as well as solar irradiance and surface temperature), since cooler, windier conditions lead to greater PV cell performance (Jerez et al., 2015a).

Summary

- Peak electricity demand in the UK has a strong negative relationship with temperature;
- Gas demand has an even stronger negative relationship with temperature, and much greater within day variability, highlighting the challenges in managing and balancing a future energy system with electrified heating;
- Wind power generation is well represented as a function of wind speed cubed;
- The relationship between temperature and wind is most important for representing extreme stress events of peak residual demand, while wind speed alone characterises the instantaneous rapid changes in wind power generation known as ramping events;
- Solar PV generation is well represented by solar irradiance (in combination with surface temperature and wind speed) and is most important for understanding extreme stress events in which supply exceeds demand (in summer);
- Weather conditions and the resulting relationship between temperature, wind speed and solar irradiance can be characterised by mean sea level pressure patterns;
- In an energy system with high installed wind capacity, peak residual demand (demand - wind power generation) in the UK is associated with a large area of high pressure located directly over the UK, causing extreme low wind speeds and cold conditions;
- These extreme residual demand conditions are associated with the negative phase of the North Atlantic Oscillation (the pressure difference between Iceland and the Azores);
- Conversely, ramping and wind-curtailment events are associated with an area of low pressure to the north of the UK, and low pressure weather systems passing over the UK;
- When representing extreme stress on the future energy system it is important to represent the effect of temperature, wind speed and solar irradiance on the whole energy system (supply and demand), in particular considering the residual demand;

- Additional meteorological variables have been used to model electricity demand, however further analysis is required to quantify their relationship with extreme stress events.

3.2 Spatial and temporal variability and dependence of these important meteorological variables at different scales

Thus far, the previous section identifies three meteorological conditions that may cause extreme stress on a highly renewable energy system:

1. Peak residual demand events: very low temperatures and extremely low wind speeds, characterised by high pressure located over the UK during winter months
2. Ramping and wind curtailment events: extremely variable high wind speeds, associated with areas of low pressure moving across the UK during autumn months
3. Peak energy surplus events: high levels of solar irradiance, most likely experienced during summer months

To better understand the impact these meteorological conditions might have on the future energy system the spatial and temporal variability of such conditions must be explored at various scales.

Local

Wind is a highly variable element whose magnitude can change dramatically depending on local climatology and terrain (Watson, 2014). Understanding the distribution of wind speeds at a local scales is important for estimating the capacity factor and energy yield of co-located wind turbines (Watson, 2014). As described by Burton et al. (2011), hills result in local regions of increased wind speeds. This is considered to be due to two effects: wind speeds generally increase with height above sea level, and hence hill tops project into a higher wind speed layer, as well as the accelerating effect the hill has on the wind flow as it is pushed up and over the higher terrain (Burton et al., 2011). Further, coastal regions often experience windier conditions due to the difference in temperatures, and therefore zones of low and high pressure over land and sea respectively[3]. In a similar way, temperature differences in areas resulting from variable altitude can cause strong winds descending from higher ground (Burton et al., 2011). Conversely, some terrain can cause reduced wind speeds such as sheltered valleys, and areas protected behind hill and mountain ranges (Burton et al., 2011). In addition, Albadi and El-Saadany (2010) note the major role vegetation type can plays in the local variation of wind speeds. Burton et al. (2011) go on to explain how these local variations in topology and climatology lead to turbulence, defined as fluctuations in wind speed on a relatively fast time scale. Therefore, local variations in wind speeds are most associated with ramping and wind curtailment extreme stress events.

[3] https://www.metoffice.gov.uk/learning/wind

In a similar way, local variations in temperature result from differences in topology and land use. For example, temperatures are colder at higher altitudes and in rural areas where there are fewer buildings warming the surrounding air, more bodies of water and vegetation leading to evaporation which cools the air, and less air pollution to trap solar energy (Wallace and Hobbs, 2006). These local differences in temperature could result in very different energy requirements in nearby locations with different land use properties, complicating energy distribution.

Lohmann et al. (2016) explore the local variability of solar irradiance, noting two key forms: variability in irradiance itself which primarily affects the yield of a PV system, and variability in irradiance increments (changes over specified intervals of time) which impact the balancing of generation and demand. Lohmann et al. (2016) describe three distinct sky types: overcast, clear and mixed sky conditions. As might be expected, mixed sky conditions are shown to have higher probabilities of strong fluctuations in solar irradiance, compared with overcast and clear skies, and are therefore most potentially problematic in terms of local short-term variability in irradiance increments. This highlights an alternative potential ramping stress event resulting from local fluctuations in irradiance, occurring during mixed sky conditions which poses a challenge for managing the energy system at local scales. In contrast, Lohmann et al. (2016) found that longer periods of low PV generation experienced over the whole of the UK were associated with overcast conditions, where large stratus-type clouds dominate, resulting in consistently low PV yields.

National

Figure 8 presents the annual average mean (left) and minimum (right) temperature over the UK. Temperatures are generally warmer in the south and around the coasts of the UK. Therefore, for an individual residence energy demand is likely to be higher where it is colder (in the north, at higher altitudes) and in rural areas. However, on a national scale, high demand is likely to vary with population density in combination with temperature.

Figure 9 presents the mean and variability of daily wind speed during the period 1871-2012, taken from Bett et al. (2017). This figure demonstrates how wind speeds are, on average, greater and more variable in Scotland and the North Sea compared to the rest of the UK. This highlights the potential gain in locating wind turbines in these northerly locations, but also the challenge that may come for the higher variability in wind speeds.

A number of studies have found that, due to the finite size of weather systems and hence similar weather conditions, spreading the geographical location of renewables, and in particular wind turbines, can help to reduce the variability of their combined output (Sinden (2007); Drake and Hubacek (2007); Oswald et al. (2008); Santos-Alamillos et al. (2014); Grams et al. (2017)). For example, Drake and Hubacek

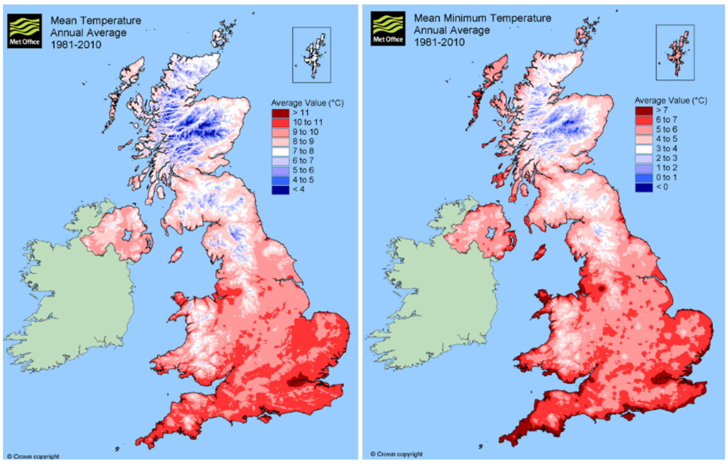


Figure 8: Annual average (1981-2010) mean temperature (left) and mean minimum temperature (right) in the UK [https://www.metoffice.gov.uk/public/weather/climate].

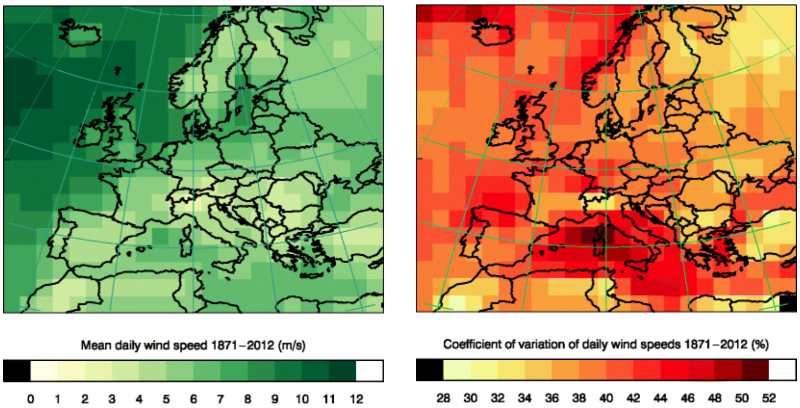


Figure 9: Taken from Bett et al. (2017): Maps of 140-year wind speed mean and variability in terms of the coefficient of variation, i.e. the ratio of the standard deviation to the long-term mean.

(2007) identify a potential reduction in national wind power variability of 36% when wind power capacity is distributed over four sites spanning the UK rather than a single site. Sinden (2007) studied the correlation between wind power generation at 2080 pairs of recording sites (over the period 1970-2003) to explore the range in spatial dependence of wind power output within the UK. This relationship is shown in Figure 10, indicating that wind turbines located >600km apart have very little correlation in wind power output at a given time and can therefore compliment each other in producing wind power nationwide.

Further, in relation to extreme stress events, Thornton et al. (2017) found that weather patterns associated with high (top 5%) temperature-driven demand days (i.e. very cold conditions) have a variety of spatially distributed wind capacities, suggesting that a spread of wind turbines across the UK would maximise the average availability of wind power during these extreme demand events. Thornton et al. (2017) identified 4 groups/clusters of similar weather patterns that cause high demand in the UK. Figure 11 shows the wind capacity factor anomaly (i.e. difference from mean) for these 4 weather patterns.

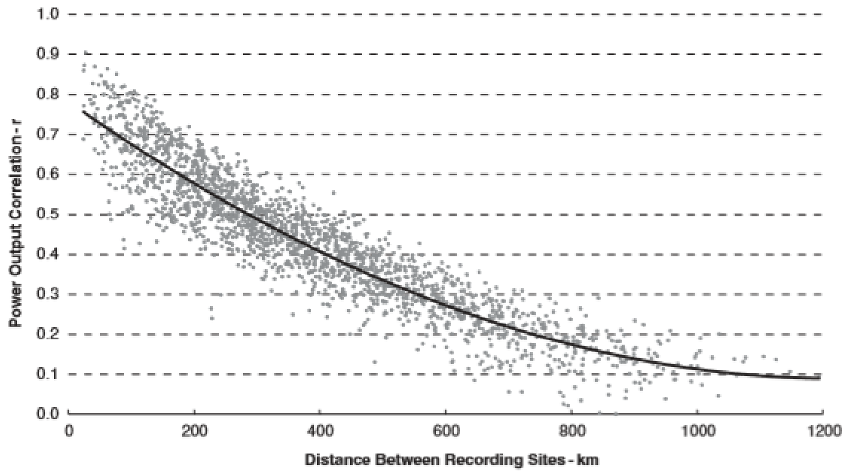


Figure 10: Taken from Sinden (2007): Wind power output correlation versus distance between UK sites.

For each pattern the wind capacity factor anomaly varies within the UK. For example, in cluster 1, wind capacity factor is below average in Scotland and Northern Ireland, but above average in England and Wales. This suggest that during high demand events associated with this type of weather pattern, wind power capacity located in England and Wales could be used to supplement power supply in Scotland and Northern Ireland. In addition, Figure 11 shows the corresponding cluster mean temperature anomalies over the UK (and Europe). This shows how in cluster 1, for example, temperatures are more anomalously low (and hence demand is greatest) in the south of the UK, where wind capacity factor is higher, making energy distribution easier. Whereas for cluster 3, temperatures and wind capacity factor are both anomalously low in the south, and less so in the north, requiring transportation of generated wind power from the north to the south.

As discussed in the previous section, ramping and wind curtailment extreme stress events on the energy system are generally associated with local, small scale variability in wind speeds. As a result, fewer studies focus on the national dependence and variability of such events. Drew et al. (2017), however, highlight how the recent UK trend towards installing very large clusters of offshore wind farms together in zones exacerbates the effect of ramping events. They present a case study of a single ramping event experienced in the Thames Estuary (one of the largest cluster of wind farms in the world) on 3^{rd} November 2014, and show how such a localised, large ramping event on time scales of less than 6 hours can have a significant impact on the cost of balancing the power system on a national level. Again, this highlights the importance of spreading wind turbines and wind farms throughout the UK for reducing the severity of extreme stress events.

Burnett et al. (2014) present a map of the monthly average daily sunshine duration hours (1961-1990) in the UK, averaged over the whole year, and for June and December, shown in Figure 12. In December sunshine hours are very low throughout the UK, particularly in the north and west. A similar spatial pattern is seen in June, where the highest levels of sunshine hours are seen in the south east and, in

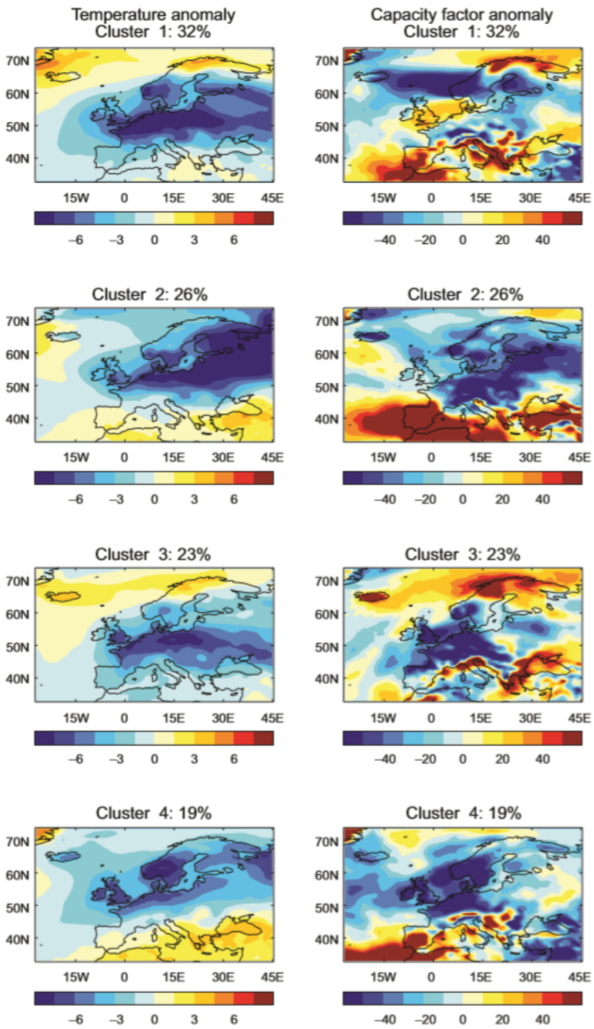


Figure 11: Taken from Thornton et al. (2017): Average temperature anomalies (left) and Wind power capacity factor anomalies [% difference from climatology] (right) for weather types ("clusters") that describe high winter demand days (top 5% 1979-2013). Anomalies are relative to the winter climatology from 01/01/1979 - 31/03/2013.

particular, on the south coast. These maps could aid in proposing locations for new PV potential, with the optimal location potentially being central western England, where sunshine hours are relatively high in winter and moderate in summer, so helping to mitigate extreme peak residual demand in winter and minimise surplus energy stress events in summer.

Further, Pozo-Vázquez et al. (2004) and Colantuono et al. (2014) explore the relationship between the North Atlantic Oscillation (NAO) and solar irradiance in the UK. Both studies demonstrate how the NAO has a significant influence on the winter spatial and temporal variability of solar irradiance. Specifically, Pozo-Vázquez et al. (2004) present the correlation between NAO index and the monthly sum of sunshine duration in grid cells throughout Europe. They show that there is a strong negative correlation between NAO and solar irradiance in northern UK, and a mixture of weak positive and negative correlations in the south of the UK. Therefore during an NAO positive phase (associated with cloudy, warmer and windy conditions) solar irradiance is low in northern UK but moderate in southern UK, while in an

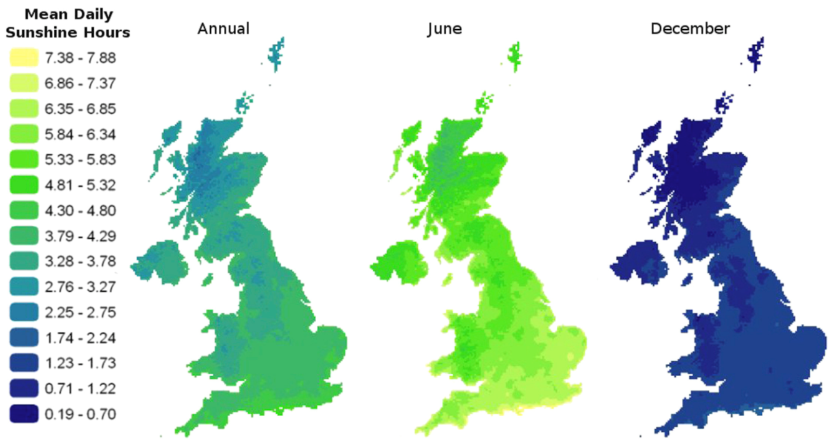


Figure 12: Taken from Burnett et al. (2014): Monthly average daily sunshine duration hours (1961-1990).

NAO negative phase (associated with clear, cold and still conditions) solar irradiance is high in northern UK and moderate in southern UK. Therefore, as seen for wind, weather patterns result in contrasting solar conditions in different parts of the UK. Colantuono et al. (2014) go on to explore the same relationship at higher spatial resolution over the UK, and find that winter NAO index is positively correlated with solar irradiance in the East of the UK, and negatively correlated in the West. In combination, these studies suggest a North-West - South-East co-variability in solar irradiance in the UK, during different winter energy demand conditions. As a result, Colantuono et al. (2014) note how spatially varying the location of PV panels could help even out year-to-year variability in solar power yield.

Europe Wide

Interconnectivity with other European countries will be vital for increasing back up and flexibility in the future UK energy system. For example, in the Assessment (National Infrastructure Commission, 2018) the whole system energy model assumes interconnectivity with Europe, supplying the UK with 18GW of energy by 2022 (consistent with all planned Ofgem interconnector projects). It is therefore very important to understand how energy supply and demand in the UK co-varies with the rest of the continent to discern the potential role interconnectivity could play in reducing the severity of extreme stress events.

The left column of Figure 11, taken from Thornton et al. (2017), shows how during the four weather patterns that cause high demand in the UK, temperatures are also anomalously low in many other parts of Europe. As noted by Thornton et al. (2017), this is particularly true for the northern half of Europe where temperatures can be up to 6°C below the winter average. This suggests that when temperature driven demand is high in the UK, high energy demand is also likely in neighbouring countries. In addition, the right column of Figure 11 shows that the majority of European countries also experience below average wind capacity factor (many more than 20% below average) during these high UK demand conditions. Southern European countries, in particular Spain and Portugal are an exception, with moderate temperatures during weather patterns associated with clusters 2 and 4, and much higher wind capacity factor (up to 50% more than average) during weather patterns associated with clusters 1, 2 and 4. This anti-correlation between wind speeds in the UK and Iberia was also seen by Monforti et al. (2016) and Santos-Alamillos et al. (2014), and is related to the dipole response of wind fields to the NAO (Jerez et al., 2013). Thornton et al. (2017) show that a similar situation dominates during peak demand days (top 1%), as presented in Figure 13. During these peak demand days temperatures are anomalously low over most of Europe, while wind capacity factor is low over Scandinavia, northwest UK and central Europe, moderate over southern UK and anomalously high over Denmark, Iberia and the Mediterranean. This suggest that during high and peak demand events in the UK, supply could be supplemented by wind power generated in southern Europe.

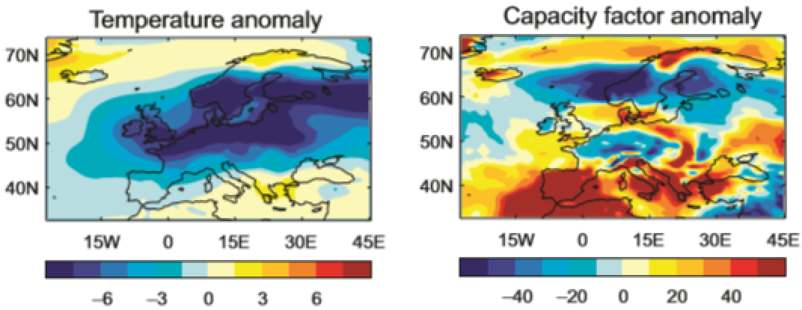


Figure 13: Taken from Thornton et al. (2017): Average temperature anomalies (left) and Wind power capacity factor anomalies [% difference from climatology] (right) on peak demand days (top 1% 1979-2013). Anomalies are relative to the winter climatology from 01/01/1979 31/03/2013.

In a similar way, Figure 6 taken from Bloomfield et al. (2018), shows temperature and wind speed anomalies during the top ten peak residual load events (1985-2015), for increasing installed wind power capacity. Similar to the conclusions of Thornton et al. (2017), this figures indicates that during these extreme stress events in the UK, temperatures are also anomalously low over Central Europe but wind speeds are above average in Spain and Portugal.

At a longer temporal scale, Bloomfield et al. (2018) explore how weather conditions vary throughout Europe during *years* of high residual demand, termed Total Annual Energy Requirement (TAER): the annual demand that has to be met by non-renewable sources. These results are present in Figure 14. Similar to the short peaks in demand, for these longer temporal extremes, they find that, during the six highest years of TAER, there are anomalously lower winter-mean temperatures over Central-Northern Europe. This suggests that during years in which UK demand is high, other European countries also experience cold conditions and hence high demand, potentially leading to European-scale scarcity of supply (Bloomfield et al., 2018). They find, however, that during these years the winter-mean anomalously low wind speeds in the UK are localised to the UK and the North Sea. As noted by Bloomfield et al. (2018), this suggests that pan-European planning and interconnection of renewables could help to manage the inter-annual variability of TAER.

Grams et al. (2017) present the percentage change in wind electricity generation as a result of seven

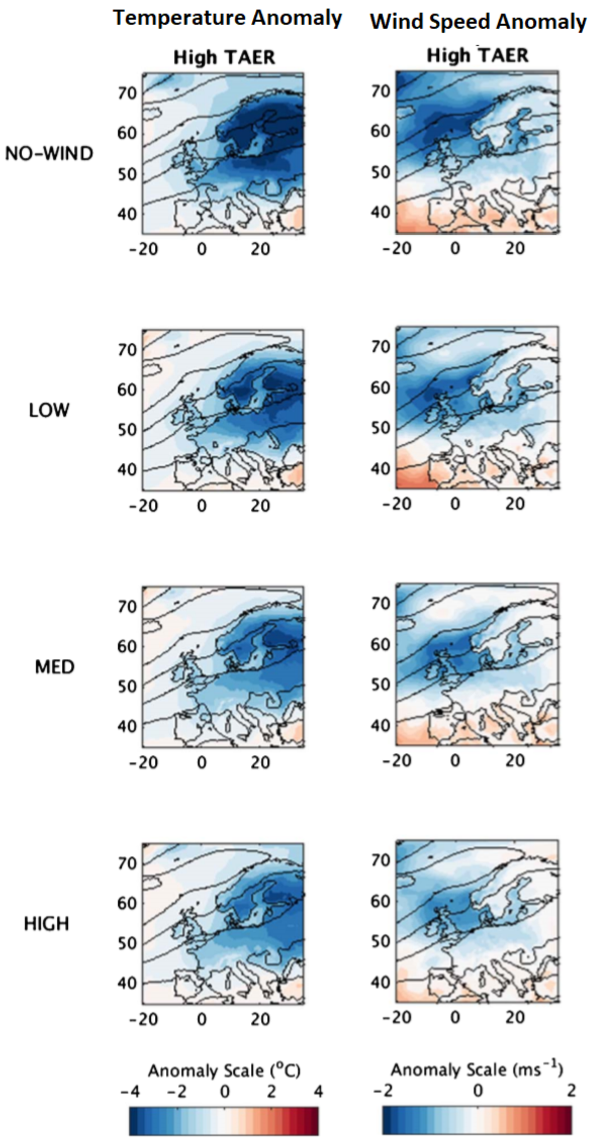


Figure 14: Taken from Bloomfield et al. (2018): Winter-mean anomaly composites (from the 1980-2015 mean) of the six highest years of TAER, for 2m temperature (left) and 10m wind speed for the NO-WIND, LOW, MED and HIGH scenarios (as introduced in Section 3.1). Mean-sea-level-pressure contours are given in black at 4hPa intervals.

European weather patterns in countries throughout Europe. This is summarised in Figure 15. As discussed in Section 3.1, the Greenland Blocking regime (GL) causes extremely cold temperatures and reduced winds in the UK, and the European Blocking regime (EuBL) also causes very low wind speeds and minimal wind power generation in the UK. Figure 15 reiterates this conclusion by showing that in the UK wind electricity generation is most greatly reduced by the GL (blue) and EuBL (green) regimes. The same relationship between weather regimes and wind power generation in many Central-Northern European countries, for example Ireland, Denmark, Germany and Poland. The GL weather regime characterises the peak residual demand conditions identified by Bloomfield et al. (2018) and Thornton et al. (2017). Similar to these aforementioned studies, the negative change in wind power generation in the UK as a result of the GL regime, is reversed in Southern European countries such as Spain, Portugal, Italy and Malta. This further supports interconnectivity with these countries to ensure wind power

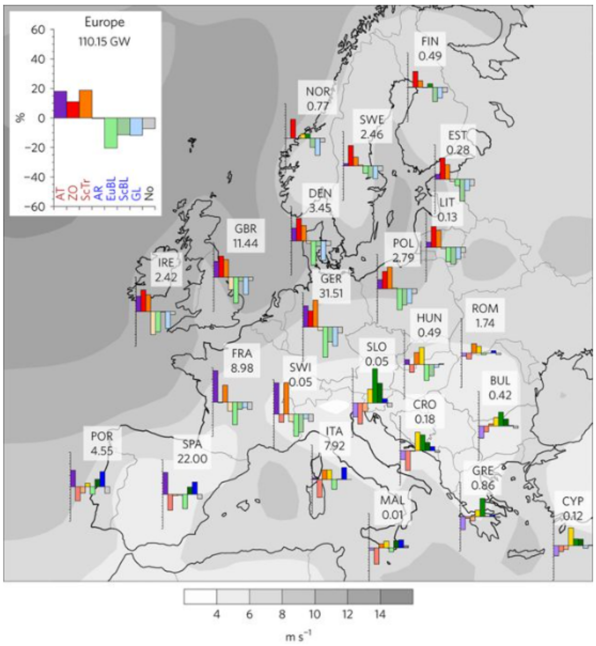


Figure 15: Taken from Grams et al. (2017): Country-specific relative change of wind electricity generation during cyclonic regimes (red labels, inset), blocked regimes (blue labels), and no-regime times (grey) shown as percent deviations from winter mean. Barplot labels indicate country ISO code and 2015 installed capacity (in GW). Shading: winter mean (DJF 1979-2015) wind speed 100m above ground (m/s).

supply during extreme residual demand stress events in the UK. Figure 15 highlights an additional potentially beneficial interconnectivity between the UK and Europe. During the EuBL regime, when wind power generation is at its lowest in the UK, a very large positive increase in wind generation is observed in South-Eastern European countries such as Slovenia, Croatia, Bulgaria and Greece.

Ely et al. (2013) focus on the relationship between wind power generation in the UK, hydropower generation in Norway and temperature-driven demand in the combined region (UK and Scandinavia). In particular they focus on how this relationship varies with the North Atlantic Oscillation (NAO). They find that, due to the annual cycle of reservoir levels, March is a critical period for the combined behaviour of the three energy system components. During this month the hypropower reservoirs are reaching their annual minimum while temperature driven demand remains high. Therefore, the potential for hydropower to meet the shortfall in power supply during periods of low wind in the UK is at its lowest around the month of March. Ely et al. (2013) identify that during March, a negative NAO event can cause anomalously low temperatures across the UK and Scandinavia, paired with anomalously low wind power production in the UK, leading to an extreme residual demand event at a time when the hydropower reservoirs are very low. They go on to recommend using management techniques to ensure a sufficient reservoir minimum level is reserved for March, based on meteorological forecasts of the NAO ahead of winter.

Fewer studies explore the European-wide co-variability of solar irradiance. Pozo-Vázquez et al. (2004) show that the North-South NAO dipole in wind speeds described above also exists for sunshine hours and solar irradiance. Pozo-Vázquez et al. (2004) explore the correlation between monthly NAO index

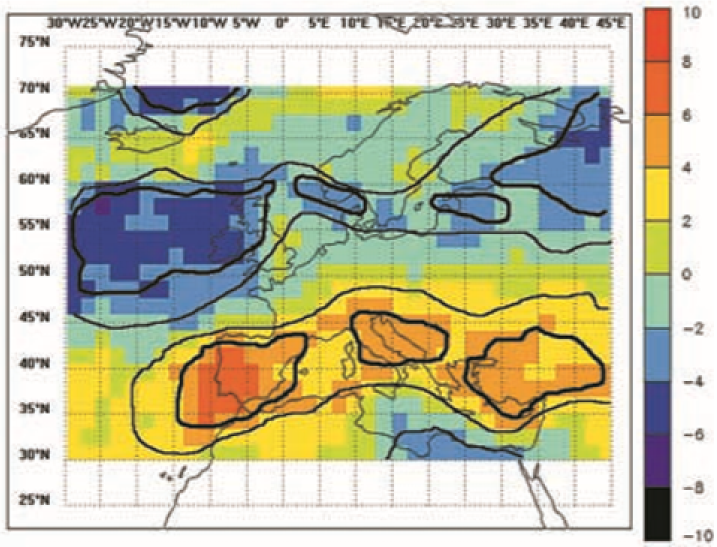


Figure 16: Taken from Pozo-Vázquez et al. (2004): Correlation (multiplied by ten) between monthly NAO index and surface solar irradiance (1949-2002). The thin contours indicate areas of local statistical significance at 95% level and thick contours at 99% level.

and solar irradiance (1949-2002), presented in Figure 16. Pozo-Vázquez et al. (2004) note how positive correlations are found over the whole of the Mediterranean, while negative values are found over northern Europe, particularly North-West UK. This further highlights how interconnectivity between the UK and Southern Europe could help to mitigate extreme stress events: both during positive NAO events when solar power generation is high in Southern Europe and surplus power can be sent to the UK where solar power generation is low, and during negative NAO events when solar power generation is high in the UK and surplus power can be sent to Southern Europe where solar power generation is low. Pfenninger and Staffell (2016) investigate the long term trends in solar PV generation in many European countries. They identify that the UK has the lowest average PV capacity factor in Western Europe, followed by the Netherlands and Germany, with Italy having the highest average PV capacity factor. This in combination with Figure 16 indicates that interconnectivity with Italy could be particularly important when extra power is required to meet demand in the UK, and interconnectivity with South Germany could be useful when a surplus of solar power is generated in the UK, and hence a lower solar capacity factor is experienced in this overall low solar generating region.

Finally, Santos-Alamillos et al. (2017) explore the meteorological potential for planning a high performance European electricity super-grid, to guide European energy policy-makers in the deployment of future renewable generation plants to best achieve a desired balance of mean output versus day-to-day variability. They consider both wind and solar installed capacity, throughout Europe. They discuss how, if the objective is to minimise fluctuations, capacity should be installed in countries with the most predictable power production and in countries whose renewable production profile complements that of the previous countries. Current installed PV and wind capacities throughout Europe are presented in Figure 17 (a) and (b). Figure 17 (c) and (d) then show what additional PV and wind power capacities are required to minimise fluctuations when retaining current power yield. This scenario results in additional

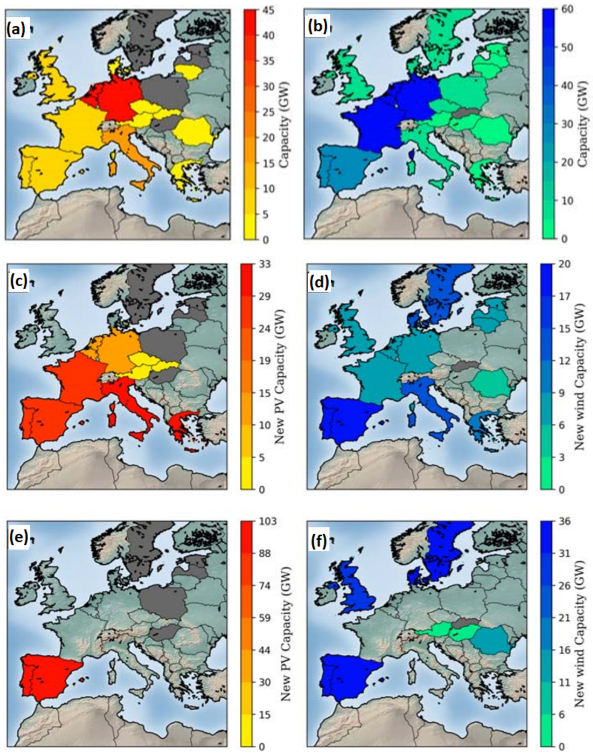


Figure 17: Taken from Santos-Alamillos et al. (2017): Current [as of 2017] installed capacity of (a) PV and (b) wind in Europe, new (c) PV and (d) wind installed capacities to minimise energy fluctuations while retaining current power yield, and new (e) PV and (f) wind installed capacities to maximise energy yield while retaining current levels of power fluctuation.

resources being installed across many countries in Europe, including additional wind power capacity in the UK, balanced by the additional wind capacity installed in Spain and Italy. On the other hand, Santos-Alamillos et al. (2017) discuss how, if the aim is to maximise average power yield, then capacity should primarily be installed in countries with the highest power production, followed by countries able to balance the wind resource of these countries. The additional PV and wind power capacities required to maximise yield while maintaining the current level of energy fluctuations are shown in Figure 17 (e) and (f) respectively. For this scenario, additional solar PV capacity is only installed in Spain, where solar potential is high, and additional wind capacity is installed in the UK, Sweden and Denmark, again balanced by additional wind capacity installed in Spain. Therefore, as noted by Santos-Alamillos et al. (2017), again this highlights the importance of exploiting the spatial-temporal balancing of the wind resource between the Iberian Peninsula and northern Europe.

Instantaneous

Understanding the temporal variability in UK energy demand and supply is also important for minimising stress on the energy system. Instantaneous fluctuations are often observed in meteorological variables related to electricity supply (rather than demand) and have been studied in particular in relation to wind power ramping events. As described by Cannon et al. (2015), such ramps in wind power generation often occur at moderate wind speeds where turbine output ranges from zero to a rated maximum power, providing challenges for transmission system operators. They also note how ramping events can occur at extremely high wind speeds when turbines are shut down for safety, though these events are much rarer (Sinden, 2007). Wind power ramping events can happen as a result of turbulent air. Burton et al. (2011) describes how turbulence is characterised by fluctuations in wind speed on relatively fast time scales, typically less than 10 minutes. Turbulence can occur as a result of friction with the earth's surface, or local changes in temperature, and often these two effects are interconnected for example when a mass over air flows over a mountain range and is forced up into cooler regions of air (Burton et al., 2011).

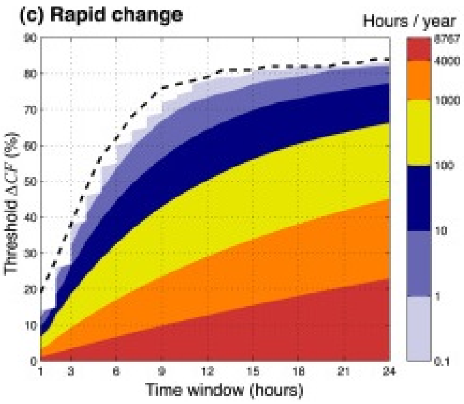


Figure 18: Taken from Cannon et al. (2015): The frequency of hours for which there is a subsequent ramp in generation of at least ΔCF (% change in capacity factor) within the given time window. The dashed lines mark the most extreme events in the 33 year time series (1980-2012).

Cannon et al. (2015) explore the frequency of rapid change ramping events in the UK (1980-2012). Figure 18 shows the average frequency of hours for which there is a subsequent ramp in generation of at least ΔCF (% change in capacity factor) within a given time window. Focusing on Time window (x axis) equal to 1 hour, the resulting plot indicates that sub-hourly fluctuations in wind power generation rarely exceed a 10% change in capacity factor ($<$ 1 day per year), while 1,000 hours per year precede a ramping event that causes approximately a 3% change in capacity factor within an hour. This suggest that fluctuations in wind speed at very short time scales do not cause very extreme changes in wind capacity factor. Cannon et al. (2015) do, however, note that the data set used within this study is likely to underestimate temporal variability in time windows less than 6 hours, hence the frequency of these rapid changes in wind generation may be higher then those shown in Figure 18.

Staffell and Pfenninger (2018) present the distribution of 1-hourly ramps in UK residual demand (demand minus renewable power supply), more relevant for understanding the future energy system. This distribution is shown in Figure 19, for the current energy system as well as for future systems based on the National Grid's Future Energy Scenarios for 2020, 2025 and 2030 (National Grid, 2019b). These future systems incorporate increased installed PV and wind capacities as well as changes in demand due to electrified heating and vehicles. As identified by Staffell and Pfenninger (2018), the width of the frequency distribution increases with 5 year intervals, such that by 2030, ramps of the order of +/- 15GW

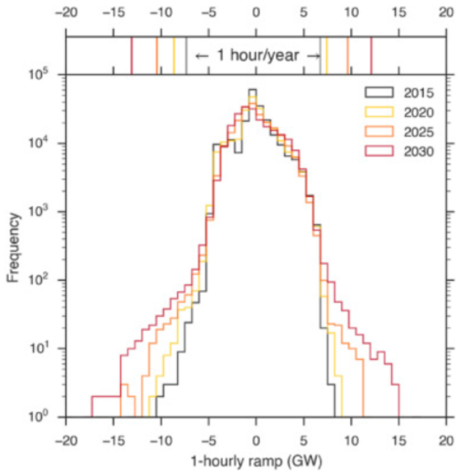


Figure 19: Taken from Staffell and Pfenninger (2018): The distribution of 1-hourly ramps in residual demand across 25 simulated weather years, for 2015, and for the 2020, 2025 and 2030 scenarios (bottom part), and the magnitude of 1-hourly ramps with an expected frequency of once per year (top part).

are possible, while ramps of lower magnitudes become more frequent. They note how the increasing magnitude of ramps expected to occur once a year on average (top part of Figure 19) is important for consideration when planning backup and storage for the 2030 power system.

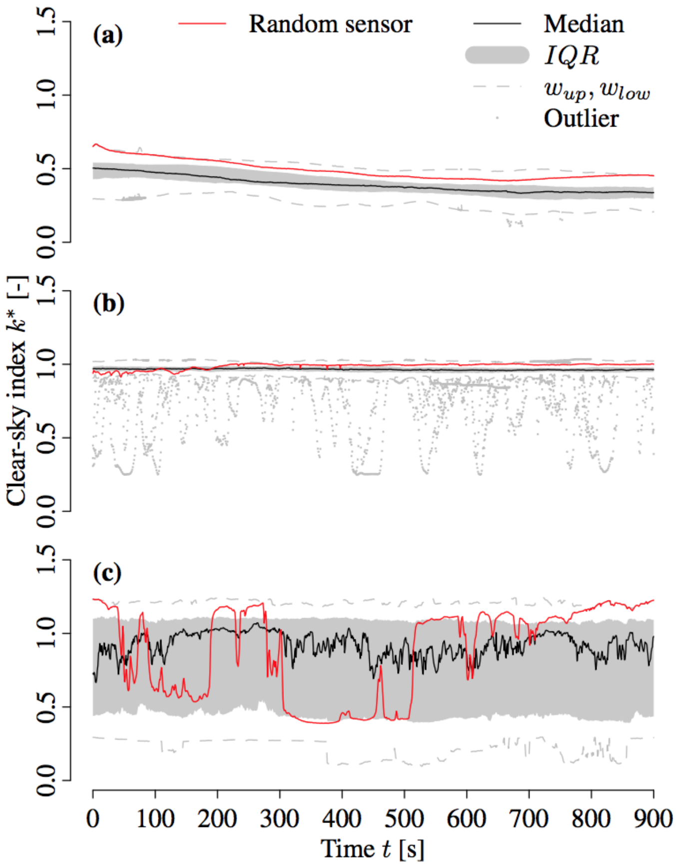


Figure 20: Taken from Lohmann et al. (2016): Examples of different temporal variability in clear sky index for three distinct cases of sky types: (a) mostly overcast, (b) mostly clear, and (c) mixed. These representative subsets were manually selected from the Jlich campaign (see Lohmann et al. (2016)) and span 15 min each. The time series of randomly selected sensors (red curves) are contrasted with summary statistics of field variability, represented as box plots (with median and inter-quartile range (IQR)).

Lohmann et al. (2016) study the short term variability of solar irradiance using a metric known as the clear sky index, based on 99 PV panels deployed over a 80km^2 area. Figure 20 presents three examples of the temporal variability of the clear sky index in the three sky types (mostly overcast, mostly clear, and mixed). Figure 20 (a) and (b) shows how during overcast and clear conditions, the clear sky index and hence irradiance remain relatively constant, with the variability in the lower whisker of the box plot in (b) explained by small clouds passing over individual PV panels. In contract, Figure 20 (c) shows how during mixed sky conditions there is considerable variability throughout the domain at all times, with a consistent inter-quartile range (IQR) of approximately 0.5. Lohmann et al. (2016) note how the trace of the example sensor clearly illustrates the predominant condition of mixed skies in this case, with an alternation between cloud coverage and clear sky exposure. Indeed, for this sensor it can be seen that the clear sky index can fluctuate dramatically instantaneously. Similarly, Marcos et al. (2011) explore power output fluctuations in large scale PV plants using one year of observations at a one second resolution and identify that power fluctuations of up to +/- 50% can occur from one second to the next, and changes of more than 90% within 20 second time windows. These dramatic fluctuations in PV power production could be extremely challenging to manage at short time scales in future energy systems with increasing solar PV capacities.

Within Day

There are well established diurnal cycles in energy demand, dominated by human behaviour. Figure 21 shows this cycle for January and June, 2015, taken from National Grid (2015). On a day in the winter in which temperatures are low, demand is likely to increase, increasing the within day winter peaks in demand. This can be seen in Figure 21 (a), in the shifting up and down of the diurnal demand patterns. In addition, weekdays generally have higher demand overall due to industry (Thornton et al., 2016). As previously noted, UK gas demand, used predominantly for heating, has a very high within-day variability and is more sensitive to changes in temperature. This indicates that a transition to electrified heating could drastically change the variability and peaks within the demand diurnal cycles shown in Figure 21, particularly during winter. Further, the increase in electric vehicles could dramatically effect the diurnal demand profile if not managed in the future (e.g. smart charging).

Sinden (2007) present the average diurnal cycle of wind capacity factor in the UK (for each season separately) over the period 1970-2003. This cycle is shown in Figure 22, and identifies how wind capacity factor is highest in the winter and, for all seasons, wind capacity factor peaks in the mid-late afternoon. Sinden (2007) discuss how this pattern matches the pattern of solar thermal radiation and the resulting thermal induced winds that occur in the warmest part of the day.

However, wind capacity factor varies a great deal more than this within a given day. Now studying

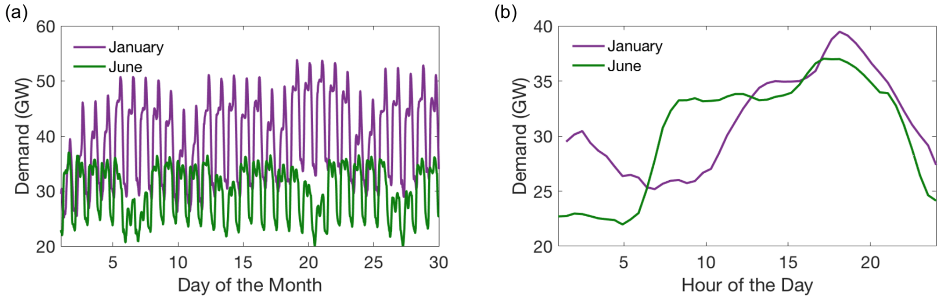


Figure 21: Taken from National Grid (2015): UK hourly electricity demand data (a) the months of January (purple) and June (green), and (b) for the first day of January (purple) and June (green) 2015.

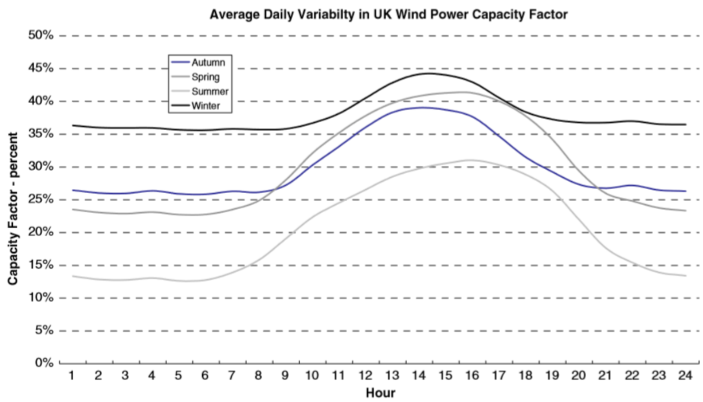


Figure 22: Taken from Sinden (2007): Average hourly wind power availability by season (averaged over 34 years of wind speed data, 1970-2003).

the full range of time windows in Figure 18 (taken from Cannon et al. (2015)), it can been seen how, within the period 1980-2012, it is relatively common (1,000 hours/year) to have within day ramping events in which the wind power capacity factor varies by 40% within a 24 hour time window. This Figure also shows how on average once a year the wind power capacity factor varies by 80% within a 24 hour time window. Cannon et al. (2015) note how the percentage change in wind capacity factor (ΔCF) increases rapidly with time window up to around 9-12 hours, after which it plateaus. They describe how this corresponds to the transition time of a typical low pressure weather system passing over the UK.

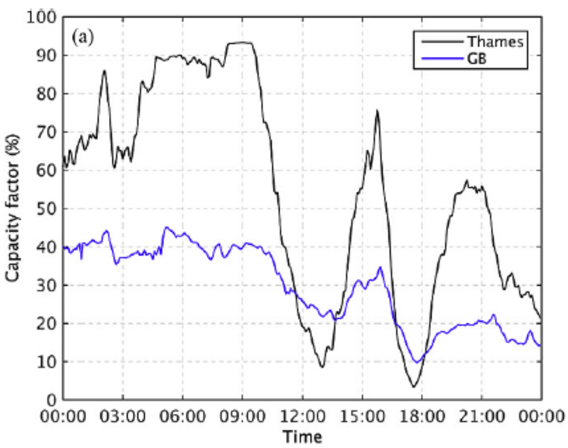


Figure 23: Taken from Drew et al. (2017): Wind power generation on the 3rd November 2014: 5 min mean generation of the Thames Estuary wind farms (black) and GB-aggregated (blue).

Drew et al. (2017) present a time series of the change in wind power generation in the Thames Estury during a very extreme ramping event in November 2014, shown in Figure 23. As can be seen in Figure 23, during this event an 80% decrease in wind capacity factor was experienced within a 3 hour time window (9:00-12:00), as well as other large changes later in the day. Since the Thames Estuary constitutes a large proportion of the national installed wind capacity, these fluctuations in wind capacity factor are also seen in the UK/GB aggregated wind capacity factor. This demonstrates how locating large numbers of wind turbines in fewer locations will increase the within day variability of wind power supply and increase the occurrence of large scale wind ramping events.

Similarly, Oswald et al. (2008) explore the variability of wind power supply, but for an increased level of installed wind capacity (25GW) across the UK energy grid. They study Met Office hourly wind speed data for 12 years of January and develop a model for power output (calibrated using Ofgem records). Oswald et al. (2008) identify that their wind power model experiences power swings of 70% within 12 hours in winter. They go on to discuss how this will require individual generators to go on or off line frequently, thereby reducing the utilisation and reliability of large centralised plants, and leading to increases in the cost of electricity and reductions in potential carbon savings.

Bloomfield et al. (2018) study wind power curtailment events (defined as wind generation instantaneously exceeding 70% of total demand) for different levels of installed wind capacity. They find that such events do not occur until 30GW of wind power generation is installed, and identify how, due to the diurnal cycle of demand and the most frequent occurrence of curtailment events being between 10pm and 4pm, extremely large volumes of installed wind power are required for wind power curtailment to become more frequent.

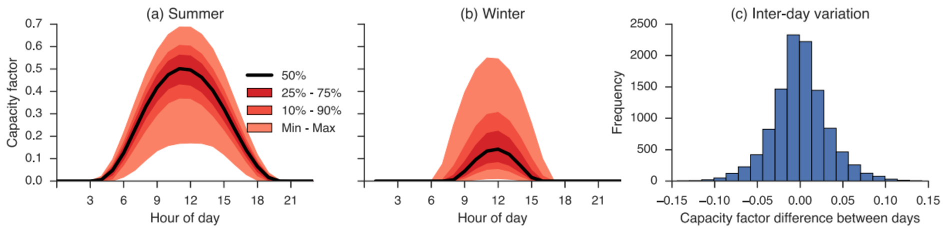


Figure 24: Taken from Pfenninger and Staffell (2016): Diurnal variability of PV capacity factors in the UK from hourly simulations for 30 years (1985-2014).

Solar irradiance has a more predictable diurnal cycle compared to wind power (Pfenninger and Staffell, 2016), since it depends largely on the intensity of the sun and therefore the hour of the day. Pfenninger and Staffell (2016) present the diurnal variability of PV capacity factors in the UK from hourly simulations for 30 years (1985-2014). This is shown in Figure 24 and identifies how much lower the median hourly capacity factor is in winter, with some simulated winter days producing almost no solar power.

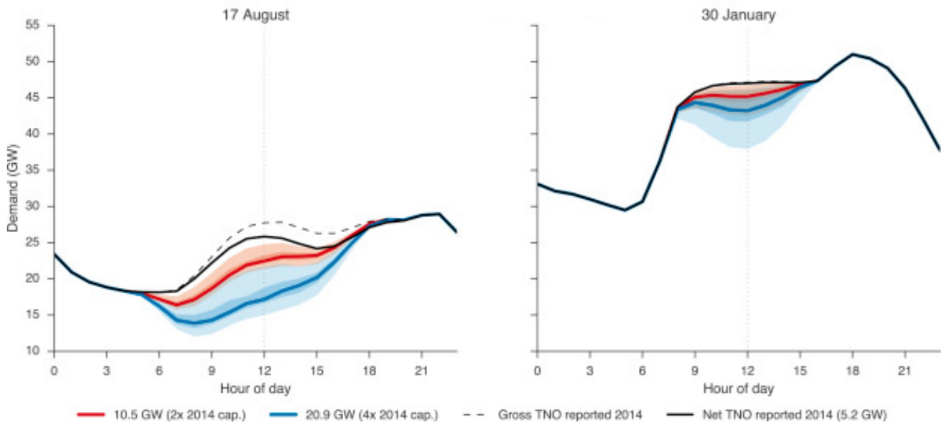


Figure 25: Taken from Pfenninger and Staffell (2016): Electricity demand in Great Britain in 2014 net of different installed PV capacities. The minimum and maximum net demand days in 2014 are chosen, the black dashed line represents gross demand, and the thick black line the net demand with 2014 installed PV capacity. The thick coloured lines are the median across 30 years, while the two lighter shades of each colour indicate the 25%75% and the minimum-maximum range.

Pfenninger and Staffell (2016) go on to explore how the diurnal net demand cycle (demand minus solar supply) will change with increasing installed PV in the UK power system, presented in Figure 25. The results highlight the widening range of situations the network operator will have to cope with on a day-to-day basis with increasing solar PV. For example, on a winter day in the UK PV production barely makes a dent in net demand and the stark contrast between summer and winter indicates the difficulty facing power systems with high shares of solar PV, and the degree to which other power sources or storage must be available to fill in these net demand gaps. Indeed, Pfenninger and Staffell (2016) note how National Grid says that accommodating more than 10 GW of PV capacity will not be possible without making operation of the transmission system significantly more difficult (National Grid, 2019c).

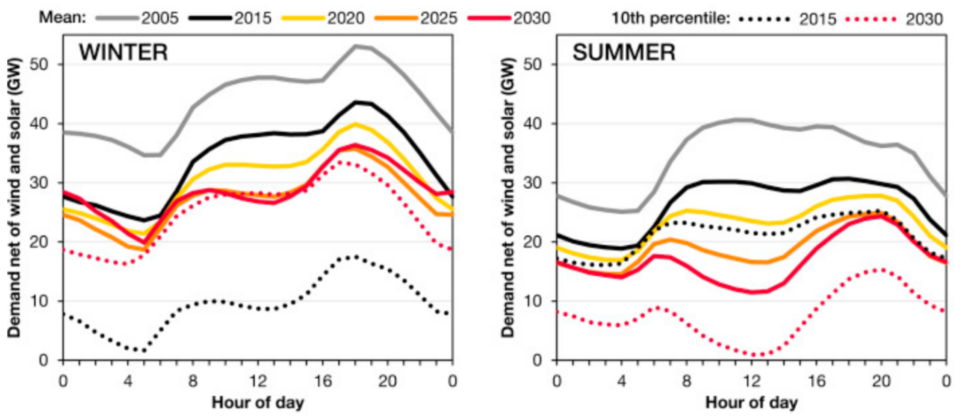


Figure 26: Taken from Staffell and Pfenninger (2018): Evolution of the average diurnal profile in January (left) and July (right) for demand net of renewables, for the National Grid future scenarios out to 2030 (National Grid, 2019b). Solid lines show the mean across all days in the month (and across all 25 weather years for future ensemble simulations), while dotted lines show the tenth percentiles. The red and black dotted lines in the plot for winter should be swapped over [correction confirmed via email from the author].

To explore how within-day variation in energy supply and demand may change in the future, Staffell and Pfenninger (2018) plot the diurnal cycle of residual demand (net of wind and solar PV generation) during an average January and July day, based on their full energy system model with changing renewable capacities and demand behaviours in future years, shown in Figure 26. Staffell and Pfenninger (2018) note how the greatest changes between now and the energy system of the 2030's can be seen in summer, as the coordinated output of a growing installed PV capacity reduces average summer daytime demand to below the levels seen overnight. Indeed, by 2030, overnight demand in winter and midday demand in summer would routinely fall to (or below) zero, which may pose a challenge for future energy system management.

Multi-day

Multi-day variations in electricity demand and weather-dependent renewable supply predominantly depend on European-wide weather regimes. For example, as noted by Bloomfield et al. (2018), on daily to weekly timescales UK wind power capacity factor is related to synoptic scale (approximately 1,000 km) weather events termed regimes, with zonal (west-east) regimes resulting in highest aggregate wind power generation, and blocked regimes resulting in lowest aggregate wind power generation. Indeed, Grams et al. (2017) show how multi-day fluctuations in Europes wind power are closely associated with the sequence of Europe-wide weather regimes (discussed in relation to Figure 15). Similarly, Thornton et al. (2017) identify how, in general, multi-day periods of high demand and below average winds are associated with Central European and Greenland high pressure patterns (clusters 3 and 4 in Figure 11), while multi-day periods of high demand and above average winds are associated with Scandinavian high and Atlantic low patterns (clusters 1 ans 2 in Figure 11). However, Thornton et al. (2017) also show how wind power capacity factor can vary across days within these multi-day weather types, as presented in Figure 27, reflecting the daily variation in the weather regime patterns and magnitudes.

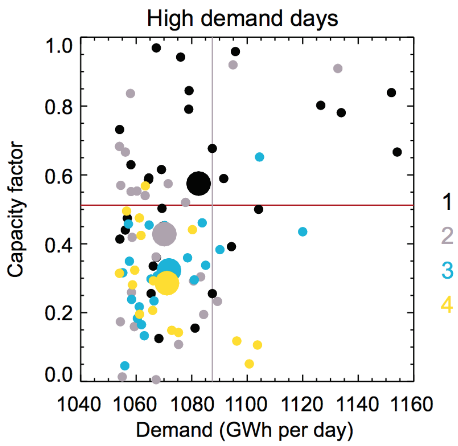


Figure 27: Taken from Thornton et al. (2017): Daily electricity demand and GB mean wind power capacity factor during high demand days. Each day is coloured by its MSLP cluster number (see Figure 11). The mean properties for each cluster are indicated by a large circle. The vertical grey line defines the lower boundary of the peak demand days and the horizontal red lines mark the winter average wind power capacity factor.

As previously introduced, Oswald et al. (2008) explore the variability of wind power supply when an increased level of wind capacity (25GW) is installed across the UK energy grid. More specifically, Oswald et al. (2008) present time series of electricity demand and modelled wind power supply (from the

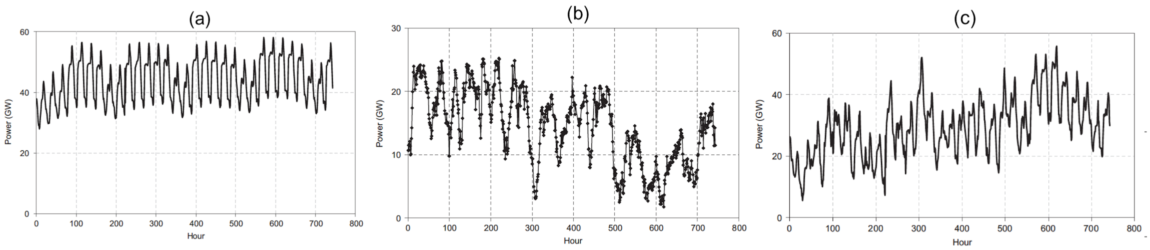


Figure 28: Taken from Oswald et al. (2008): (a) UK electricity demand, (b) modelled UK wind output, and (c) the residual demand (output - demand), for January 2005.

25GW wind fleet) for the 744 hours of January 2005, shown in Figure 28. The demand variability is as expected (as in Figure 21 (a)), while the multi-day wind power supply is highly variable. The resulting residual demand time series, shown in Figure 28 (c), it therefore also highly variable over the 31 days. Oswald et al. (2008) identify how, for example, around the 300$^{\text{th}}$ hour an 18GW fall in 22 hours is closely followed by a 14GW rise in 16 hours. They describe how, to achieve this fluctuation, a large proportion of the nation's generating capacity would need to ramp down, disconnect from the grid and then within 38 hours be ramped back up and reconnected.

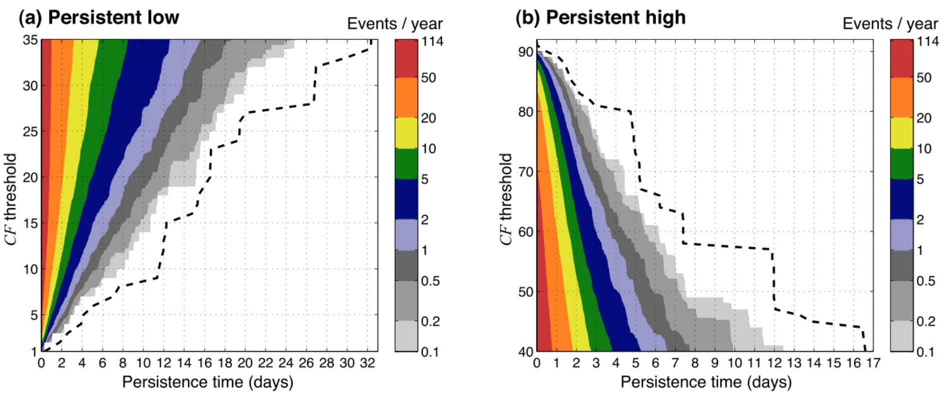


Figure 29: Taken from Cannon et al. (2015): The mean frequency of extreme generation events derived from the MERRA reanalysis (1980 - 2012). (a) The frequency of persistent low generation events expressed as a function of the threshold below which the capacity factor (CF) remains for at least the given persistence time. (b) The frequency of persistent high generation events expressed as a function of the threshold above which CF remains for at least the given persistence time. As previously discussed, the variability in CF over time windows less than around 6 h is likely to be underestimated. The dashed lines mark the most extreme events in the 33 year time series.

As well as the ramping events previously discussed, Cannon et al. (2015) explore the frequency of persistent low and high wind generation events in the period 1980-2012, as shown in Figure 29. These results show, for example that on average approximately 10 times a year (the yellow band), the wind power capacity factor drops below 25% for four days in a row, and above 70% for two days in a row. In addition, it can be seen that on vary rare occasions, e.g. once in 10 years (light grey band) the wind power capacity factor drops below 10% for eight days in a row, and above 80% for three days in a row. Cannon et al. (2015) also identify how less extreme low generation events tend to persist longer than less extreme high generation events (as can be seen from the larger range in days on the x axis in Figure 29 (a)). They suggest that this may be a consequence of atmospheric blocking weather regimes, which are associated with low winds (and high demand), and can persist for weeks (Masato et al., 2009).

The mutli-day variability in solar capacity factor is also dependent on multi-day weather regimes which bring different clear sky conditions (Pozo-Vázquez et al., 2004). Figure 24 (c) shows the inter-day variation in solar capacity factor, as calculated by Pfenninger and Staffell (2016). They identify how the difference between capacity factors on each day are approximately normally distributed around a central zero point. This indicates that subsequent days have similar capacity factors, potentially a result of multi-day weather regimes. However, within this histogram changes of up to 10% are shown, hence at rare occasions a considerable day-to-day change is observed. This could therefore be a transitioning from one form of regime to another (e.g. from a zonal to a blocking regime).

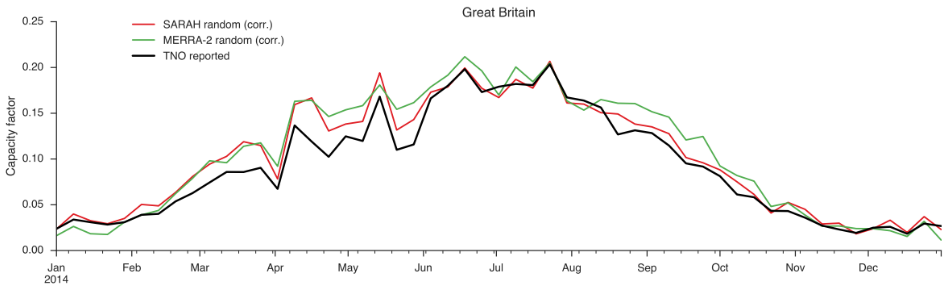


Figure 30: Taken from the supplementary material for Pfenninger and Staffell (2016): Weekly mean solar capacity factor in Great Britain in 2014, comparing corrected national-level simulations with TNO reported output.

Pfenninger and Staffell (2016) also calculate the weekly mean solar capacity factor in Great Britain throughout 2014, shown in Figure 30. This is just a single year, however it gives an indication of how the UK solar capacity factor varies over multiple days. In particular, this figure shows how week-to-week variability in solar capacity factor was especially high in Spring in this year.

Seasonal

The seasonal variation in temperature driven electricity demand (1975-2013) is shown in Figure 1, taken from Thornton et al. (2016). As would be expected, demand is highest in winter when it is darker and colder, and lowest in summer when it is consistently warmer and lighter. Spring and autumn experience a large range of demands since meteorological conditions can be highly variable during these seasons. However, Thornton et al. (2016) find that as in winter, demand in autumn and spring has a strong negative relationship with temperature. The variability in spring and autumn demand can therefore be explained by variability in temperature.

Thornton et al. (2017) present the seasonal variability in the demand-wind capacity factor relationship previously presented for winter only (in Figure 3). This is shown in Figure 31. This figure highlights how when all seasons are considered (black line), during the lower three-quarters of demand days as demand increases so does average wind power capacity factor. Thornton et al. (2017) describe how this reflects the variation in temperatures and wind speeds with season, with calmer, warmer conditions

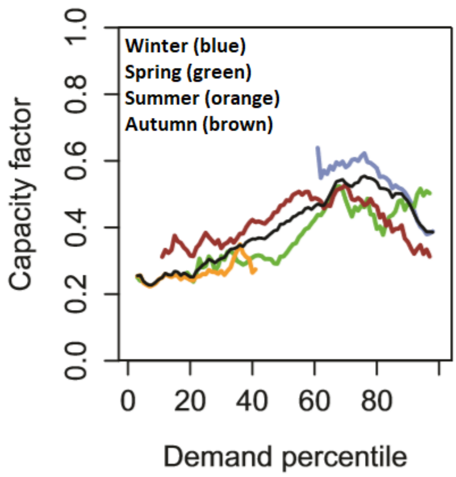


Figure 31: Taken from Thornton et al. (2017): Variation in UK average wind power capacity factor with percentile of electricity demand, averaged over a 5% demand bin, for each season (colours) and all days in year (black).

in summer and cooler, windier conditions in late autumn and early spring. However, as previously discussed, for higher demand (associated with late autumn and winter) the wind power reduces with higher demand, with a slight upturn for very high demand.

The seasonal variability in average diurnal cycle of wind power capacity factor is shown in Figure 22. Sinden (2007) discuss how the increase in daytime wind capacity factor is most pronounced in summer, with overnight capacity factor of around 13% and peak daytime capacity factor of 31%. In contrast, on average in winter the capacity factor only increases by approximately 8% from night to day. Indeed, in the summer, the capacity factor increases earlier in the day compared to other seasons. This is suggested to be due to the seasonal patterns in solar warming which induce thermal winds to a greater extent in summer.

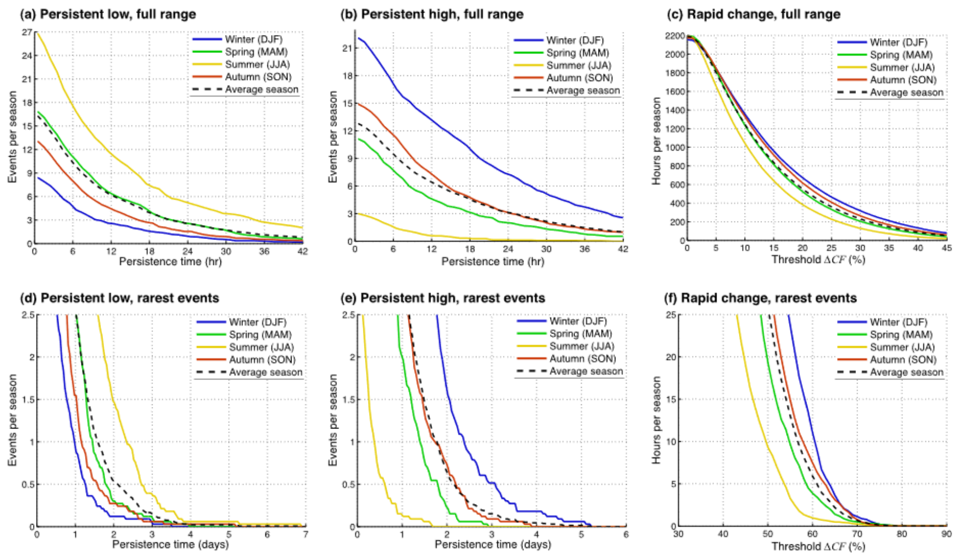


Figure 32: Taken from Cannon et al. (2015): The mean seasonal frequency of extreme generation events derived from the MERRA reanalysis (1980-2012), for four seasons and a mean season. Panels show (a) persistent low generation (CF ≤6.3%), (b) persistent high generation (CF ≥69.6%), and (c) ramps in generation within a 12h time window. Panels (d,e,f) are as in (a,b,c) but show only the rarest events.

Cannon et al. (2015) explore the seasonal variability in the frequency of wind extremes, as shown in Figure 32. They identify a substantial difference in the number of low and high wind episodes in summer and winter. In summer more persistent low wind events are experienced (capacity factor $\leq 6.3\%$), while in winter, persistent high wind episodes are far more frequent (capacity factor $\geq 69.6\%$). Spring and autumn experience a moderate level of both extremes, with autumn more similar to winter and spring more similar to summer. Figure 32 also shows how winter, closely followed by autumn and spring, experiences a higher frequency of ramping events within a 12 hour window, and the most extreme ramping events. Cannon et al. (2015) describe how this is likely due to the greater number of cyclones (storms) affecting the UK during these seasons.

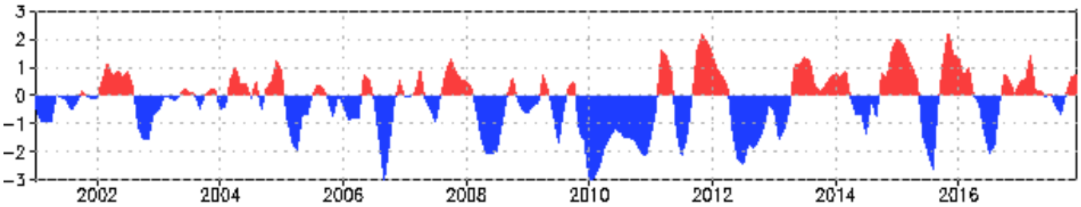


Figure 33: Taken from NOAA Weather Prediction Service, Climate Prediction Centre (2019): The standardised 3-month running mean value of the NAO index. The departures are standardised using the 1981-2010 base period statistics.

As noted by Bloomfield et al. (2018) and previously discussed in Section 3, there is a growing evidence that at seasonal time-scales (i.e. 3 months), large scale climatic modes of variability such as the North Atlantic Oscillation have a significant impact on the power system (Pozo-Vázquez et al. 2004; Brayshaw et al. 2011; Bett et al. 2017; Ely et al. 2013; Zubiate et al. 2017; Thornton et al. 2017). As described in Section 3, the positive phase of the NAO, characterised by a zone of low pressure over Iceland and high pressure over the Azores, is generally associated with anomalously warm, wet and windy conditions in northern Europe, while the negative phase, characterised by high pressure over Iceland and low pressure over the Azores, causes cold and calm conditions. Figure 33 shows the 3-month running mean value of the NAO index (2001-2018). This figure demonstrates how the NAO index tends to 'flip flop' between positive and negative phase with some temporal correlation, meaning that the NAO phase in the next time step is more likely than not to be the same as the previous time step. Very cold and still conditions were experienced in the UK in the winter of 2009/10, which can be seen to be associated with a very extreme negative NAO period, as would be expected.

Bloomfield et al. (2018) explore residual load/demand (load required in excess of wind power generation) for each season and for increasing installed wind capacity (NO-Wind: 0GW, LOW: 15GW, MED: 30GW, HIGH: 45GW). The total, and inter-annual standard deviation of, residual load in the period (1980-2015) for the four installed wind capacities is presented in Figure 34. This figure shows how, as expected, for all seasons the total residual demand decreases and the year-to-year variability increases with increasing installed capacity (blue to yellow). Bloomfield et al. (2018) note how in the NO-Wind

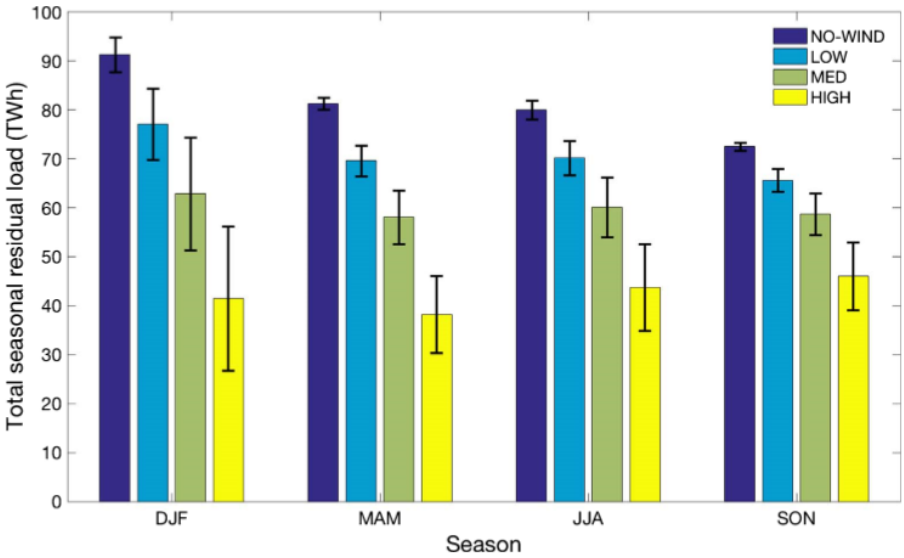


Figure 34: Taken from Bloomfield et al. (2018): Total seasonal residual load/demand (i.e. the maximum load demanded from generators other than wind power) over the period 19802015, with bars showing the inter-annual standard deviation for the NO-WIND,LOW, MED and HIGH scenarios.

scenario the largest total seasonal residual load is in winter, while in the HIGH capacity scenario the total residual load is similar for all seasons. Hence, interestingly, increasing the wind capacity in the energy system is likely to reduce the seasonal variability, but increase inter-annual variability, of total residual demand.

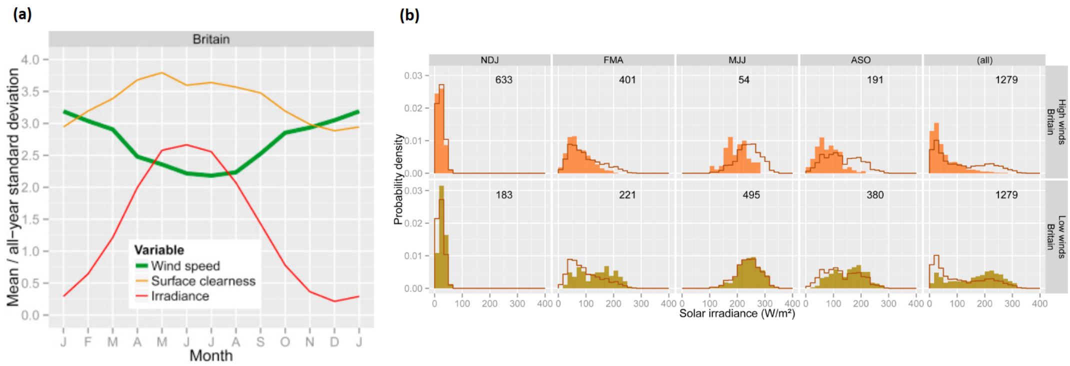


Figure 35: Taken from Bett and Thornton (2016): (a) Annual cycle of monthly mean wind speed, irradiance, and surface clearness, compared to the all-year standard deviations of their daily data. Note that the results for January are repeated after December to show continuity of the annual cycle. (b) Distributions of daily-mean irradiance for Britain. Each column shows a different season, as labelled. The outline histograms are for all days in the given season, and the filled histograms show the distribution when selecting only high-wind or low-wind days (upper and lower rows, as labelled). The number of low/high-wind days in each case is shown in each panel.

Fewer studies explore the seasonal variability of solar irradiance and solar PV capacity factor. Bett and Thornton (2016) investigate the climatological relationship between wind and solar energy supply in the UK and present the annual cycle of mean wind speed, solar irradiance, and surface clearness (an measure of how clear the sky is of clouds as measured at the surface), compared to the all-year standard deviations of their daily data (1979-2013), shown in Figure 35 (a). This demonstrates who the meteorological variables relevant for renewable energy generation vary in relation to each other over the seasons. As previously shown, wind speeds (and hence wind capacity factor) are highest in mid-late autumn and winter. As expected, solar irradiance and surface clearness are greatest in summer months. As note by Bett and Thornton (2016), Figure 35 also shows how solar irradiance has a much stronger seasonal cycle than wind speed, explained by the rotational tilt of the Earth. Bett and Thornton (2016) also present solar irradiance distributions for high and low wind days in different seasons, shown in Figure 35 (b). The results shown in Figure 35 (b) demonstrate how, in winter, solar irradiance is much lower and relatively similar in high and low wind conditions, whereas in other seasons, particularly summer, irradiance is high, more variable and the difference between irradiance in high and low wind conditions is more pronounced.

As shown in Figure 24 (a) and (b) above, Pfenninger and Staffell (2016) compare the diurnal cycle of PV capacity factor in the UK over a 30 year period (1985-2014). This figure demonstrates how there is large variability in PV capacity factor over the years with some summer days experiencing capacity factors at midday of 0.1 and some 0.7. In addition, Pfenninger and Staffell (2016) note how the worst 10% of summer days still have a PV capacity factor higher than roughly 75% of winter days.

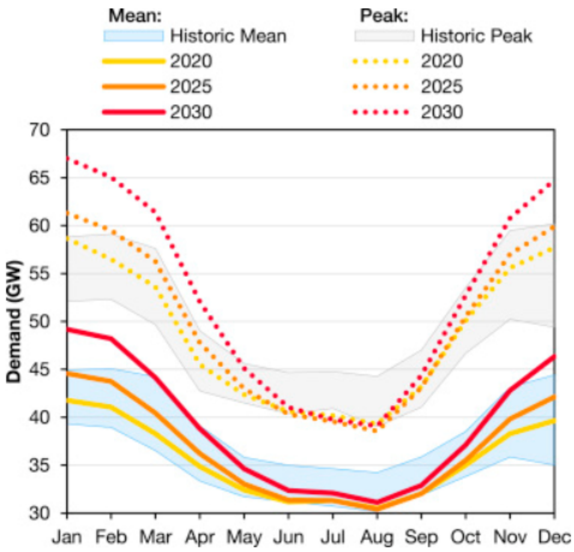


Figure 36: Taken from Staffell and Pfenninger (2018): The seasonal variation in historic and simulated future residua demand (National Grid, 2019b). Shaded areas show the historic range from 2005 to 2015, while lines show simulations from three years averaged across all weather years. Dotted lines show peak demand within each month, solid lines show the mean.

Finally, Staffell and Pfenninger (2018) explore the seasonal variation in historic and simulated future residual demand (demand minus wind and PV generation), where future scenarios involved increased renewable capacities and electricity demand, presented in Figure 36. This figure shows how the simulated mean demands in 2020 and 2025 remain within the historical range (blue region). However, by 2030 mean winter residual demand increases beyond the range of historically observed demand. This is due to the substantial projected increase in residential electrified space heating in this future scenario. Figure 36 also shows how mean peak demand (dotted lines) increases in line with average demand, with the mean simulated January peak in 2030 above 65GW. This highlight how transitioning to electrified heating will exacerbate winter peak residual demand stress events.

Summary

- Local and Instantaneous
  - Temperatures, relevant for local variations in demand, vary with proximity to the coast, residential region (rural, urban) and altitude;
  - Wind speed and solar variability at local scales are associated with turbulent air and mixed sky conditions respectively, and are most likely to cause ramping stress events on the energy system;
  - Local solar PV power generation fluctuations of up to +/- 50% can occur from one second to the next, which could be extremely challenging to manage at short time scales in future energy systems;
  - 1 hourly residual demand ramping events are likely to become more extreme and frequent in future energy energy systems with higher installed wind and solar capacities and higher demand due to electrification of the heating systems. Based on the National Grid Two Degree future energy system scenario, by 2030 1 hourly ramps of the order of +/- 15GW are possible.
- National
  - At a national level, demand varies as a combination of temperature, population density and other socio-economic factors (e.g. GPD);
  - On average, wind speeds are higher and more variable in the north of the UK;
  - Due to the finite size of weather systems, distributing turbines throughout the country helps to reduce national wind power variability;
  - On average, wind turbines located >600km apart have very little correlation in wind power generation and can therefore compliment each other in producing wind power nationwide;
  - Average sunshine hours are greatest in the south-east and the south coast of the UK;
  - The scale of weather systems cause differing solar conditions in the North-West and South-East of the UK. Hence spatially varying the location of PV panels could help to reduce variability in solar power yield in the UK;
- European wide
  - When temperatures and wind speeds are anomalously low in the UK (and hence demand is high) conditions are often also very cold and still in Northern Europe;
  - During these conditions, Southern European countries tend to experience moderate temperatures and higher than average winds, due to the dipole response of wind fields to the NAO;

  - During high and peak demand days in the UK, energy supply could be supplemented by wind power generated in southern Europe;
  - During years of high total residual demand low wind speeds are localised in the UK hence pan-European planning and interconnection of renewables could help to manage the inter-annual variability of annual residual demand;
  - Wind power generation is at its lowest in the UK during the European Blocked weather regime. During this regime wind capacity factor is above average in South-Eastern countries such as Slovenia, Croatia, Bulgaria and Greece, further highlighting the potential benefit of interconnectivity with southern Europe;
  - Interconnectivity with Norwegian hydropower is likely to be most challenged in March when reservoir levels are lowest, temperature driven demand remains high in both countries and anomalously low winds are possible in the UK;
  - The Northern-Southern dipole in conditions is also seen for solar irradiance (and hence solar PV capacity factor). In particular Southern Germany is shown to have opposing conditions to the UK, hence UK summer surplus solar power could potentially be used to supplement low solar generation in Germany;
  - A high performance European-wide energy system would involve installing additional solar capacity primarily in Southern Europe, and additional wind capacity primarily in Spain, Sweden and the UK.

- Within day
  - There is a well established diurnal cycle in energy demand, dominated by human behaviour;
  - The diurnal cycle for wind speed is more variable and less predicable than solar irradiance;
  - During historical extreme wind speed events wind capacity factor changes of up to 80% have been experienced within a 3 hour time window. This within day variability will require individual generators to go on or off line frequently, thereby reducing the utilisation and reliability of large centralised plants, and leading to increases in the cost of electricity and reductions in potential carbon savings;
  - Due to the diurnal cycle of demand and the most frequent occurrence of wind curtailment events being between 10pm and 4pm, extremely large volumes of installed wind power are required for wind power curtailment to become more frequent;
  - Increasing levels of PV capacity will have a large effect on the summer time diurnal residual demand but will make very little difference in the winter, highlighting the difficulty facing power systems with high shares of solar PV, and the degree to which other power sources or storage must be available to fill in these net demand gaps;
  - Based on future energy system scenarios, by 2030 overnight demand in winter and midday demand in summer would routinely fall to (or below) zero.

- Multi-day
  - Multi-day variations in electricity demand and weather-dependent renewable supply predominantly depend on European-wide weather regimes;
  - However wind power capacity factor can vary across days within these multi-day weather types;
  - During the period 1980-2012, on average approximately 10 times per year the wind power capacity factor dropped below 25% for four days in a row, and was above 70% for two days in a row;
  - In addition, approximately once every 10 years the wind power capacity factor dropped below 10% for eight days in a row, and was above 80% for three days in a row;
  - Multi-day solar capacity factor is most variable in Spring.
- Seasonal
  - Demand has a strong negative relationship with temperature in autumn, winter and spring and is highest in winter;
  - During spring, summer and early autumn wind capacity factor increases with demand, while the opposite relationship is observed for late autumn and winter;
  - There are substantially more low wind episodes in summer compared to winter and a higher frequency of ramping events in autumn and winter due to the greater number of cyclones (storms) affecting the UK during these seasons;
  - The NAO is a key driver of seasonal (and inter-annual) variability and extremes of energy demand and supply;
  - Increasing installed wind capacity in the energy system is likely to reduce the seasonal variability, but increase inter-annual variability, of residual demand;
  - Surface clearness and wind speed have lower month-to-month variability than solar irradiance;
  - In summer, solar irradiance is higher, more variable and more different in high and low wind conditions compared to other seasons;
  - Based on the National Grid Two Degree future energy system scenario, by 2030 mean winter residual demand increases beyond the range of historically observed demand, highlighting how transitioning to electrified heating will exacerbate winter peak residual demand stress events.

3.3 The difference in extreme stress events in summer and winter and their relative risks

Extreme stress on the energy system is felt in different ways in different seasons. In particular, winter and summer experience different challenges in managing supply and demand.

Winter

Most studies aimed at understanding stress on the UK energy system focus on winter and peak residual demand stress. These studies aim either to quantify the potential for wind and solar power generation during temperature-driven high demand conditions in winter (e.g. Thornton et al. 2017 and Pozo-Vázquez et al. 2004), or to understand how peak residual demand, demand net of renewable generation, will change in a changing energy system with increased renewable capacity (e.g. Bloomfield et al. 2018).

During winter, electricity demand is highly dependent on temperature. Therefore, winter demand peaks during periods of very cold temperatures, associated with an area of high pressure near the UK (i.e. during a negative NAO phase). With increasing installed renewable capacity these winter extreme stress events depend increasingly on wind speed and solar irradiance in combination with temperature. As previously discussed in Section 3.1, winter *residual* demand peaks when wind speeds are very low in combination with low (but not the lowest) temperatures. This occurs when an area of high pressure is located directly over the UK (see Figure 6). Cannon et al. (2015) explores the frequency and length of persistent low wind capacity factor events both for the whole year and specifically in winter (as shown in Figures 29 and 32). They note how low wind generation events tend to persist longer than high generation events, since atmospheric blocking regimes, causing high pressure over the UK, persist longer than other regimes. Cannon et al. (2015) show how in very extreme cases the wind capacity factor can remain below 6.3% for up to 3.5 days in winter (Figure 32 (d)). Cannon et al. (2015) does not, however, indicate whether these persistent winter low wind events occur simultaneously with high demand (i.e. low temperatures), hence these insights cannot be necessarily linked to peak energy system stress. Further research is required to fill this gap in understanding.

During winter, solar PV capacity factor is consistently low as shown in Figure 24, in which the 30 year median (solid black line) peaks at capacity factor 0.2 and only exceeds 0 for 6 hours of the day. In addition, Pfenninger and Staffell (2016) showed how increasing the quantity of installed PV capacity has very little effect on daytime demand and no effect on peak demand in winter, as shown in Figure 25. This suggests that solar PV, even in greater quantities may not be hugely beneficial in reducing the severity of peak residual demand events in winter. However, as shown by Pozo-Vázquez et al. (2004) in Figure 16, during a negative NAO event, when winds and temperatures are low in the UK, solar irradiance will be high over the UK, particularly in the north-west (during the day). This is in agreement with the description of calm, clear, sunny conditions associated with high pressure weather conditions[4]. This suggests, if installed in the most beneficial locations, solar power generation could contribute during peak demand conditions, although only during day light hours. However, Staffell and Pfenninger (2018) show that with increased wind and solar capacity, and a possible future change to electrified heating and vehicles, the mean and peak residual demand in winter exceeds the range of historically observed demand (Figure 36). As previously noted, the potential electrification of space heating will have a large impact on the magnitude and variability of electricity demand, based on the historical observed temporal variability in gas demand. This will be felt predominately in the winter, when heating is most often required in the UK. In addition, the future uptake in electric vehicles will significantly change the diurnal demand profile, which may exaggerate the winter-time evening peak in energy demand if appropriate smart flexible technologies are not implemented.

Interconnectivity will therefore be important for managing these extreme peak demand winter stress events. As previously discussed, due to the dipole in European wide weather conditions associated with the NAO, during peak residual demand conditions in the UK, countries in the south of Europe such as Spain, Portugal and southern Italy experience moderate temperatures, and hence lower demand, and above average wind speeds. Interconnectivity with Southern Europe couple therefore be very important for mitigating extreme winter stress on the energy system in winter. In addition, studies have shown, due to the finite size of weather patterns that effect the UK on multi-day time scales, distributing renewables throughout the UK will help to manage periods of low winter generation isolated in one part of the country (Colantuono et al., 2014).

In addition, Cannon et al. (2015) show how extreme wind ramping events are most frequent and extreme in winter (Figure 32). This is likely due to the greater number of extreme wind storms that occur during this season, bringing sudden changes in wind speed over short time windows. Specifically, Cannon et al. (2015) shown how on average 5 times a winter the UK wind capacity factor ramps up by 65% within a 12 hour time window. Further, Drew et al. (2017) highlight how locating wind turbines in large groups will exacerbate such ramping events, favouring their distribution across the country.

Summer

Far fewer studies explore stress on the UK energy system in the summer. Some include summer (and other seasons) within their analysis for comparison (e.g. Cannon et al. 2015 and Pfenninger and Staffell 2016), but none focus exclusively on understanding summertime stress. This is likely because in summer, UK energy demand is low and hence there is a lower risk of supply not meeting demand. In the summer of 2018, however, an unusually long heatwave was experienced in the UK. The high pressure system responsible for this heat wave also caused a 'wind drought', during which wind speeds were

[4] https://www.metoffice.gov.uk/learning/atmosphere/high-and-low-pressure

well below average for a very prolonged period of time (approximately 3 weeks), greatly reducing the generation of wind power. Since in the UK PV capacity is much lower than wind capacity, the shortfall in wind power generation could not be compensated for by solar, requiring additional gas power stations to be fired up to meet demand. This form of summer time stress is also highlighted by Cannon et al. (2015) who showed that prolonged periods of low wind capacity factor are considerably more frequent and persistent in summer (Figure 32), lasting up to 32 days (Figures 29). In a future energy system with fewer/no gas power stations, the right balance of wind, solar, storage and interconnectivity will therefore be required to mitigate against this form of potential summertime stress on the energy system. Indeed, the latest UK climate projections released by the Met Office in November 2018 (Met Office, 2019) indicate that summers with temperatures similar to that experienced in 2018 could have a 50% probability of occurring by 2050 (i.e. 1 in every 2 summers). Moreover, in a warming climate air conditioning may become increasingly utilised in the UK, greatly increasing summertime demand and hence the severity of these heatwave stress events.

Demand is lower in summer, particularly during the day (Figure 21 a) when wind and solar generation remain variable and moderate (e.g. as seen in Figure 31). Hence, there is the potential for excess supply. For example Bett and Thornton (2016) (Figure 35 b) shows how in the summer, during times of high wind speeds, solar irradiance can also be moderately high. Pfenninger and Staffell (2016) show how increasing UK solar capacity to 20.9GW (four times 2014 capacity), causes summertime residual demand (demand minus PV) to decrease dramatically between 6am and 6pm (Figure 25), and note how including wind power generation within the residual demand calculation could result in surplus power. Indeed, Staffell and Pfenninger (2018) show how, in their energy system of the future, midday demand in the summer could routinely drop below zero by 2030. Again, interconnectivity with Europe, in particular central and southern Europe where large scale weather systems bring opposing meteorological conditions, could provide a potential approach for distributing this excess supply.

An alternative form of summertime energy stress is experienced as instantaneous fluctuations in solar generation as a result of mixed sky conditions. The red curve in Figure 20 (c) indicates the potential variability in PV generation experienced by a PV panel within a 15 minute window during mixed sky conditions in early summer. This stress is more severe in summer, when solar irradiance is stronger and hours of sun light are longer. These short term fluctuation are challenging to manage at short time scales and will become increasingly frequent with increasing installed PV capacity. Again, distributing PV panels across the country will help to reduce the effect of mixed sky conditions on solar fluctuations, since at a given time, different locations will experience different cloudy conditions.

Summary

- Peak residual demand is the key energy stress in winter, and most considered in the literature;
- These events are associated with cold temperatures and very low wind speeds resulting from a

negative NAO phase and high pressure located over the UK;

- Persistent low wind events are experienced in winter (although persistent high wind events are considerably more common). Such events can result in the wind capacity factor remaining below 6.3% for up to 3.5 days;
- Solar contribution is very limited in winter, even in an energy system with 20.9GW installed;
- Interconnectivity with southern Europe will be important for managing winter peak residual demand stress events;
- Extreme wind ramping events are most common in winter due to the increased occurrence of windstorms;
- The diverse distribution of wind turbines throughout the country will help to manage both forms of winter-time stress;
- Low wind events also cause stress in the summer, as experienced in the summer of 2018;
- Persistent low wind events are longer and more extreme in the summer, with the potential to last up to approximately 30 days;
- A warming climate will increase the frequency of 2018-like summer temperatures, increasing the requirement for air conditioning which could exaggerate summer time stress events;
- Low daytime demand in summer can lead to excess supply, an alternative form of summertime stress on the energy system;
- Increasing renewable capacities could result in summertime residual demand routinely dropping below zero;
- Again, interconnectivity with Europe may provide an opportunity for distributing surplus summertime supply;
- Diverse distribution of solar PV panels will help to manage extreme fluctuation in PV supply experienced as a result of mixed sky conditions in summer.

3.4 The potential trade-off between different energy supplies (e.g. solar and wind, on-shore and off-shore)

The Wind and Solar Trade-off

As touched upon in previous sections, there is an apparent complimentary relationship between wind speed and solar irradiance in the UK during negative NAO conditions, which cause peak temperature-driven demand in the UK. Bett and Thornton (2016) study this relationship for all weather types in the

UK (1979-2013), focusing on climate variability rather than sub-daily or inter-annual/decadal variability. They note how it is becoming increasingly important to understand the relationship between wind and solar PV power generation, and the extent to which variability in one source can help to balance out the variability in the other, as this may have important implications for energy storage and/or back-up capacity.

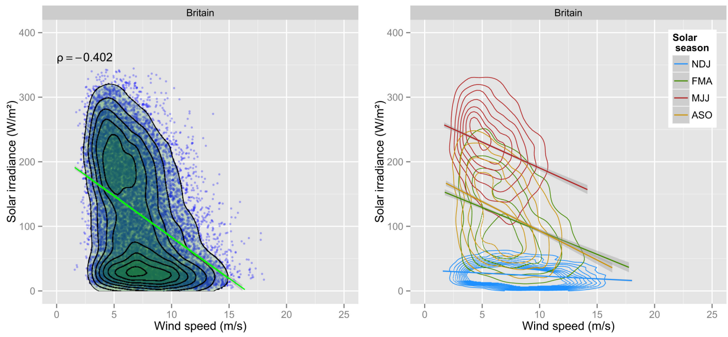


Figure 37: Taken from Bett and Thornton (2016): The joint distribution between daily-mean wind speed at 60m, and downwelling shortwave irradiance at the surface, averaged over Britain. Left: Individual daily values are plotted as blue points, and the point density is shown by contours and green shading. The linear regression line is shown in bright green, and the Pearson correlation coefficient ρ is given. Contours mark densities of points between 0 and 10^{-3} in steps of 10^{4}. Right: The same data separated into seasons, defined as indicated. Density contours are plotted between 0 and 2×10^{-3} in steps of 2×10^{-4}. The linear regression lines and their confidence intervals are also plotted for each season.

As an initial exploration of the relationship between wind and solar capacity factors, Bett and Thornton (2016) present a contoured scatter plot of wind speed and solar irradiance for the whole year, and for each season separately, shown in Figure 37. This figure demonstrates the strong seasonal cycle in irradiance, as evident from the difference in irradiance in each season, compared to wind speed whose mean remains relatively constant throughout the seasons but shows high day-to-day variability.

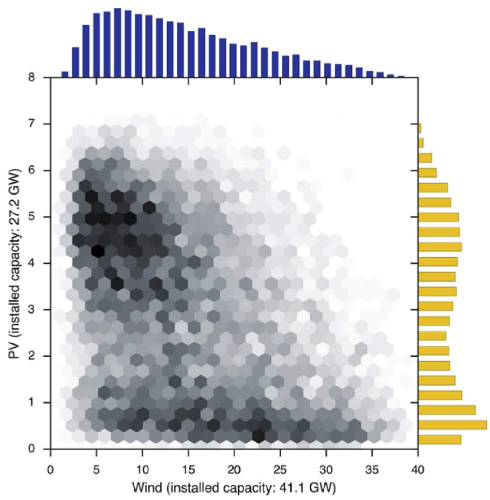


Figure 38: Taken from Staffell and Pfenninger (2018): The correlation between daily-average wind and solar output over 25 historical weather years, simulated with 2030 installed generation capacities. The shading relates to the frequency of the observed combination of wind and solar output (as shown by the histograms on each axis)

In a similar way, Staffell and Pfenninger (2018) present the correlation between national wind and PV output, but for the simulated future 2030 fleets (National Grid, 2019b), using daily mean generation across all 25 simulated weather years (shown in Figure 38). Staffell and Pfenninger (2018) note how, to some degree, lower wind output coincides with higher PV output and vice versa, with summer and winter trends creating the bimodal distribution observed by Bett and Thornton (2016) (Figure 37).

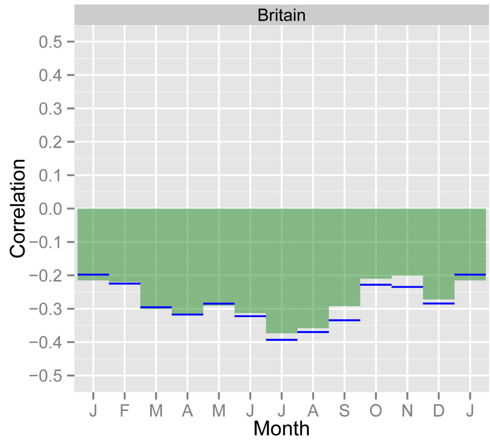


Figure 39: Taken from Bett and Thornton (2016): Monthly correlations of daily mean wind speed with irradiance (green bars) or with surface clearness (blue lines).

Bett and Thornton (2016) go on to explore the correlation between daily mean wind speed and solar irradiance in different months, as shown in Figure 39. Throughout the year there is a weak negative relationship between wind speed and solar irradiance (i.e. less windy days tend to be sunnier). The apparent weaker correlation in winter is described as being due to the wider range of clearness values at any given wind speed in winter compared to the summer. As explained by Bett and Thornton (2016), the more dynamic atmosphere in winter allows for more cloudy days to be included in the distribution, meaning that the value of the correlation coefficient will be closer to zero in the winter than the summer. Bett and Thornton (2016) note that these results agree with He et al. (2013), who showed a clear shift in wind distribution towards higher winds during cloudy conditions, especially in winter.

Following this, Bett and Thornton (2016) present the spatial variability in the correlation between wind speed and surface clearness over the UK, shown in Figure 40. Bett and Thornton (2016) describe surface clearness as being the fraction of solar irradiance that remains after being attenuated by clouds. As discussed by Bett and Thornton (2016), the western Atlantic-facing regions of Britain show a much stronger negative relationship than the east coast. This is also seen in the neighbouring sea regions in the west and east. This east-west variability in correlation is strongest in winter and the strongest negative relationships are in Scotland in the spring and Wales and south-west England in summer. As described by Bett and Thornton (2016), these western regions are hit directly by Atlantic storms, causally relating clouds and wind, while in the east, cloudiness is less dominated by low-pressure systems, and there is a greater variety of wind-cloud/irradiance states. This results in a weaker negative relationship between wind speed and surface clearness in the east. Bett and Thornton (2016) go on to discuss how the seasonal variability in the spatial correlations, shown in Figure 40, is predominantly

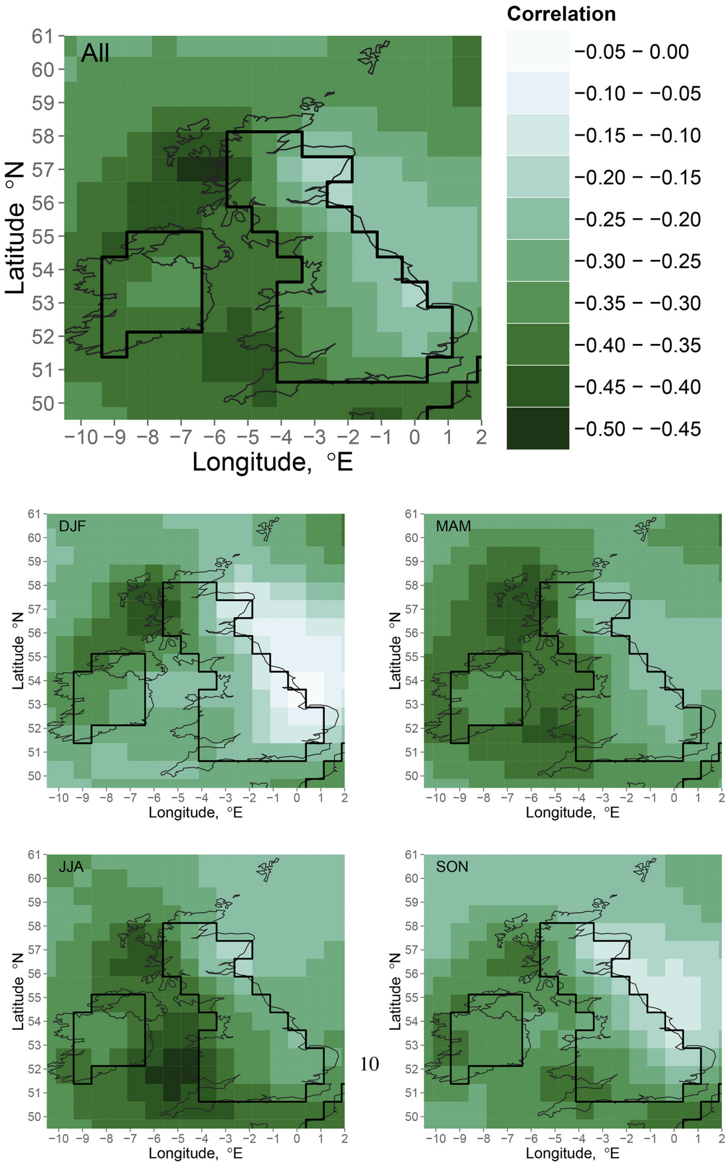


Figure 40: Taken from Bett and Thornton (2016): Maps of the correlation between daily-mean wind speed and surface clearness. The top panel shows the all-year correlation, and the smaller panels show different seasons as labelled.

due to variability in the frequency of clear and windy days throughout the year in the different regions of the UK. That is, in the east there is a higher frequency of clear/windy days in winter, compared to the west, reducing the anti-correlation between wind speed and surface clearness. Referring back to the previous section focused on summertime energy stress, the summer relationship in Figure 40 suggests that during summer wind draughts, surface clearness is likely to be more consistently high in Wales and south-west England, highlighting where additional solar PV could be installed for maximum PV potential at these times. However it should be noted that even in these locations the inverse relationship between wind and solar conditions is still relatively weak (correlation $-0.4 - -0.5$).

Finally, Bett and Thornton (2016) explore the optimal combination of solar PV and on-shore wind capacities for UK-wide energy balancing. They identify that in winter the range of relative solar power available is small, while wind power generation is highly variable. They therefore conclude that solar power has very little relative capacity to counteract low-wind days in winter unless a substantial additional amount is installed. Similarly, Grams et al. (2017) discuss the potential for co-deployment of wind and solar capacities in Europe, noting how currently mean solar generation is substantially lower than wind. Based on installed capacities as of 2017, Grams et al. (2017) show that during the weather regime that causes the lowest winter wind production (the European Blocked regime), on average wind power production falls by approximately 12GW while solar production only increases by 1GW. As a result, Grams et al. (2017) suggest that a tenfold increase of Europe's installed solar PV capacity would be required to locally balance the power loss in Europe's 2017 wind fleet during the severe wind lulls associated with the European Blocking regime.

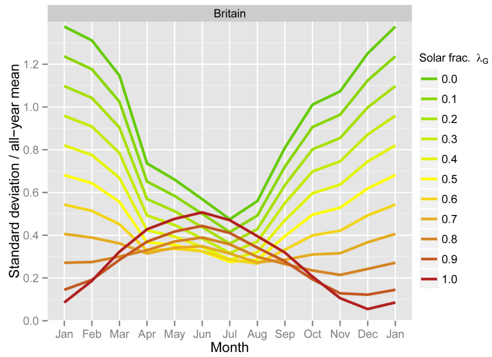


Figure 41: Taken from Bett and Thornton (2016): Relative variability of total power from solar PV and onshore wind each month, in terms of the standard deviation of daily data as a fraction of the long-term mean. Each line represents a different balancing scenario, in terms of the fraction of solar capacity compared to the total of wind and solar: the top line in green represents a wind-only scenario, the lowest line in winter, in red, represents a solar-only case.

However, Bett and Thornton (2016) find that, in summer solar power is at its strongest and most variable, while wind power remains highly variable. They therefore note that increasing the relative capacity of solar PV to compensate for low wind in winter could have the effect of increasing the total variability in summer. Bett and Thornton (2016) plot the relative variability of daily power for different ratios of solar:wind capacity scenarios, as presented in Figure 41, and identify that the scenario with the least seasonal variability is approximately 70%-solar, 30%-wind. Bett and Thornton (2016) conclude that the weak anticorrelation between wind and solar power in Britain cannot solely be relied upon to produce a well-balanced energy supply. Indeed, Bett and Thornton (2016) note how, even under the ambitious government plans for solar PV installation (as of 2015), the power supply from onshore renewables will remain much more variable in winter than summer due to the much greater capacity of wind power. Bett and Thornton (2016) note how more detailed modelling of particular scenarios, including using a spatially-resolved supply model and/or using higher temporal resolution data, would enable more precise projections of the impact of meteorology on future energy systems.

One such example of this is the 2015 study carried out by Pfenninger and Keirstead (2015), who investigate the three contrasting objectives for the future UK energy system within a common model framework: how a future power system based on different combinations of technologies works in terms if its total system cost, its greenhouse gas emissions, and its energy security. While Pfenninger and Keirstead (2015) do not focus on the trade off between wind and solar or extreme weather conditions (wind and solar resource are based on hourly observations from the NASA MERRA reanalysis, NASA 2019. Description of renalysis data given in the Appendix [Section 7]), they explore a wide variety of future scenarios with differing capacities and combinations of fossil fuels, nuclear and renewables. They find that in general different configurations are equally feasible both technically and economically, but that the most economically favourable scenarios are not necessarily favourable in terms of emissions or energy security. They identify that the availability of grid-scale storage in scenarios with high renewables and/or nuclear could reduce overall electricity costs by up to 50%, depending on storage capacity costs. Their modelling approach suggests that the UK can rely on its domestic wind and solar PV generation at lower renewable shares (50-70%). However, for an energy system with more than 80% renewable generation to be economically feasible, large-scale storage, significantly more power imports, or domestic dispatchable renewables like tidal must be available.

In a similar way, for the European-wide energy system, Rodriguez et al. (2015) use a data-intensive weather-driven modelling approach to identify a technically and economically optimal design for a simplified, highly renewable pan-European electricity system, minimising the need for backup energy, backup capacity, transmission capacity and the levelised system cost of delivered electricity. Rodriguez et al. (2015) find that the overall cost-optimal design, based on standard cost assumptions, has a 50% renewable penetration, with 94% of this from wind power production. This corresponds to 600 GW of wind power capacities, 60 GW installed solar power capacities, 320 GW conventional backup power capacity, and about five times current installed transmission capacities [as at 2015].

A number of additional studies investigate the optimal trade-off between wind and solar power in a European-wide energy system, rather than focusing on the UK. Heide et al. (2010) identify that, for a 100% renewable Europe, the optimal mix between wind:solar, in terms of the quantity of stored energy required, is 55%:45%. They also show that for decreasing percentages of renewables the ratio becomes increasingly in favour of wind rather than solar. Similarly, Huber et al. (2014) show that increasing wind and solar power generation above a 30% share in annual electricity consumption will dramatically increase flexibility requirements in Europe. They identify that this is particularly true with large capacities of solar PV, and that this is similar for all European countries in their study. As previously introduced in Section 3.2 (Europe Wide), Santos-Alamillos et al. (2017) present the optimal allocation of up to 214 GW of new renewable capacity in the European countries to firstly minimise European energy fluctuations and secondly to maximise European energy yield, as shown in Figure 17. These results show how more installed renewable capacity is required for maximising yield compared to minimising energy fluctuations. In both cases, however, the increase in solar capacity is greatest, making the renewable sources roughly equal in penetration with these two scenarios.

Finally, a number of studies explore the optimal mix of installed wind and solar power capacity within a highly renewable system in other regions in Europe (also often including wave power), e.g. the Iberian peninsula (Santos-Alamillos et al., 2012), Spain Santos-Alamillos et al. (2012, 2015), Italy (Monforti et al. 2014; Fattori et al. 2017), Denmark (Lund, 2006), Portugal (Sousa and Martins, 2013) and Sweden (Widén, 2011), and the world, e.g Canada (Hoicka and Rowlands, 2011), USA (Jacobson et al. 2015; Denholm and Hand 2011) and China (Liu et al., 2013). As noted by Bett and Thornton (2016), all such studies generally find that incorporating both wind and solar renewable sources acts to reduce the net variability in power supply, reducing the need for reserves.

The On-shore, Off-shore Wind Trade-off

Fewer studies specifically explore the relationship between on- and off- shore wind capacities. As part of their wider study to understand the relationship between wind power, electricity demand and winter weather patterns in Great Britain, Thornton et al. (2017) isolate on- and off-shore wind capacity factors to explore their relative wind potentials.

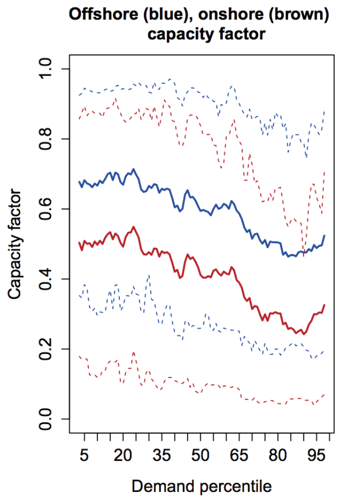


Figure 42: Taken from Thornton et al. (2017): Variation in average GB onshore (brown) and offshore (blue) wind power capacity factor with winter percentile of GB electricity demand. Capacity factors are presented as rolling 5% demand bin means. The 10^{th} and 90^{th} percentile capacity factors for each demand bin and each region are given (dashed).

Specifically, Thornton et al. (2017) plot the relationship between wind power capacity factor and UK winter temperature-driven energy demand percentile (similar to Figure 3), differentiating between on- and off-shore wind power. Thornton et al. (2017) identify how, across all demand conditions, average off-shore wind has a capacity factor 15 - 25 percentage points higher than on-shore wind, because of higher wind speeds experienced offshore (as shown in Figure 9). They go on to note how, in addition, the percentage decline in capacity factor with increasing demand is smaller for off-shore wind turbines. That is, onshore wind power nearly halves whilst offshore wind power reduces by less than a third. Further, during high demand conditions (top 10% of demand percentile), wind capacity factor is less frequently lower off-shore. Thornton et al. (2017) therefore conclude that offshore wind power is better placed to aid security of supply.

As previously noted, Drew et al. (2017) explore wind power ramping in the UK and show how spreading off-shore wind farms around the UK helps to reduce the severity of ramping events. They find that an increase in off-shore turbines, around the UK, would reduce the occurrence of prolonged periods of low generation, increase periods of prolonged high generation, but increase the ramping magnitude by a factor of five.

Summary

- There is a weak negative relationship between wind speed and solar irradiance/surface clearness in the UK;
- This relationship is strongest in the Spring and Summer, and along the west coast of the UK, due to the difference in the frequency of clear and windy days throughout the year in the different regions;
- Installed solar capacity in Europe would potentially require a tenfold increase to balance wind power generation during extreme low wind events in winter;
- However, increasing the relative capacity of solar PV to compensate for low wind in winter could increase the total variability in summer;
- In the UK, the scenario with the least seasonal variability is shown to be approximately 70%-solar, 30%-wind;
- An approximately 50:50 wind:solar set up is found to be optimal in a 100% renewable Europe, with an increasing proportion of wind power capacity for low renewable penetration;
- Wind capacity factor is approximately 15 - 25% higher off-shore compared to on-shore, and is more frequently high during temperature-driven high demand conditions.

3.5 The duration of extreme stress events

The severity of an extreme stress event depends not only on the magnitude of the difference in demand and supply, but the duration of the event. For example, a peak residual demand event lasting 1-2 days could be managed through storage, however, an event lasting, for example, 2 weeks would require alternative flexible technologies to ensure supply meets demand, e.g. interconnectivity with Europe. Frequently in the literature discussed thus far, peak residual demand is explored using daily demand data (e.g. Thornton et al. 2017) and ramping events are defined as large changes in supply in a specified time window (e.g. Staffell and Pfenninger 2018). Relatively few studies explore the duration of the conditions that cause extreme stress on the energy system, and all those identified here relate to the duration of low and high wind speed events. This highlights a gap in current understanding about the duration of high and low solar PV events, particularly in summer.

Sinden (2007) investigate the frequency and extent of low (< 4m/s) and high ($>$25m/s) wind speed events in the UK, based on over 30 years (1970-2003) of surface wind speed measurements from 66 stations. They find that, over the course of a year, low wind speed events affecting more than half of the UK are present for less than 10$\%$ of all hours, and the simultaneous occurrence of low wind speeds across 90$\%$ or more of the UK happens only one hour per year on average. High wind speed events were found to be far less common, with the UK being entirely free of high speed winds for over 96$\%$ of all hours. This study does not, however, quantify how these extreme low/high winds persist hour-to-hour.

Leahy and McKeogh (2012) studied the duration of low wind events in Ireland based on long term records of hourly surface wind speeds and directions from fourteen geographically dispersed stations in the Republic of Ireland (1980-2012). Leahy and McKeogh (2012) showed that, for all sites considered, there is a rapid drop-off in the frequency of events with persistently low wind speeds as the duration of the event increases. In particular, they showed that wind speeds rarely remain below 6 m/s for longer than 32 hours and below 4 m/s for longer than 12 hours.

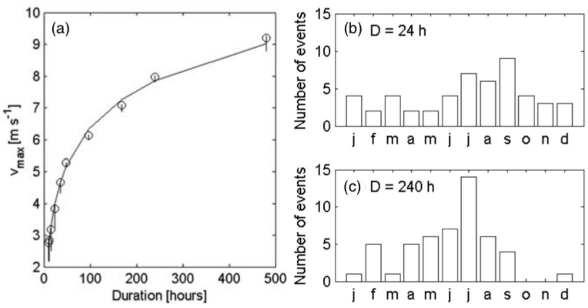


Figure 43: Taken from Leahy and McKeogh (2012): (a) Intensity-duration curve for V_{max}, the widespread low wind events with a 10-year recurrence, over several durations up to 20 days. Monthly distribution of the frequency of lowest wind speed events of (b) 1 and (c) 10 day duration.

Further, Leahy and McKeogh (2012) plot an intensity-duration curve describing how the 10 year return level wind speed threshold varies with event duration. This curve is presented in Figure 43 (a), and shows, for example, that on average within the region and period studied, once every ten years wind speeds remain below 9m/s for 20 days (500 hours) in a row. This plot shows how, as event duration increases the wind speed threshold quickly increases (i.e. less extreme low winds), indicating that very extreme low wind events do not tend to last longer than a few hours. Finally, Leahy and McKeogh (2012) show how the frequency of 1 day and 10 day persistent low wind speed events vary with month of the year, shown in Figure 43 (b) and (c). Leahy and McKeogh (2012) note how events of one day duration are seen to occur during every month of the year, with a slightly higher frequency in July, August and September, while the occurrence of ten day duration low wind speed events varies with season, with the highest occurrences during July and relative infrequent occurrences between October and March.

Cannon et al. (2015) present a similar exploration, but for wind capacity factor in the UK. They use a 33 year (1980-2012) reanalysis data set (MERRA, from NASA-GMAO, NASA 2019) to construct an hourly time series of nationally-aggregated wind power generation in Great Britain, assuming a fixed distribution of wind farms (those installed as of 2012). The results of this study have been previously presented and discussed in relation to Figures 18, 29 and 32. In agreement with the analysis of Ireland (Leahy and McKeogh, 2012), Cannon et al. (2015) find that the number of both low and high wind power generation events decrease approximately exponentially with increasing persistence. They highlight that moderately persistent low generation events (at least 2 days with capacity factor $\leq 5\%$) are found to occur approximately 1.2 times per year and that capacity factor $\leq 6\%$ was the lowest generation threshold for which there was a continuous 5 day lull in generation. In addition, as discussed in Section 3.1 'Multi-day', low generation events tend to persist longer than high generation events as a consequence of atmospheric blocking weather regimes, which are associated with low winds (and high demand),and can persist for many days, up to weeks (Cannon et al. 2015; Masato et al. 2009). Cannon et al. (2015) also show that there is considerable seasonal variability in the persistence of low and high wind speed events. In particular, there is a tendency for more extended lulls in summer, rather than winter. For example the most extreme 5 day lull in summer relates to a capacity factor $\leq 6\%$ while in winter the equivalent capacity factor is $\leq 9\%$. As previously mentioned in Section 3.3, these studies do not indicate whether these low wind events occur simultaneously with high demand, hence these insights cannot be necessarily linked to peak energy system stress. Further research is required to fill this gap in understanding.

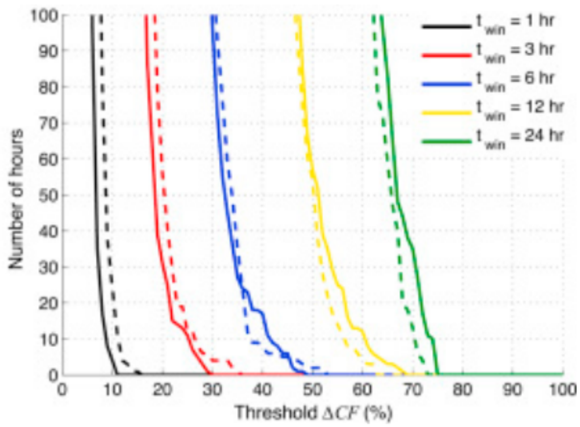


Figure 44: Taken from Cannon et al. (2015): the number of hours preceding a ramp in generation within the indicated time window (twin) for the most extreme events.

Cannon et al. (2015) note how high generation events may become increasingly important as installed wind capacity increases, requiring deliberate curtailment to ensure local load balancing, and find that on average once per winter the capacity factor remains above 69.6% for 2.5 days. Cannon et al. (2015) also explore the number of hours per year/season preceding a ramp in generation of different thresholds within a 12 hour time window, and find that ramping events are more frequent and extreme in winter (Figure 32). Cannon et al. (2015) present the same rapid change curve as in Figure 32 (f), for alternative time windows (1, 3, 6, 12 and 24 hours). This plot indicates that changes in wind capacity factor of up to 50$\%$ are possible within a 6 hour window. As previously noted and discussed by Cannon et al. (2015), however, since their results are derived from reanalysis (observation constrained climate model) data (NASA, 2019) rather than directly from observations, extreme ramps in generation must be treated with some caution since variability over shorter time scales tend to be underestimated (Cannon et al., 2015). This suggests the potential for more rapid changes in wind capacity factor than those seen here (as shown in Section 3.1 'Instantaneous').

Finally, Patlakas et al. (2017) use a statistical modelling approach for exploring the intensity-duration relationship for low wind events relevant for off-shore wind turbines in the North Sea, based on hourly model data for the period 2001 - 2010. They identify a similar exponential relationship between wind speed intensity and duration which is shown to be best modelled using a Rayleigh distribution. Patlakas et al. (2017) conclude that in the open seas, low wind speed events (< 3m/s) can last up to 4 - 5 days, while such events can last 10 days or more nearer shore.

Summary

- Based on wind speed data from 66 sites in the UK (1970-2003), the simultaneous occurrence of low wind speeds (< 4m/s) across 90$\%$ or more of the UK happens on average only one hour per year, and the UK is entirely free of high speed winds (> 25m/s) for over 96$\%$ of all hours;
- The study of fourteen geographically dispersed weather stations in the Republic of Ireland (1980-2012) showed that on average once every ten years wind speeds remain persistently below 9m/s for 20 days. Persistent low wind speed events are found to be more frequent in summer and very rare in winter;
- All studies find that the number of low and high wind power generation events decrease approximately exponentially with increasing persistence/duration;
- Using 33 years (1980-2012) of reanalysis modelled wind speeds it was found that moderately persistent low generation events (at least 2 days with capacity factor $\leq 5\%$) occur approximately 1.2 times per year; low generation events tend to persist longer than high generation events as a consequence of atmospheric blocking weather regimes; these persistent low events (capacity factor below 6.3$\%$) are more frequent and extreme in summer and can last up to 6 days; on average once per winter the capacity factor remains above 69.6$\%$ for 2.5 days; and changes in wind capacity factor of up to 50$\%$ are possible within a 6 hour window;
- Statistical modelling of North Sea wind speeds (2001-2010) identified that low wind speed events (< 3m/s) can last up to 4 - 5 days, while such events can last 10 days or more in locations nearer shore;

- Further research is required to understand how the frequency and duration of low and high wind events relate to high demand and therefore extreme stress on the energy system.

3.6 The effect of climate change on the distribution of these important meteorological variables and hence on extreme stress events

In all of the previously introduced papers there is either no mention of the effect of climate change on the meteorological variables associated with extreme energy system stress, or it is concluded that climate change does not play an important role in the analysis. This is even found to be the case for studies focused on potential future energy systems, such as Pfenninger and Staffell (2016), Staffell and Pfenninger (2018) and Bloomfield et al. (2018). Indeed, Staffell and Pfenninger (2018) discuss how studies show limited or no change in either wind or solar resources over the next 50 years. This conclusion is based on the results of Pryor and Barthelmie (2010), Hdidouan and Staffell (2017), Wild et al. (2015) and Crook et al. (2011). However, these papers use spatially coarse global climate models which, as described by Hosking et al. (2018) are not wholly suited to the task of assessing regional impacts of climate change. This is because low resolution models do not have the spatial granularity to model small-scale atmospheric processes which effect regional climate conditions.

In a similar way, Grams et al. (2017) note how studies suggest that mean wind speed will not change under climate change, referencing the results of Tobin et al. (2015) and Hdidouan and Staffell (2017), and conclude that since robust climate change signals occur on a longer time horizon than renewable energy investments, basing their study on current climate will 'probably be valid for the coming decades'. In addition, no mention is made in these aforementioned papers of the effect of climate change on energy demand which will be linked to changes in temperature.

Temperature

In the latest UK climate projections, released by the Met Office in November 2018 (Lowe, J. A. et al., 2018), there is a clear signal that temperatures experienced in the UK will increase in agreement with previous studies and the Intergovernmental Panel on Climate Change fifth Assessment Report (IPCC AR5 - summaries in IPCC 2014). The magnitude of this increase depends on the level of climate change mitigation employed globally, characterised by the Representative Concentration Pathways (RCP). A description of the RCPs used in UKCP18 are given in the Appendix (Section 7.4).

Figure 45 shows some of the key findings presented in the UKCP18 overview report (Lowe, J. A. et al., 2018) related to the potential effect of climate change on UK temperature. In each panel of Figure 45 the projected change in temperature is present for two RCPs: RCP2.6, the most optimistic scenario in which the world aims for and is able to implement sizeable reductions in emissions of greenhouse

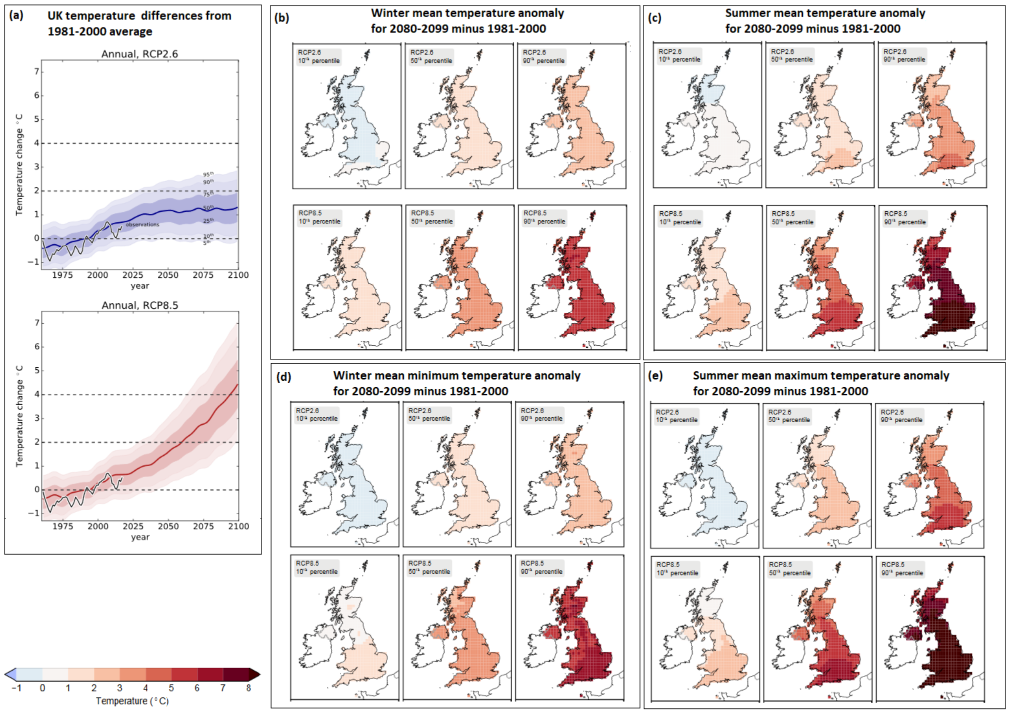


Figure 45: Taken from Lowe, J. A. et al. (2018): (a) UKCP18 UK area mean temperature changes for the lowest emission scenario (RCP2.6, blue) and highest emission scenario (RCP8.5, red). The shading boundaries show the 5^{th}, 10^{th}, 25^{th}, 50^{th} (median, central solid line), 75^{th}, 90^{th}, and 95^{th} percentiles of the probability distribution. NCIC observations (https://www.metoffice.gov.uk/climate) are shown as a black line for the historical part of the curves. Values are expressed relative to the 1981-2000 baseline used in UKCP18 projections. Changes in 20-year (b) mean winter temperature, (c) mean summer temperature, (d) mean winter minimum temperature, (e) mean summer maximum temperature for RCP2.6 (top row) and RCP8.5 (bottom row) in °C. Results are shown for the 10^{th} (left column), 50^{th} (middle column) and 90^{th} (right column) percentile outcomes. The 50% probability is the central estimate, the 10% level is very likely to be exceeded and the 90% level is very unlikely to be exceeded. All plots cover the period 2080 to 2099 relative to a 1981-2000 baseline. The colour scale for (b), (c), (d) and (e) is shown in the bottom left corner.

gases and limits warming to 2°C, and RCP8.5, the most pessimistic scenario in which the nations of the world choose not to switch to a low-carbon future. Equivalent results for two intermediate scenarios, RCP4.5 and RCP6.0 are shown on pages 20-23 of the UKCP18 overview report (Lowe, J. A. et al., 2018). As is evident in Figure 45 (a), the severity of the increase in UK temperatures is highly dependent on the future emissions scenario, with the separation of scenario responses becoming more pronounced during the second half of the 21^{st} century. As noted in the UKCP18 overview report (Lowe, J. A. et al., 2018), Figure 45 (b)-(e) indicate that the warming amount is different in the summer and winter, with more warming in the summer, leading to a greater amplitude of the seasonal cycle of temperature than at present. They also note how some regional variations in warming can be seen and are most evident in the summer and at higher percentile results. This pattern manifests as a north-south warming gradient, with greater warming in the south. In the winter the regional variations in warming are less clear but there is some evidence of enhanced warming over parts of Scotland in some scenarios. Specifically, even in an optimistic RCP2.6 future, based on the results presented in Figure 45 (c) winter minimum temperatures are on average most likely to rise by between 1 and 2°C throughout the UK by 2100; and based on the results presented in Figure 45 (d) summer maximum temperatures are on average most likely to rise by between 2 and 3°C in the south of the UK by 2100. Further, in the UKCP18 headline findings report (Met Office, 2019) notes how, in the recent past (1981-2000), the chance of seeing a summer as hot as 2018 was low ($< 10\%$), while currently (2018/19) the chance is between 10-20%, and due to further warming will increase to $\sim 50\%$ by 2050.

This projected warming in the UK will have an effect on energy demand and the resulting stress on the energy system. For example, winter time low temperature-driven stress events may become less severe and frequent. No literature focusing on how changes in temperature will impact winter time energy demand was found, highlighting a potentially important gap in knowledge. In addition, and potentially of more concern, is the impact summer time warming will have on human heat stress and the need for cooling. Thornton (2018) describe how during the last decade a number of Southern European countries have seen a larger demand peak in summer than in winter, in contrast to earlier decades, thought to result from the increasing use of air conditioning. A similar summer demand peak may become common in the UK as the climate warms and becomes more like the current climate in Southern European countries.

Wood et al. (2015) review the impacts of climate change on UK energy demand, and note how the 2012 UK Climate Change Risk Assessment (CCRA) (Capon, R. and Oakley, G., 2012) identifies increased cooling demand in summer as a key risk to the energy system, while reduced heating demand in winter may reduce energy system risk. Wood et al. (2015) discuss the findings of studies such as Auffhammer and Mansur (2014) and Schaeffer et al. (2012) and conclude that there is the potential for a marked increase in energy demand for comfort cooling and the maintenance of climate-controlled environments during summer months, with household demand for comfort cooling potentially causing a new summer evening peak (similar to the current profile of heating demand) and overnight demand during heat waves when temperatures remain high throughout the night. Referring back to Section 3.3, this would greatly increase the severity of summer time heat waves, associated with below average wind speeds in the current climate (although they may not be in future climates). Wood et al. (2015) go on to recommend that such climate impacts could be moderated by ensuring buildings are designed to cope with warmer temperatures to avoid air conditioning being the solution in warmer summers.

Wind Speed

The equivalent effect of climate change on wind speeds in the UK is less clear. The UKCP18 results indicate a slight disagreement between the 15 members of the Met Office Hadley Centre model, HadGEM3-GC3.05 (PPE-15), and 13 other climate models selected from the 5$^{\text{th}}$ phase of the Coupled Model Intercomparison Project (CMIP5, World Climate Research Programme 2019), used to inform the latest Intergovernmental Panel on Climate Change (IPCC) Assessment Report.

As shown in Figure 46, the Met Office Hadley Centre model indicates a slight increase in winter near surface wind speeds over the UK for the second half of the 21$^{\text{st}}$ century. However, this increase is very small compared to inter-annual variability, and the uncertainty shown by the climate model ensemble

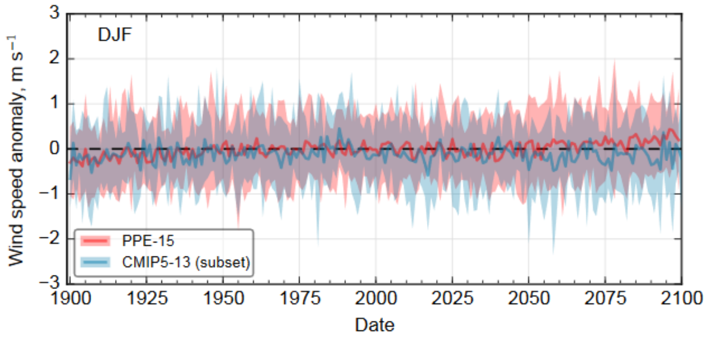


Figure 46: Global projections for changes in winter (DJF) mean near surface wind speed over the UK for 1900-2100 with respect to 1981-2000. The red line is the mean of the 15 memeber Met Office Perturbed Parameter Ensemble (PPE) (Lowe, J. A. et al., 2018) and blue line is the mean of the CMIP5 13 model ensemble (World Climate Research Programme, 2019). The red and blue shading represents the range of values from PPE-15 and CMIP5-13 respectively. Plot available from `https://www.metoffice.gov.uk/binaries/content/assets/mohippo/pdf/ukcp18/ukcp18-factsheet-wind.pdf`

spread (shaded region). On the other hand, the mean of the CMIP5 models shows no trend in the wind speed over the UK.

The same unclear future change in wind speed is acknowledged in the energy literature, as previously mentioned at the beginning of this section. Hosking et al. (2018) discuss how, in studies based on the previous two CMIPs (CMIP5 and CMIP3), the annual mean wind speed is shown to increase in Northern Europe (Pryor and Barthelmie, 2010) and decrease in southern Europe (Carvalho et al., 2017). However, as noted by Hosking et al. (2018), the magnitude and details of these changes very between climate models. This climate model variation was also identified by Tobin et al. (2015), who study the effect of climate change on European wind power and conclude that climate change should neither undermine nor favour wind energy development in Europe, but that understanding climate change effects in particular regions may help optimise the wind power development and energy mix plan. Similarly, Hdidouan and Staffell (2017) find that the effect of climate change on UK wind capacity factors to 2100 are mixed, with increases in some regions and decreases in others, while the year-to-year variation generally increases. Hdidouan and Staffell (2017) emphasise the importance of further detailed studies on this topic and the need to consider climate change when planning a resilient future energy system. Hosking et al. (2018) go on to note, that that there is, however, a general agreement in the literature that there will be a substantial decrease in winter storm frequency in the Mediterranean Zappa et al. (2013). This could effect the potential wind power contribution from interconnectivity with southern Europe during times of peak demand in the UK.

Hosking et al. (2018) employ a novel data set created as part of the 'Half a degree Additional warming, Prognosis and Projected Impacts (HAPPI) project. Within the HAPPI project climate modelling groups around the world were asked to undertake a series of experiments specifically designed to quantify the relative risks associated with 1.5 and 2°C of warming (Mitchell 2017, www.happimip.org/). Hosking et al. (2018) use this data set to answer the question 'How would a future 1.5°C warmer world affect wind energy generation across Europe?'

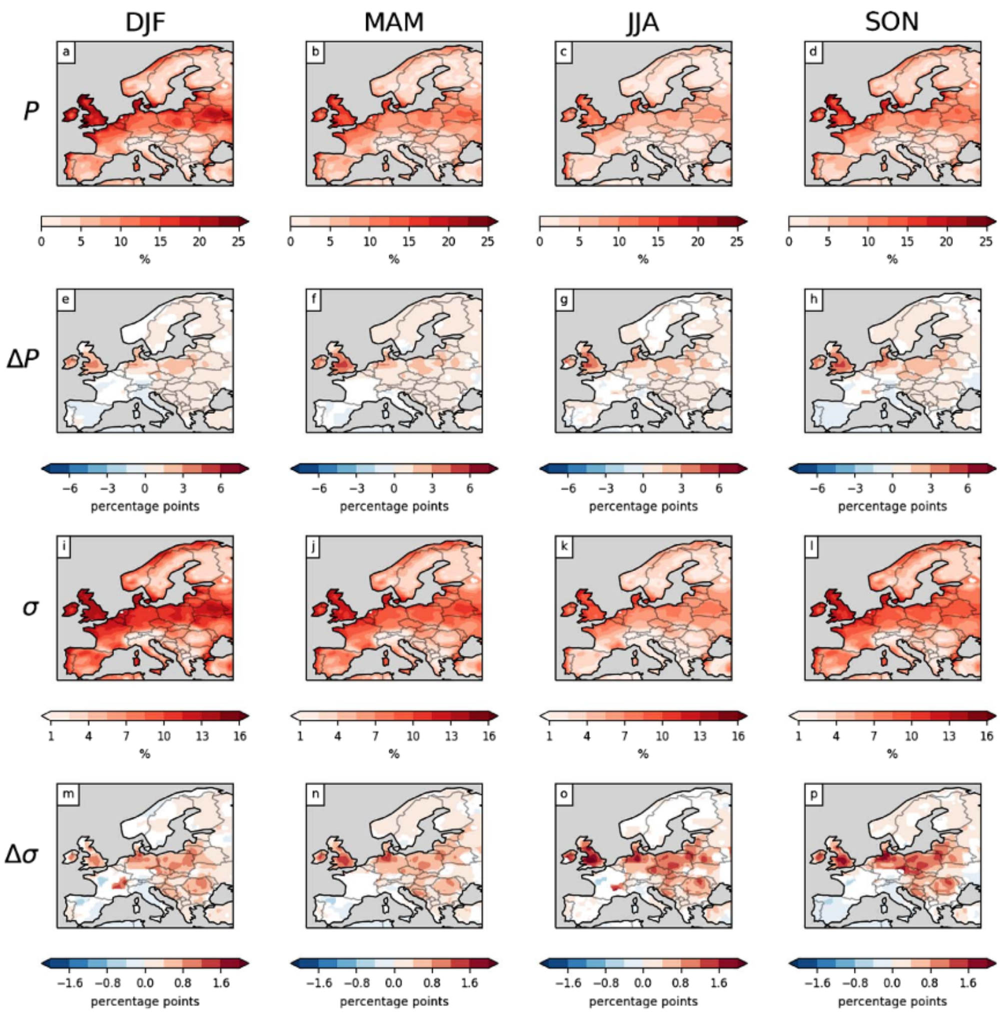


Figure 47: Taken from Hosking et al. (2018): Multi-model mean values of wind generation load factor (P) derived from the historical experiment near-surface (10 m) wind data are shown in the first row (panels (a)(d)), while the second row (e)(h) shows the change between the historical and 1.5°C experiment (ΔP). The third row (i)(l) shows the historical standard deviation (σ) in daily wind generation, while the bottom row (m)(p) shows the change under 1.5°C ($\Delta\sigma$). The columns represent the four seasons: winter (December-January, DJF), spring(MarchMay, MAM), summer (June-August, JJA) and autumn (September-November, SON).

Based on the results presented in Figure 47, Hosking et al. (2018) conclude that there is an increase in power generation potential over much of Europe, with the greatest increase observed in the UK ($\sim 4\%$). In addition, Hosking et al. (2018) note that the daily variability in wind speed increases over much of central and northern Europe with the largest seasonal change in summer. Again, this increase is greatest in the UK. This could result in the energy system becoming harder to manage. Focusing on the UK, Hosking et al. (2018) find that wind energy production during spring and autumn could become as productive as the current winter, and summer winds could resemble levels currently seen in spring and autumn. Hosking et al. (2018) therefore conclude that the potential for wind energy in Northern Europe may be greater than assumed in previous studies, and while there is the potential for Southern Europe to see reductions in their wind resource, these decreases are likely to be negligible. Within this study, however, Hosking et al. (2018) do not consider off-shore wind speeds.

Solar Irradiance

As seen in previous sections, fewer studies focus on solar irradiance and the effect climate change might have on this meteorological variable in relation to the energy system. Jerez et al. (2015b) note how two studies, based on the low resolution CMIP5 global climate projections, indicate small but generally positive impacts of climate change on mean solar PV potential over Europe under the RCP8.5 scenario (Crook et al. 2011; Wood et al. 2015). Burnett et al. (2014) study the effect of climate change on solar energy recourse, focusing specifically on the UK, using the Met Office UKCP09 climate projections.

(a)

Region	Current baseline average resource (Wm^{-2})	Emissions scenario	Change at probability level (Wm^{-2}), 2050's			Change at probability level (Wm^{-2}), 2080's		
			10%	50%	90%	10%	50%	90%
UK	101.2	Low	−0.9	3.5	8.0	−1.0	3.7	8.7
		Medium	−1.2	3.0	7.4	−1.1	3.9	9.2
		High	−0.9	3.6	8.5	−1.9	4.4	11.2

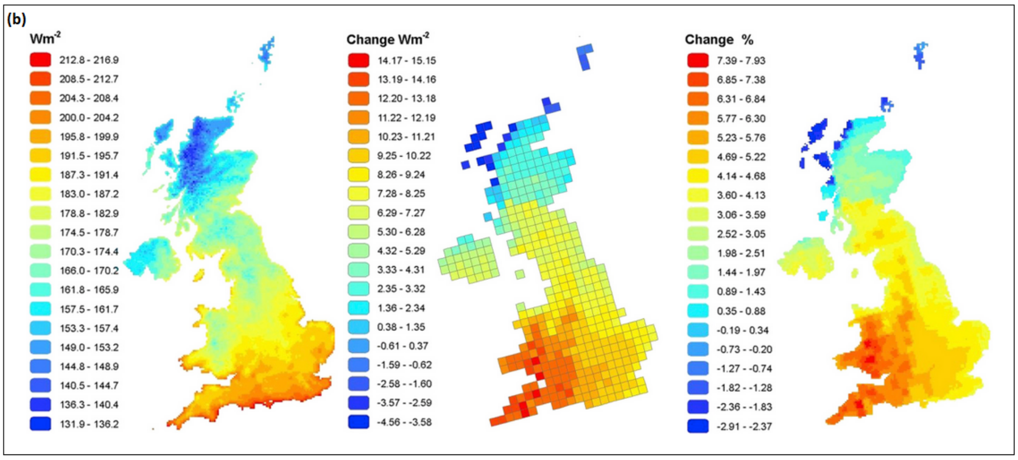


Figure 48: Taken from Burnett et al. (2014): (a) Annual solar radiation baseline resource, 2050's and 2080s change in W/m^2 for 10%, 50% and 90% probability levels. (b) Summer solar resource: baseline (left); (middle) 2050s change in W/m^2; and (right) percentage change from baseline.

Burnett et al. (2014) present a table showing how the annual solar irradiance baseline resource is projected to change under low, medium and high UKCP09 emissions scenarios, shown in Figure 48 (a). The 10%, 50% and 90% probabilities are given. The 50% probability is the central estimate, the 10% level is very likely to be exceeded and the 90% level is very unlikely to be exceeded. The results in this table suggest that, while there is a small chance of no change in solar irradiance, the central estimate for all emissions scenarios is positive and largest for the highest emissions pathway. In addition, Burnett et al. (2014) present a maps of the spatial variation of the change in solar irradiance to explore where this change will be most felt. This exploration is present specifically for the medium emissions scenario, shown in Figure 48 (b). As described by Burnett et al. (2014), Figure 48 (b) indicates significant solar irradiance increases in the south-west, with the increases becoming less significant further north. Much of Scotland experiences little change from the baseline, except in the far north and westerly regions of the Highlands of Scotland, where there are slight decreases in solar irradiance.

Jerez et al. (2015b) identify a contrasting negative change in potential solar PV production in the UK and over the whole of Europe in a future climate. For this analysis, Jerez et al. (2015b) use the recent EURO-CORDEX ensemble of high-resolution climate projections together with a PV power production model, focusing on the RCP8.5 scenario. Over most of Europe the change in PV potential is of the magnitude of between -5%-0%. These contradictory results indicate the importance of further exploration of the effect of climate change on solar irradiance and solar PV potential, particularly using the most up-to-date UK climate projections available.

As an additional consideration, Wild et al. (2015) identify how anthropogenic air pollution and associated accumulation of aerosols in the atmosphere may have substantially contributed to variations in surface solar radiation. Specifically, they describe how the decline in surface solar radiation at widespread observation sites from the 1950s to the 1980s is in line with the strongly increasing air pollution during this period, whereas the subsequent partial recovery of surface solar resources since the 1980s fits with the successive implementation of effective air pollution regulations, leading to a decline in aerosol burdens and more transparent atmospheres for solar radiation particularly in industrialised countries since the 1980s. This highlights how air pollution may be an additional important atmospheric parameter to include in climate models to ensure accurate representation of future solar PV potential.

As well as quantifying the change in individual meteorological variables, such as temperature and wind speed, the UKCP18 project (Lowe, J. A. et al., 2018) have published results showing, for two groups of global model projections (Met office PPE and CMIP5 - as shown in Figure 46), the projected change in the number of days experiencing Weather Patterns (WPs) associated with negative and positive NAO conditions (WP1 = NAO- and WP2 = NAO+) in winter using RCP8.5, presented in Figure 49. The NAO-conditions are characterised by the pressure pattern shown in the left upper panel in Figure 49 (area of high pressure over Iceland), identified as being responsible for the very cold, still conditions that cause extreme stress on the energy system in winter in the current climate (Section 3.1). Figure 49 identifies that, for the Met Office ensemble (PPE) there is evidence of a transition to more days in the NAO+ state towards the end of the century, possibly suggesting a lower occurrence of the NAO- associated extreme energy stress conditions, while the CMIP5 models shown little change. These results are in agreement with Figure 46. Lowe, J. A. et al. (2018) note, however, that it is unclear if this observed change in the PPE models is due to natural variability or is part of a human driven trend. In addition, it should be noted that in future climates, UK meteorological conditions associated with the NAO could be different, e.g. NAO- could be warmer and calmer.

Summary

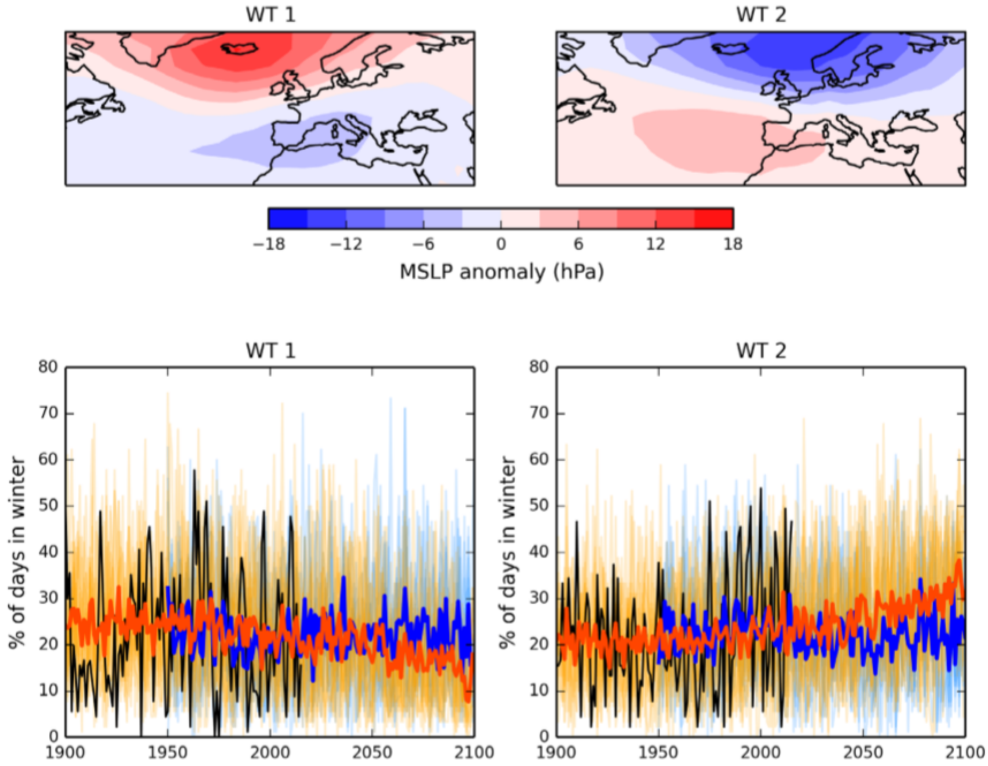


Figure 49: Taken from Murphy, J. M. et al. (2018): Upper panels show observed anomalies (hPa) in mean sea-level pressure (MSLP) relating to daily weather types (WT) 1 and 2, characterising NAO- and NAO+ respectively. The anomalies are calculated relative to a long-term annual mean climatology from 1850-2003. Lower panels show the percentage of days during December to February assigned to WT1 (left) and WT2 (right) during 1900-2100 in 15 members of Met Office Perturbed Parameter Ensemble (PPE) (Lowe, J. A. et al., 2018) (orange), and during 1951-2100 in nine ensemble members of CMIP5 climate models (World Climate Research Programme, 2019) (blue) for which daily weather typing is available. The thicker, darker lines show ensemble-mean values. Black line shows observed historical values generated from the EMULATE dataset (Ansell T. J. et al., 2006), based on daily fields from 1900-99. Results are based on RCP8.5

- No identified studies focus on understanding extreme stress on the energy system in combination with a changing climate, highlighting an important gap in current understanding;
- The latest climate change projections for the UK (UKCP18) confirm that UK temperatures are expected to rise due to climate change. The severity of the increase is highly dependent on the future emissions scenario. Warming is greatest in summer and in the south of the UK. Even in the most optimistic emission scenario winter minimum temperatures are on average most likely to rise by 1-2°C by 2100 and the chance of seeing a summer as hot as 2018 will increase to $\sim 50\%$ by 2050;
- These rising temperatures could reduce the severity of peak demand stress events in winter but increase summer energy system stress, especially if there is an increased uptake in air conditioning, creating an additional evening and over night peak in demand;
- The effect of climate change on wind speeds and solar irradiance is less well understood, with studies showing conflicting results;
- For wind speed, the general consensus indicates that wind power and its variability may increase slightly in the UK. This change is, however, likely to be smaller than inter-annual variability and

smaller than current uncertainties in climate projects (spread in climate model ensembles);

- Differing studies, based on different climate models, show increases and decreases in solar irradiance and PV potential in the UK;
- Future solar irradiance may also be linked to changing levels of air pollution in the atmosphere;
- The UKCP18 climate projections indicate a possible decrease in the number of winter days in the negative phase of the NAO (NAO-) and a corresponding increase in NAO+ days. This is consistent with the projected increase in wind speeds.

3.7 How extreme stress events can be characterised/categorised

Based on the literature reviewed and discussed in the previous sections, five potential characterisations of extreme stress event have been identified.

Peak winter residual demand (demand net of renewable power supply)

- This form of stress events occurs when temperatures are low (hence demand is high) and wind speeds are very low in winter, linked to blocking conditions during negative phases of the North Atlantic Oscillation (NAO);
- These extreme stress events will become more severe if gas heating is transitioned to electrified heating;
- Solar irradiance is higher during these conditions than during other winter days, however a large increase in installed solar capacity would be required in the UK to compensate for low wind power potential during these extreme stress events. Installing this quantity of PV potential would, however, significantly increase variability in renewable power supply in summer. In addition, the short winter days mean solar PV is available for a limited portion of the day, and most likely not available during evening peaks in demand;
- During winters in the historical period (1980-2012) persistent low wind events (capacity factor below 6.3%) were shown to last up to approximately 3.5 days, and 24 hour persistent low winds were experienced on average once per winter;
- The duration and frequency of these stress events is not directly addressed in the literature. The duration and frequency of low wind events in winter has been explored, but no insight is given as to whether these low wind events coincide with peak demand (low temperatures). This gap in the literature is discussed further in Section 3.8;
- During these peak winter residual demand events Northern Europe tends to also experience cold conditions, however the low wind conditions are more local to the UK, hence suggesting the potential for wind power supplied from the continent;

- Due to the dipole in weather conditions created by the NAO, opposing conditions are likely in Southern Europe and the Mediterranean (i.e. warmer and windier than average), highlighting an important interconnectivity opportunity. However, climate change signals suggest in general that wind speeds will become weaker in Southern Europe;
- The installation wind turbines off-shore is expected to improve the security of supply. Higher wind speed at sea result in, on average, 20% greater capacity factor for off-shore wind resource. In addition, it is found that off-shore turbines more frequently experience high wind speeds during peak demand conditions;
- Climate change studies indicate that the UK winter climate will become warmer (and possibly windier), suggesting a decrease in the severity of peak winter residual demand stress events.

Ramps in wind power supply

- This form of extreme stress event is characterised by large changes in wind speed and hence wind power production during a short time window;
- These events are most frequent and extreme in autumn and winter, linked to the occurrence of European windstorms. Surplus wind power due to these ramping events is greatest in autumn compared to winter, because demand is lower;
- Historical case study events indicate the potential for wind capacity factor to change by 80% in a 3 hour time window;
- A future energy system with increased installed wind capacity will be more vulnerable to extreme variability in power supply from wind ramping;
- Diversifying the location of installed wind capacity will minimise national variability;
- There is some indication that climate change could increase the variability of wind speeds in Europe, and in particular the UK, potentially increasing the frequency of ramping events.

Surplus solar PV power supply

- This type of energy system stress event is most common in the summer, when solar PV potential is greatest and moderately high wind speeds are possible;
- In a future energy system with increased installed wind and solar capacity, residual demand (demand net of renewable energy supply) could frequently drop below zero at midday during the summer (if no flexible technologies are incorporated);
- Opposing solar irradiance conditions are experienced in Southern Europe, indicating a potential opportunity for the distribution of surplus PV power in the UK;
- No clear climate change signal has been found for solar irradiance. A study focused on the UK indicated the potential increase in solar irradiance, particularly in the south-west of the UK;

- No literature was identified in which the frequency and duration of high PV events was explored.

Ramps in solar PV power supply

- This form of extreme stress event is characterised by large instantaneous fluctuations in solar irradiance and hence solar power production;
- These instantaneous fluctuations are associated with mixed sky conditions (i.e. patches of cloud as opposed to overcast or clear sky conditions);
- Historical case study events demonstrate how multiple instantaneous fluctuations in solar irradiance can be experienced within a few minutes;
- As with wind power ramping, diversifying the location of installed PV panels minimises overall variability.

Summer wind drought

- As experienced in July 2018, blocked weather conditions associated with summer heatwaves also result in very low wind speeds for prolonged periods of time;
- While demand is low in summer, these very low winds result in wind power unable to meet this low demand;
- During these conditions solar irradiance and solar PV potential are high, however at the current level of installed PV capacity, solar power cannot compensate for the low wind power supply during these extreme stress events;
- Spatial variability in the relationship between wind speed and surface clearness suggests that during very low wind speed conditions in the summer, surface clearness is largest in south-west England and Wales, identifying the most appropriate location for new PV capacity to mitigate against summer wind drought energy system stress;
- In 2018 additional gas power stations were fired up to meet demand;
- Prolonged periods of low wind speed are more frequent and persistent in summer, for example the wind capacity factor remained below 6.3% for more than 25 hours on average 5.3 times per summer in the period 1980-2012;
- The UKCP18 climate change projections suggest, even in the most optimistic future emissions scenario, summer maximum temperatures could increase by up to 6°C by 2100 in southern England, and that hot summers like 2018 could happen on average once in every two years by 2050. This suggests this form of extreme stress on the energy system could become increasingly frequent and severe;

- An increased uptake in air conditioning, as a result of increasing temperatures, could create an additional summer time evening and over night demand peak, further increasing stress on the energy system during these events;
- No literature has been identified in which the frequency and duration of this form of extreme stress event is explored under climate change and changing energy demand profiles.

3.8 Theme 1 Conclusion

What is missing from the National Infrastructure Assessment?

- The assessment only considers one potential meteorological stress event on the energy system, in which demand is increased by 5GW and wind capacity is capped at 5%;
- This stress event therefore only characterises the 'Peak winter residual demand' form of stress event identified in the previous section;
- It is unclear as to whether these stress conditions are physically plausible, and if so, how common such an event might be, now and in the future.
- The resilience of the system to stress events of different durations has not been considered;
- The energy system analysis within the Assessment makes no consideration of the spatial and temporal variability and dependence between demand and renewable energy supply. This consideration may be important for identifying approaches for balancing the energy system;
- No consideration is made about the potential for different renewable technologies to complement each other in different meteorological conditions, which again, may help to balance the system;
- The effect of climate change on the meteorological conditions that cause extreme stress on the energy system is not included.

Does this literature provide any answers?

- The literature has identified four additional extreme energy system stress events that could occur as a result of adverse weather;
- In the studies reviewed, meteorological conditions that cause energy system stress conditions are identified based on historical or climate model data sets, ensuring they're physically plausible;
- Studies discussed in Section 3.2 highlight the importance of designing an optimal, resilient future energy system incorporating insights about the spatial and temporal variability and dependence in relevant meteorological conditions. For example, the apparent meteorological dipole between north and south Europe, the anti-correlation between wind speed and solar irradiance, particularly in summer and in south-west UK, and the seasonal link between peak winter demand and the North Atlantic Oscillation;

- Studies have explored the duration and frequency of historical high and low wind events, identifying that low wind episodes can last for many days. This highlights the importance of considering stress events of different durations;
- Important trade-offs between different forms of renewable are explored in the literature, indicating further potential techniques for developing a future, more resilient system. For example, both generally and during peak energy demand conditions, higher wind speeds are experienced off-shore compared to on-shore;
- Studies focused on the effect of climate change on energy demand and renewable supply identify a clear increase in temperature, reducing winter demand, but increasing summer time cooling demand. However, the effect of climate change on wind speed and solar irradiance is less clear, with different studies showing different signals.

What are the remaining gaps in knowledge, not addressed in the literature?

- A greater proportion of the literature focuses on wind energy supply rather than solar. Further work is required to gain equivalent insights for solar;
- Most studies aimed at understanding extreme stress on the UK energy system focus on the 'Peak winter residual demand' form of event. Very few consider wind and solar ramping or summer time wind droughts, which may become increasingly frequent and extreme in a changing climate;
- Very few studies therefore consider multiple forms of stress on the whole energy system as a result of temperature (demand), wind speed (wind power supply) and solar irradiance (solar PV power supply). The one exception is Staffell and Pfenninger (2018), however this study does not consider climate change or potential unseen extreme meteorological conditions not included in their historical period of meteorological data;
- A majority of studies focus on a limited historical period of meteorological data, most often spanning roughly 30 years. This approach may lead to underestimation of extreme stress on the energy system because it may be possible to experience something more extreme, but that has not been observed within this limited period. Statistical extreme value analysis techniques can be used to quantify potential, more extreme conditions. No studies were found to employ these techniques;
- While some studies explore the frequency and duration of high and low wind events, no link is made to the demand conditions during these events. Hence, there is a gap in understanding the frequency, duration and magnitude of different extreme stress events which are characterised by large differences in supply *and* demand. For example, how frequently renewable supply can't meet demand during winter, and for how long; the duration of different magnitudes of summer time wind drought; and the relative frequency of winter and summer peak residual demand events. It is important to also study this in a changing climate. Thornton et al. (2017) (referenced in the Assessment) discuss the occurrence of low wind power during peak demand conditions (cluster

4 in their analysis), indicating that 3 days per year experience these conditions. This frequency is, however, an artefact of the methodology used, i.e. defining the top 1% of days in their 34 year data set as 'peak' demand days. If instead, the top 2% of days were considered to be peak, and a much longer historical period used, the number of days per year with low wind speeds may be a completely different number. More robust statistical approaches are required to explore this;

- Literature focused on extreme stress on the energy system does not consider climate change, while literature focused on the effect of climate change on the energy system do not consider extreme stress conditions. This is therefore a very important gap that requires further research;
- Greater assurance about the effect of climate change on the energy system could be gained from using the most up-to-date, high resolution UK climate change projections, UKCP18.

Which areas addressed within the literature need further analysis to be relevant for the Commission?

- Within the literature reviewed, conclusions are based on many different historical and future energy systems. That is, with differing capacities and spatial distributions of wind and solar, differing future demand profiles and different data sets. Relevant studies must therefore be interpreted or repeated based on the specific future evolution of the energy system as specified by the Assessment, using optimal data sets and statistical techniques;
- Many types of extreme stress event have been discussed, the importance of each type for the Commission must be understood to focus future exploration;
- The level of extreme deemed unacceptable by the Commission must be identified (e.g. no black outs) to inform the level of extreme stress to consider in future analysis;
- A better understanding of how adverse meteorological conditions could be incorporated into the Commission's existing energy model will identify how these literature insights and methodologies could be used most effectively.

What does the literature suggest needs to be incorporated within the whole system energy model?

- All forms of extreme stress event;
- The spatial and temporal co-variability of relevant meteorological conditions, relevant for understanding where to locate new renewables, and when and where different stress events may occur;
- The effect of climate change on relevant meteorological conditions;
- The frequency and duration of extreme stress events of different magnitudes.

What methodologies and data sets are available to perform this further analysis and fill these gaps?

This will be discussed in detail in Section 5.

4 Theme 2: The role of prediction in mitigating stress events (up to a few days in advance)

Short-term weather forecasts are used extensively by the energy sector to improve forecasting of demand and renewable supply (Foley et al. 2012; Taylor and Buizza 2003). Indeed, being able to accurately forecast relevant meteorological conditions will become increasingly important for managing and mitigating stress in a future, highly renewable energy system.

4.1 Predictability of relevant meteorological variables

As described by Ferranti et al. (2015), the chaotic nature of atmospheric circulation and the sensitivity of its evolution to its initial state (Lorenz, 1963), means meteorological forecasts are more skilful in some flow configurations rather than others. That is, certain types of atmospheric flow turn out to be more stable and hence predictable, while others are unstable and unpredictable. Further, Troccoli (2008) highlights how forecast skill is also likely to depend on regional characteristics such as altitude and latitude.

As previously discussed, temperature, wind speed and solar irradiance are the meteorological variables of most relevance for understanding extreme stress on the energy system. A majority of the current literature and available forecast verification results are concerned with understanding the predictability of meteorological conditions of all magnitudes, and therefore do not focus on conditions that cause extreme stress events on the energy system. In particular, relevant studies based in the UK or Europe are found to focus on the skill in predicting wind power supply, rather than solar supply and power demand. For example, Foley et al. (2012) review a number of wind power forecasting models, noting how the ultimate goal of every wind power prediction model is to estimate the wind power output as early and as accurately as possible. Foley et al. (2012) conclude that recent innovations in both Numerical Weather Prediction (NWP) model resolution and statistical approaches for bias correction have facilitated distinct advances in wind power forecasting. Foley et al. (2012) go on to describe how hybrid methods, delivering the benefit of the NWP and statistical techniques are optimal.

Sharp et al. (2015) evaluate the accuracy of hourly wind speed forecasts for the UK, using in situ onshore and offshore measurements in locations relevant for power supply. Sharp et al. (2015) show that the forecasts are generally in good agreement with the observations, that forecast skill is similar on- and off-shore, and that wind speed forecasts are less accurate at high elevations and when wind speeds are either very high or low. In a similar study, Pinson and Hagedorn (2011) present a comparison of wind speed observations with the European Centre for Medium-range Weather Forecasting (ECMWF) ensemble forecasts for wind speed (out to 6 days), concluding that there is generally high forecast skill, and that this skill notably increases with increasing forecast model spatial resolution. Sweeney et al.

(2013) assess a number of methods for reducing the errors in wind speed forecasts for the energy sector. They identify seven methods, all found to effectively reduce model bias, noting how the most effective bias correction approach depends on the specific application of the wind forecast.

A very limited number of studies were found exploring forecast skill relevant for solar power production, and none where found that focus on the UK. Chaturvedi (2016) review a number of solar power forecasting approaches and specify possible forecast evaluation metrics, providing guidance on how to select the most appropriate forecast technique according to requirements. Lorenz et al. (2009) present an evaluation of German PV power prediction based on forecasts of solar irradiance up to three days ahead provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). Lorenz et al. (2009) note specifically that, based on a single station in Germany, the one day-ahead solar irradiance forecast has a relative root mean squared error of 36$\%$, and that this error decreases with increasing number of sites considered in combination.

The Met Office produces multiple daily forecasts, with varying lead times, for many meteorological variables throughout the UK, including temperature, wind speed and solar irradiance. Since the atmosphere is a chaotic system which can evolve in many ways, the uncertainty in the future atmosphere is quantified by producing an ensemble of forecasts, each made with small alterations to the starting conditions and/or the forecast computer model. Ensemble forecasting is explained in detail on the Met Office website[5]. This ensemble of forecasts, often termed the probabilistic forecast, undergoes a post-processing stage in which systematic biases are removed (also explained on the Met Office website[6]). Forecast verification is then routinely carried out based on these post-processed probabilistic Met Office forecasts and observations from sites throughout the United Kingdom, in order to understand forecast skill for different meteorological conditions. A common approach for doing so is to compare the area under the Relative Operating Characteristic (ROC) curve, known as the ROC score.

The ROC curve is constructed using a large quantity of historical data and focuses on a specific meteorological variable (e.g. temperature) and forecast lead time (e.g. 72 hours in advance). The ROC curve characterises the relationship between the forecast 'hit rate' and 'false alarm rate' for varying forecast probability thresholds (i.e. the proportion of ensemble forecasts in agreement). For a given event (e.g. temperature $< 0°$C) and forecast probability threshold (e.g. 40$\%$), the hit rate is defined as the number of times during the study period the event 'temperature $< 0°$C' was forecast to occur by at least 40$\%$ of the ensemble members and was later observed to occur, while the false alarm rate is defined as the number of times in the period the event was forecast by at least 40$\%$ of the ensemble members but did not occur. This is calculated over a range of forecast probabilities (0-100$\%$). As described on the Met Office website[7], a skilful forecast system will achieve hit rates that exceed the false alarm rates creating

[5] https://www.metoffice.gov.uk/research/weather/ensemble-forecasting
[6] https://www.metoffice.gov.uk/research/weather/verification-impacts-and-post-processing
[7] https://www.metoffice.gov.uk/research/climate/seasonal-to-decadal/gpc-outlooks/user-guide/interpret-roc

a ROC curve with a larger area and hence a larger ROC score. This score can be calculated for different events associated with a meteorological variable (e.g. temperature $< 0°$C, $< -2°$C and $< -4°$C), over multiple months, to compare the forecast skill associated with different meteorological conditions over time.

Figure 50: Taken from the Met Office VisualEyes internal forecast verification tool: Monthly 12-month moving average of the ROC scores associated with the 72 hour lead time probabilistic Met Office site-specific forecasts for events associated with (a) surface temperature, (b) surface wind speed, (c) maximum temperature and (d) minimum temperature from April 2016 to February 2019. The locations of the forecast sites used in each plot are shown in each plot.

Figure 50 presents ROC scores associated with surface temperature, surface wind speed, maximum temperature and minimum temperature, averaged over a number of locations throughout the UK. The higher the ROC score, the greater the forecast skill and a ROC score of 1 indicates a perfect forecast. These results therefore highlight how forecast skill is very good for all parameters, but consistently greater for temperature, compared to wind speed. In addition, for all meteorological variables, greatest forecast skill is observed for events in which moderate thresholds are exceeded and least skill is observed for extreme high and low thresholds. This suggest that extreme weather conditions which are most likely to be associated with stress on the energy system are generally predicted with less skill compared to average weather conditions.

Sharpe et al. (2018) present a detailed exploration of the skill of the Met Office probabilistic forecast system in predicting heavy rainfall, maximum summer day time temperature, minimum winter night time temperature and strong winds, for forecast lead time ranging from 6 to 120 hours, over a 21 month period between December 2013 and August 2015. Sharpe et al. (2018) use four verification techniques, specifically suited to verifying extreme rare events (Stephenson et al., 2008), and find forecast skill for all extreme meteorological variables based on each method. Maximum summer day time temperature is identified as the most skilful, while heavy rainfall is the least. Based on the ROC curve verification method, Sharpe et al. (2018) find that maximum summer temperature, heavy rainfall and wind speed forecasts are better at identifying extreme events at a range of 24 hour compared to 96 hour, whereas (somewhat surprisingly) minimum winter temperature forecasts detect more events at 96 hour lead times compared to 24 hour.

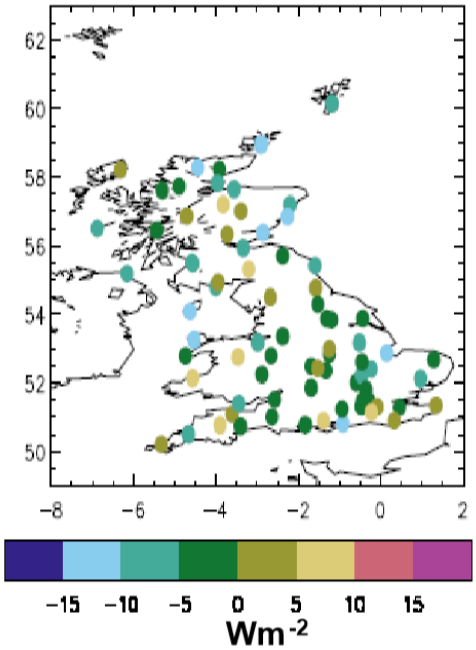


Figure 51: Taken from slides created by Joana Mendes of the Met Office Energy, Industry and Infrastructure group: Average bias between solar irradiance forecast from the Met Office 1.5 km UKV Numerical Weather Preditions (NWP) model [https://www.metoffice.gov.uk/research/news/2012/ukv] and weather station observations in the period 19/06/2013-31/12/2014 for hourly forecast lead times out to 36 hours ahead.

Routine forecast verification carried out by the Met Office (as presented in Figure 50) does not include solar irradiance as a meteorological variable. Some solar irradiance forecast verification has, however, been carried out by scientists within the Energy, Industry and Infrastructure group at the Met Office. Figure 51 presents the results of this initial exploration, in the form of the bias between solar irradiance forecasts and station observations averaged over the period 19/06/2013-31/12/2014 for hourly forecast lead times out to 36 hours ahead, throughout the UK. Figure 51 shows how the bias is generally between -5 and 5W/m^2, with a tendency for a more negative bias across the country. Numerical Weather Prediction models are, however, continually improving and this figure is likely to show reduced bias if verification were repeated at present day.

As described by Lohmann et al. (2016), the evolution of small scale synoptic features such as fair weather cumulus clouds, causing rapid successions of sunlight exposure and cloud shadow, relevant for accurate representation of solar irradiance fluctuations at multiple locations, are challenging to forecast. This challenge is also identified by Van Weverberg et al. (2015), how show how in particular the fraction of cloud cover at high levels (6-20km from the surface) is over estimated by Global Circulation Models throughout most of the day.

The Met Office provide solar irradiance forecasts to National Grid for energy forecasting. Similar to the negative bias observed in Figure 51, National Grid identified that these forecasts had the tendency to under-estimate solar irradiance, particularly in the first few hours of the forecast (24 hours to 48 hours ahead) and around midday and in the afternoon. As a result, a collaborative project between the Met Office and National Grid was initiated, aimed at improving and the Met Office solar irradiance forecast in three ways. Firstly by making refinements to the existing solar irradiance forecasting capabilities, secondly by developing statistical post-processing techniques for improving the forecast output, and finally by developing a solar irradiance 'Nowcast' product[8] to provide frequent and accurate short range forecasts relevant for balancing the energy system in response to instantaneous fluctuations in solar irradiance. This collaborative project will hereafter be referred to as the 'Solar Project'.

The results of the Solar Project showed that the regional UK Met Office ensemble forecasting system (MOGREPS-UK), previously used to provide National Grid's solar irradiance forecast out to 48 hours, tended to over-forecast cloud. The global configuration (MOGREPS-G) was found to have less of a cloudy bias, and was subsequently used in place of MOGREPS-UK, reducing the under-estimation of solar irradiance previously observed in the first few hours of the forecast. In addition, a statistical quantile regression post-processing approach was developed to correct for systematic biases in the solar irradiance forecasts. This method was shown to improve forecast skill, particularly for very low and very high solar irradiance, and was able to reduce the previously observed afternoon bias.

Summary

- A limited number of studies evaluating meteorological forecast skill relevant for the UK energy sector were identified;
- These studies focus predominantly on wind forecasting and identify that forecast skill is improved by using a high resolution Numerical Weather Prediction (NWP) model in combination with an application relevant statistical bias correction (post-processing) method. Forecast skill is lower for wind speeds at high altitudes and for very high and low winds;
- The Met Office produce ensembles of weather forecasts to quantify their uncertainty in the evolution of the chaotic atmosphere. The temperature and wind speed components of these ensemble forecasts are routinely verified against observations;

[8] https://www.metoffice.gov.uk/services/industry/water/nowcast

- Forecast skill is greatest for temperature (including maximum and minimum), compared to wind speed (and rainfall);
- Forecast skill was shown to be lower for events in which meteorological variables exceed very high or low thresholds, hence skill is best for moderate values;
- The Met Office UKV solar irradiance forecasts in the period June 2013 - December 2014 had a greater tendency to be negatively biased across the country;
- A recent project carried out in collaboration with National Grid aimed to improve the Met Office solar irradiance forecasts. The UK ensemble forecast system (MOGREPS-UK) was found to over-forecast cloud and was replaced by the global configuration (MOGREPS-G). A statistical post-processing approach was developed to improve the Met Office solar irradiance forecast skill, found to be particularly effective in improving forecast of very low and very high solar irradiance levels.

4.2 Predictability of extreme stress conditions

Studies considering the predictability of extreme energy system stress conditions focus on wind ramping events. As highlighted by Bossavy et al. (2017), making reliable forecasts of exactly when ramp events will occur is a significant challenge, since Numerical Weather Prediction (NWP) model errors in predicting the underlying weather conditions will result in inaccurate forecasting of ramp timing (i.e. the time at which the ramp will occur). Bossavy et al. (2017) develop a methodology for providing suitable uncertainty estimation associated with the forecast of the ramp timing based on an ensemble of forecasts from a NWP model. They show how, in doing so, they improve the reliability of the ramp forecast, particularly when compared to a single deterministic forecast, which can provide very inaccurate ramp times. Bianco et al. (2016) present a novel wind energy ramp metric for specifically measuring the skill of NWP models in forecasting these extreme events. This metric is based on identifying hit rates and false alarms in matched forecast and observed ramp events. Bianco et al. (2016) demonstrate its usage based on a 9-day case study in South Dakota, USA and identify that skill is greater for forecasting up-ramp events compared to down-ramp events.

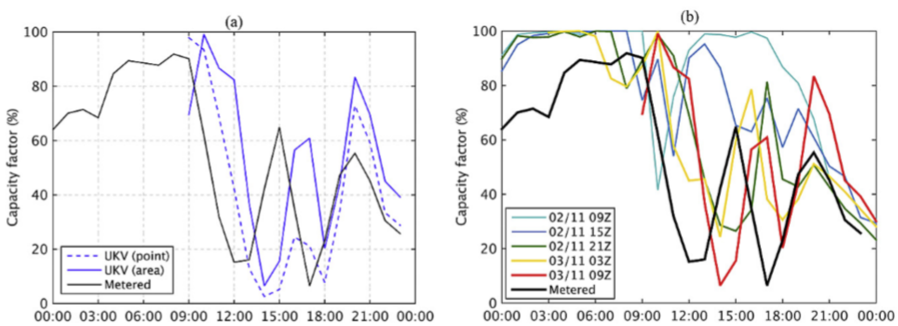


Figure 52: Taken from Drew et al. (2017): The hourly generation of the wind farms in the Thames Estuary compared to (a) wind power derived from the Met Office UKV1.5 forecast wind speeds (forecast initialised at 03/11/2014 at 09:00) at the precise location of each turbine (point) and with the maximum wind speed within 10 km of each turbine (area), and (b) wind power forecast for a range of lead times.

Drew et al. (2017) highlight the importance of forecasting regional wind power ramping based on a case study in the Thames Estuary. They show how the state-of-the-art Met Office UKV1.5 high resolution forecast model[9] is able to provide valuable information up to 12 hours ahead of time, helping to mitigate the impact of a wind ramping event in the Thames on 3$^{\rm rd}$ November 2014, as shown in Figure 52.

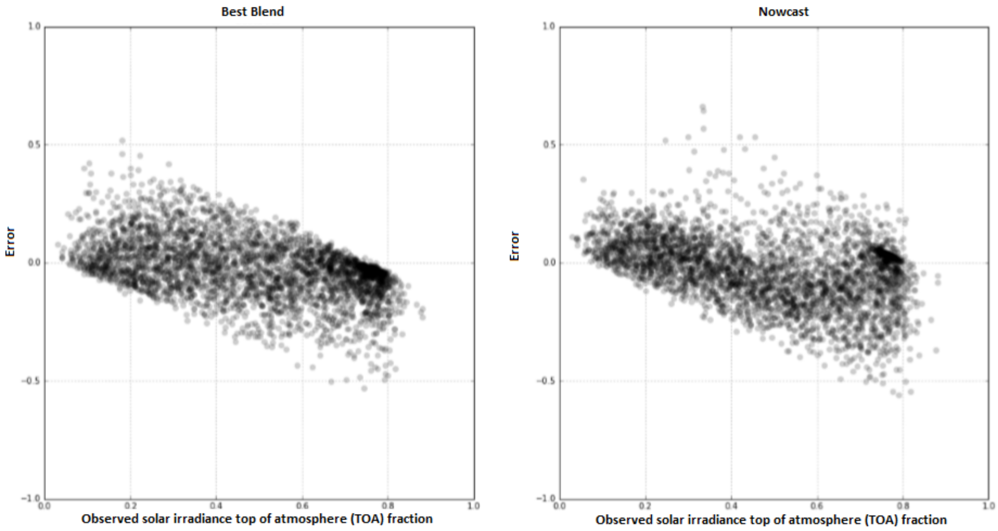


Figure 53: Taken from the Solar Project work package 3 report: Error (forecast - observed) in the Best Blend (left) and Nowcast (right) solar irradiance top of atmosphere (TOA) fraction. Forecast values are integrated to represent the hourly-average solar irradiance during the observation period. Errors are normalised by dividing by TOA solar irradiance. Each dot is from a single 12GMT T+0 hour forecast for a single station on a single day in the 3-month test period (Apr-May 2017); dots are semi-transparent so that clusters show as darker patches.

The Nowcast product developed as part of the National Grid and Met Office collaborative Solar Project was specifically designed for forecasting the very short-term evolution of solar irradiance (no further than 6 hours ahead in time), relevant for mitigating stress associated with solar ramping events. Based on observed solar irradiance at 42 observation sites during the period 1 April to 30 June 2017, verification was carried out on the Nowcast product to explore how the error in solar irradiance top of atmosphere (TOA) fraction (surface solar radiation divided by the TOA solar radiation) from the new Nowcast product compared to the error in the previously used 'Best Blend' of Met Office forecast outputs. These results are presented in Figure 53 and indicate that the Nowcast is generally favourable in cloudier conditions (lower TOA fraction), while the Best Blend outperforms for sunnier conditions. However, although the errors in the Nowcast forecasts during sunny conditions show more variability than the Best Blend forecasts, more of the Nowcast errors are concentrated around zero for very sunny conditions (highest TOA fraction). In addition, the Best Blend forecast displays a generally increasing under-forecast with increasing sunshine, suggesting a model bias. Indeed, since mixed sky, cloudy conditions are most relevant for energy system stress events at these very short timescales, these results suggest that the Nowcast product provides an improved, less biased forecast of relevant meteorological conditions.

[9] https://www.metoffice.gov.uk/research/news/2012/ukv

Little work has been done to specifically verify the predictability of alternative extreme energy system stress conditions, such as peak residual demand in winter, and summer time wind draughts. However, through exploration of the Met Office blog, some indication of the forecast skill of such events can be qualitatively understood. For example, the 'Beast from the East' cold snap experienced in February/March 2018 was described as being "very well predicted", with the first signs of its occurrence "appearing around one month before the start". The month-ahead indication of the extreme cold event was based on an observed Sudden Stratospheric Warming[10] event in the upper atmosphere, known to increase the risk of very cold conditions in the UK in subsequent weeks. This early indication meant that clear and regular updates on the increasing levels of risk could be issued from late January onwards[11]. Similarly a blog post in early June 2018[12] described how the long-range outlook for summer 2018 suggested an increase in the chance of high pressure patterns across the UK, which in turn increases the chance of above-average temperatures, indicating the potential for a summer heat wave. Again, this prediction was made over a month in advance of the event, hence similar advanced warnings of future events would provide the energy industry with time to prepare and implement alternative strategies.

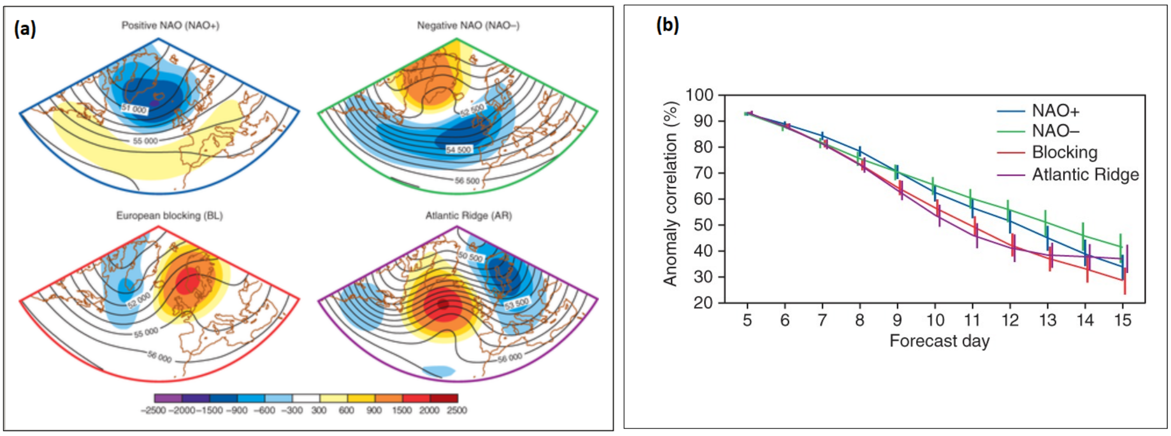


Figure 54: Taken from Ferranti et al. (2015): (a) Geographical patterns of the four EuroAtlantic climatological regimes (both anomalies and full fields) for the October to April cold season. The MSLP anomalies (colour shading) are shown. (b) Anomaly correlation of the ensemble means over Europe (12.5W42.5E, 35.0N75.0N) for the four forecast categories as a function of forecast range. Red refers the BL regime, blue to the NAO+, green to the NAO and violet to the AR regime. The bars, based on 1,000 subsamples generated with the bootstrap method, indicate the 95% confidence intervals.

Rather than exploring the forecast skill for energy system relevant meteorological variables one-by-one, when aiming to assess the predictability of extreme stress conditions, resulting from specific combinations of meteorological conditions (e.g. winter time low temperature and low wind speed in combination), it is more relevant to explore the predictability of the mean sea level pressure (MSLP) patterns, or weather regimes, that characterise these conditions. For example, Ferranti et al. (2015) present a verification of the ECMWF ensemble forecasts of four winter-time weather regimes: NAO+, NAO-, European

[10] https://www.metoffice.gov.uk/learning/wind/sudden-stratospheric-warming
[11] https://blog.metoffice.gov.uk/2018/03/07/a-review-of-our-long-range-outlook-for-the-recent-cold-snap/
[12] https://blog.metoffice.gov.uk/2018/06/11/will-summer-be-a-washout-or-a-scorcher-2/

blocking and Atlantic Ridge, based on the anomaly correction, a measure of spatial pattern matching[13]. The MSLP patterns associated with these four regimes and the comparison of the predictability of each pattern at different lead times are shown in Figure 54. Of these regimes, the NAO- and blocking patterns are of most relevance to winter-time peak residual demand (as discussed in Section 3). Figure 54 (b) identifies that forecasts have similar skill in all regimes out to 6 days, at which point forecasts initiated in the NAO+ regime show most skill until 9 days. As noted by Ferranti et al. (2015), between day 9 and day 13 the forecasts initiated in a Blocking or Atlantic Ridge flowtypes show less skill than the forecasts initiated in the NAO- or NAO+ regimes, and by day 15, forecasts initiated in the Blocking regime have the lowest anomaly correlations. Ferranti et al. (2015) identify that this forecast skill comes from the stability, and therefore predictability of the NAO-like weather regimes, while the persistence of, and transition into, European blocking regimes is less predicable and is therefore underestimated.

Similarly, Neal et al. (2016) developed a method for clustering North Atlantic weather patterns into a larger set of 30 weather regimes occurring throughout the year (not just winter), including NAO+ and NAO- type patterns. They show how these 30 regimes can be further clustered into 8 regimes (Figure 55 a) and present a verification of forecast skill in predicting each regime at varying lead times, based on the ECMWF ensemble forecast model (01/01/10-31/12/14), shown in Figure 55 (b). This verification is based on the Brier Skill Score (Brier, 1950), a commonly used measure of forecast skill which takes into account resolution, reliability and uncertainty. Similar to Ferranti et al. (2015), patterns 1 and 2, characterising NAO- and NAO+ respectively, show greatest forecast skill over all lead times, particularly in winter and for NAO+. As described by Neal et al. (2016), for the annual scores, the remaining six patterns are clustered tightly in terms of their Brier skill scores, with overlapping confidence intervals. In particular Neal et al. (2016) note how patterns 6 (high pressure over the UK), 7 (low close to the UK) and 8 (Azores high) have the worst forecast skill overall, with scores dropping to 0 by day 12. Based on insights from Section 3, the results of Neal et al. (2016) suggest that those regimes most relevant for wind draughts and cold/hot conditions in winter/summer are best characterised by patterns 1 (NAO-), 5 (Scandinavia high) and 6 (High centred over the UK). These results indicate that, in winter, better forecast skill is expected for pattern 1, while similar but slightly lower skill is expected for patterns 5 and 6, with pattern 5 retaining a positive skill score beyond 10 days. In summer, the patterns have more similar forecast skill compared to winter, with pattern 5 being forecast with slightly greater skill beyond 6 days.

A novel medium-to long-range forecasting tool has been developed by the Met Office, based on the 30 weather regimes, introduced by Neal et al. (2016) and shown in Figure 56. This tool is known as 'Decider' and provides an approach for forecasting weather regimes allowing for simple interpretation of future likely weather impacts. When an ensemble forecast is produced, the tool assigns each ensemble member to the closest matching weather regime of the set of 30, providing a probabilistic insight into

[13] https://confluence.ecmwf.int/display/FUG/Anomaly+Correlation+Coefficient

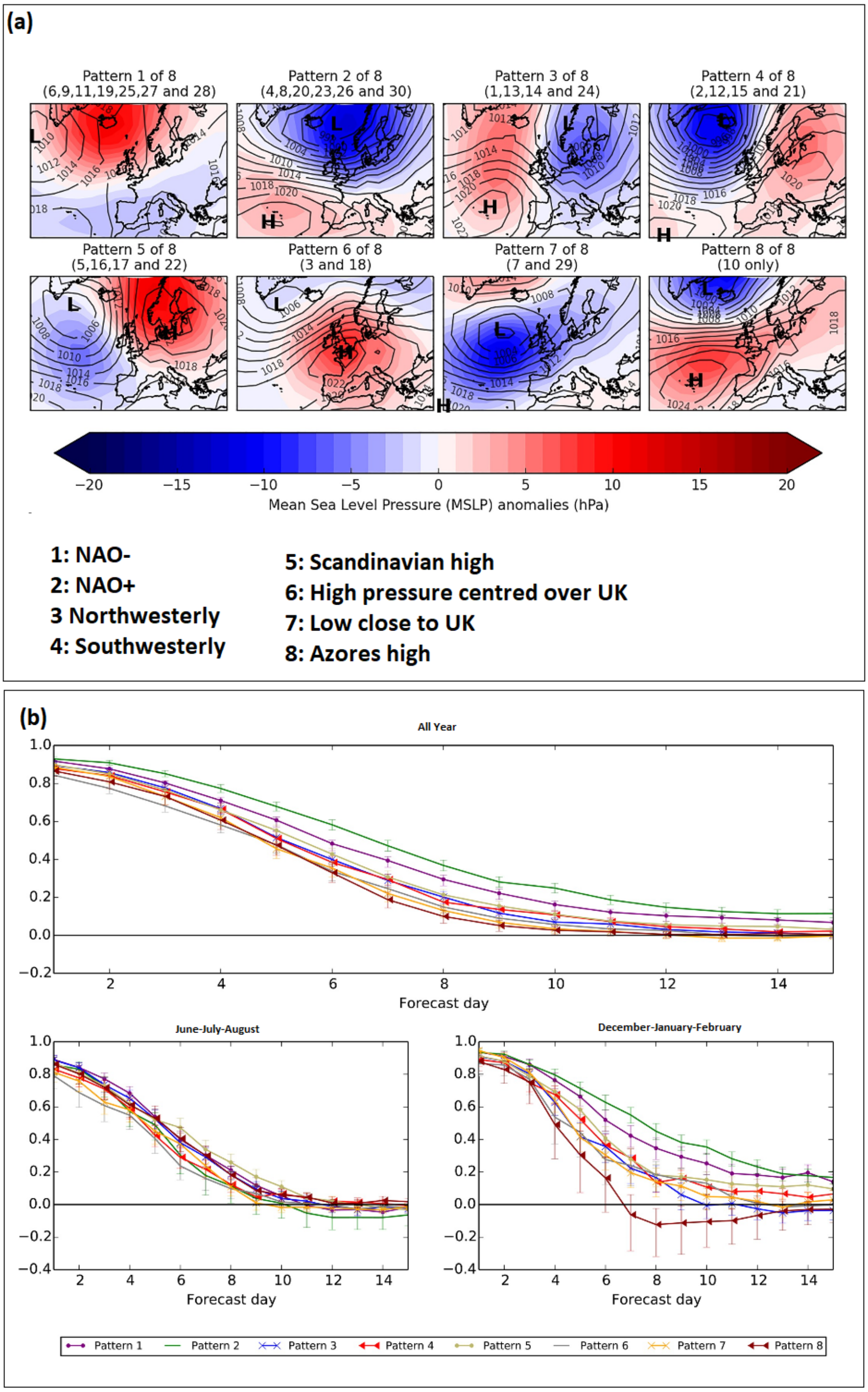
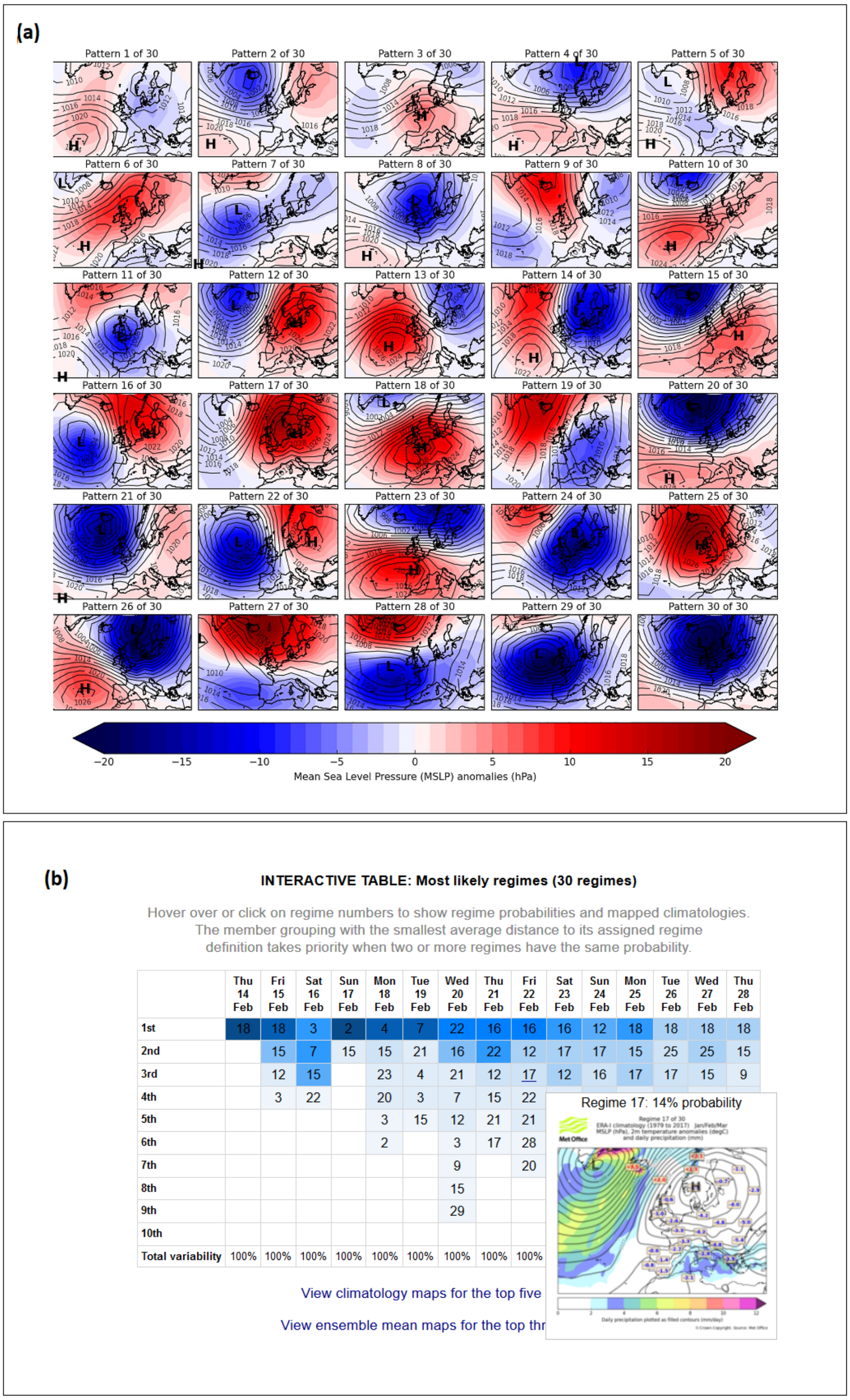


Figure 55: Taken from Neal et al. (2016): (a) Composites for the eight weather patterns. Numbers in brackets show the subpatterns from the set of 30 used to form the new composites. Mean sea level pressure (MSLP) anomalies plotted as filled contours (hPa) and MSLP mean values plotted in foreground (2 hPa intervals). (b) Brier skill scores for each of the eight weather patterns; (top) annual scores; (bottom left) JuneJulyAugust scores; (bottom right) DecemberJanuaryFebruary scores. Confidence intervals at the 90% level are shown by the vertical lines and are generated from 10,000 bootstrap samples.

the occurrence of different weather regimes throughout the forecast period. An example of a 15 day forecast from Thursday 14$^{\text{th}}$ February 2019 using the Decider tool is presented in Figure 56 (b). This



	Thu 14 Feb	Fri 15 Feb	Sat 16 Feb	Sun 17 Feb	Mon 18 Feb	Tue 19 Feb	Wed 20 Feb	Thu 21 Feb	Fri 22 Feb	Sat 23 Feb	Sun 24 Feb	Mon 25 Feb	Tue 26 Feb	Wed 27 Feb	Thu 28 Feb
1st	18	18	3	2	4	7	22	16	16	16	12	18	18	18	18
2nd		15	7	15	15	21	16	22	12	17	17	15	25	25	15
3rd		12	15		23	4	21	12	17	12	16	17	17	15	9
4th		3	22		20	3	7	15	22						
5th					3	15	12	21	21						
6th					2		3	17	28						
7th							9		20						
8th							15								
9th							29								
10th															
Total variability	100%	100%	100%	100%	100%	100%	100%	100%	100%						

Figure 56: Taken from Neal et al. (2016) and the Met Office internal Decider website: (a) Definitions for the set of 30 weather patterns. Mean sea level pressure (MSLP) anomalies plotted as filled contours (hPa) and MSLP mean values plotted in foreground (2 hPa intervals). (b) An example of a Decider 15 day forecast showing the 10 most likely regimes to occur each day, with the most likely at the top of the table. The darker the blue shading, the greater the agreement between the ensemble forecasts. Hovering over a regime number brings the corresponding MSLP pattern with associated temperature and rainfall anomalies, as shown for regime 17.

forecast indicates a 100% probability of being in regime 18 on Thursday 14$^{\mathrm{th}}$ February; that regime 18 is most likely to persist for 15$^{\mathrm{th}}$ February, although there is a moderate chance of a transition into regime

15; that on Saturday 16$^{\text{th}}$ February there is approximately equal likelihood of being in regimes 3, 7 and 15; and on Sunday 17$^{\text{th}}$ February the occurrence of regime 2 is very likely. As lead time increases and the forecast moves out to beyond 10 days, the ensemble forecast spread increases resulting in a larger number of possible regimes on each day.

The Decider tool provides anomaly (difference from average) maps for temperature, wind speed and cloud cover in the UK associated with a typical day in each regime (1-30) in each month. Through examining these anomaly maps, the regimes most likely to result in extreme stress on the energy system have been identified:

- Peak winter residual demand: regimes 17, 18, 25, 27, 28;
- Winter wind ramping: regimes 20, 26, 30;
- Surplus summer-time solar power: regimes 17, 23, 25, 27;
- Summer wind draught: regimes 5, 9, 12, 16, 17, 18.

Since these weather anomaly maps represent average conditions, characteristics such as mixed sky conditions, which vary at short time scales, cannot be easily interpreted, therefore identifying regimes associated with solar ramping extreme stress events is less straight forward. Examples of anomaly maps of temperature, wind speed and cloud cover (where relevant) for each of the other four extreme stress event types are shown in Figure 57.

Figure 57 (a) shows the temperature and wind speed anomaly maps for two of the 30 regimes that could cause winter time peak residual demand. During regime 17, Dec/Jan/Feb temperatures are low, particularly in the south east, and wind speeds are very low throughout the UK, while during regime 28 extremely low temperatures and low winds are experienced in all locations during these months. Figure 57 (b) shows temperature and wind speed anomaly maps for regime 26, identified as being potentially relevant for causing wind ramping. In winter months during this regime, temperatures are anomalously high in the south of the UK. This means demand is low, while wind speeds are very high throughout the UK, possibly characterising the increased occurrence of windstorms and hence wind ramping. For this regime the wind speed anomaly map also shows higher than normal winds throughout Autumn (not shown here). Figure 57 (c) presents the temperate, wind speed and total cloud cover anomaly maps associated with regime 23 in Jun/Jul/Aug, indicating that this regime is associated with roughly average temperatures, much higher than average wind speeds, particularly in the north, and very clear skies. These conditions could therefore lead to a surplus of solar PV power generation. Finally, conditions associated with a summer time wind drought are presented in Figure 57 (d), characterised by regime 16. In summer months, during the regime, temperatures are very anomalously high. This increases demand for cooling, whilst at the same time wind speeds are anomalously low, reducing the potential for wind power generation. Cloud cover is also very low suggesting the potential for solar PV power

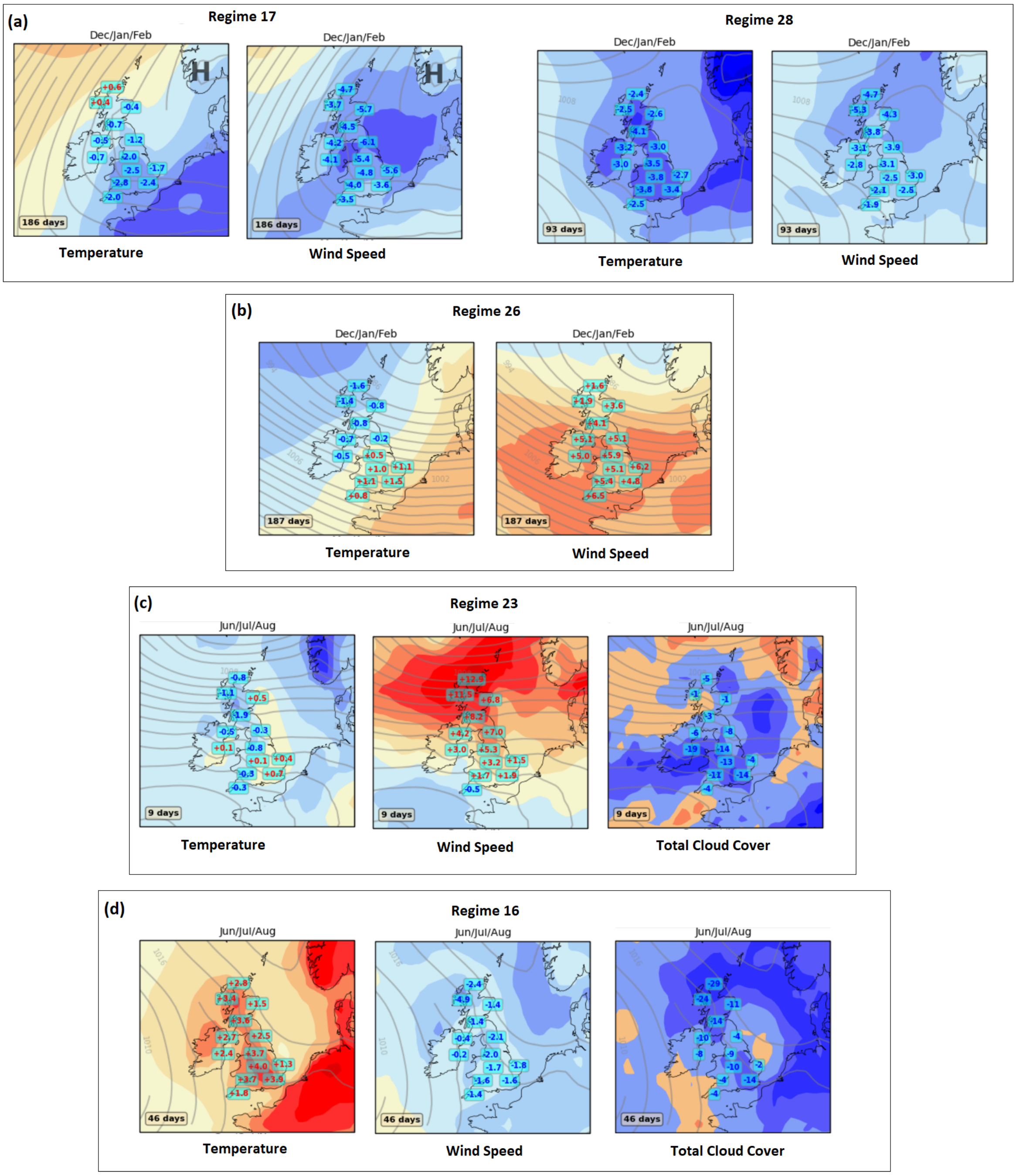
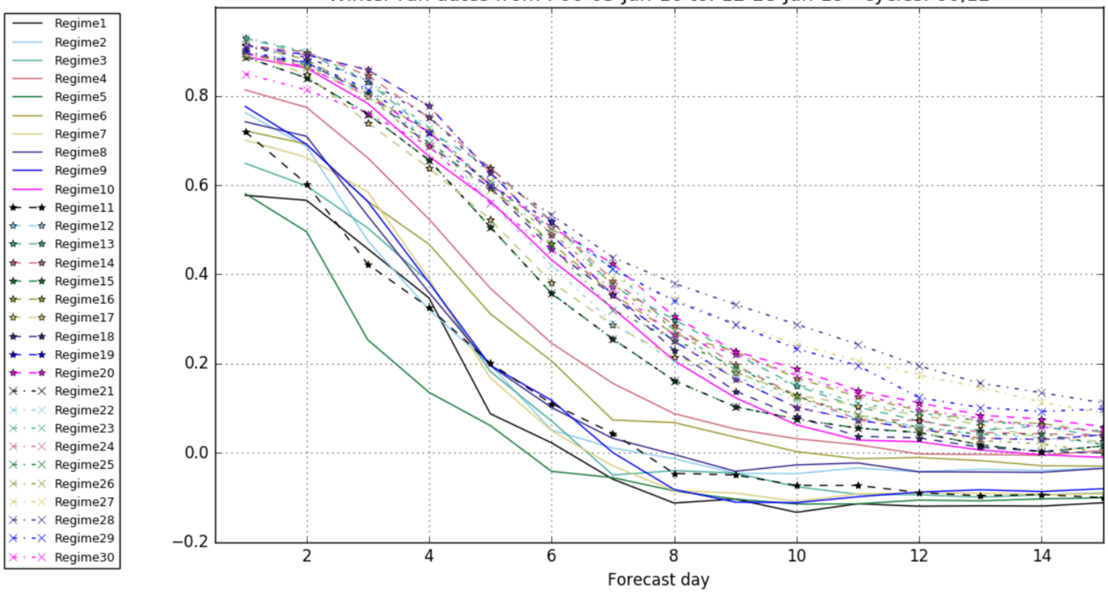


Figure 57: Taken from the Met Office internal Decider website: Temperature (degrees Celsius), wind speed (knots) and total cloud cover (%) anomaly (difference from average) maps for regimes identified as being associated with (a) peak winter residual demand, (b) winter wind ramping, (c) surplus summer-time solar, and (d) summer wind draught, in relevant seasons.

generation. However, as discussed in previous sections (e.g. Section 3.3), a large increase in installed solar capacity would be required to meet demand.

The skill with which each of the 30 regimes is forecast in summer and winter, based on the ECMWF ensemble forecast and the Brier Skill Score, is presented in Figure 58. Of the 30 regimes we are interested in observing the forecast skill in predicting regimes 17, 18, 20, 25, 26, 27, 28, 30 in winter, and regimes 5, 9, 12, 16, 17, 18, 23, 25, 27 in summer (as per the bullet points above). While the individual

(a)



(b)

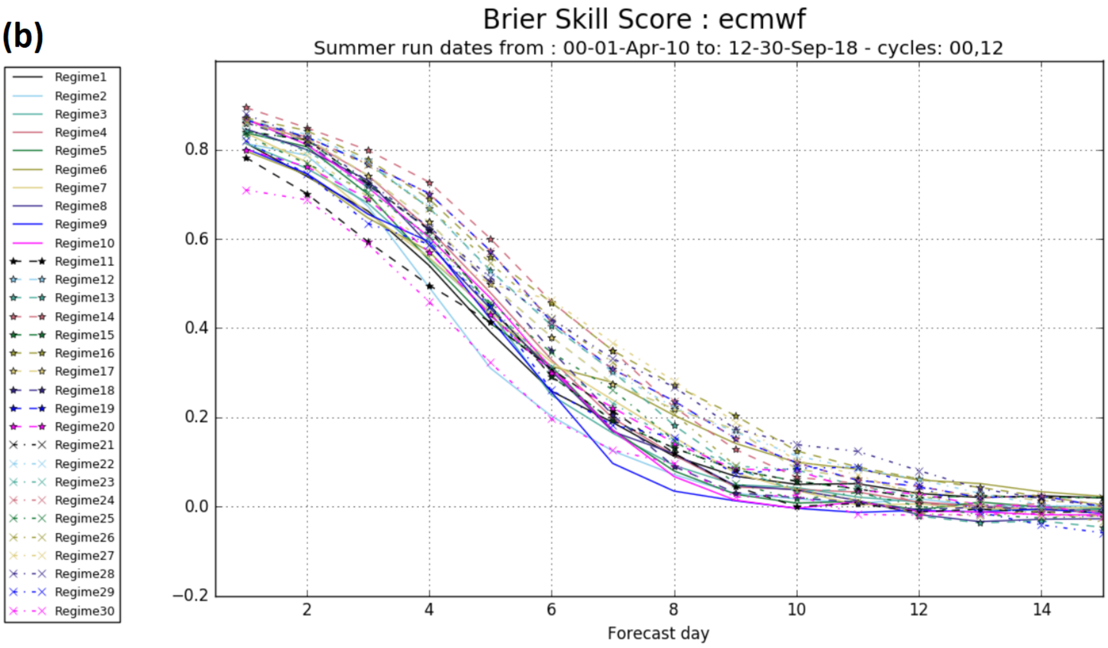


Figure 58: Taken from the Met Office internal Decider website: Brier skill scores for each of the 30 Decider regimes using the ECMWF ensemble forecasts from January 2010 to January 2019; (left) Winter scores; (right) summer scores.

lines on the plots are hard to distinguish (further work would be required to isolate regimes of interest), it can be seen that, in winter, all of the regimes of interest are forecast with skill out to 12-14 days. Indeed, regimes 27 and 28 have higher skill scores than all other regimes beyond 10 days, remaining above 0.1 out to day 15. This suggests greater skill in forecasting peak winter residual demand conditions at medium range (10-15 days), compared to wind ramping conditions. In summer, all regimes have very similar forecast skill, remaining above zero until approximately day 10. It can be seen how regime 16 (relevant for summer wind draughts) has one of the highest forecast skills throughout, particularly between day 6 and 10, this suggests such events can be predicted with reasonable skill up to 1.5 weeks ahead of time.

The skill in forecasting peak winter residual demand events was also demonstrated by the Decider medium range forecast of the 'Beast from the East' in February/March 2018. The Decider tool identified the date of occurrence and persistence of regime 27, characterising the very cold conditions, with very high probability two weeks ahead of time. As the lead time decreased, the Met Office were able to forecast with greater detail using very high resolution Met Office models, enabling detailed warnings of the cold and snowy conditions. Conditions such as this could result in a period of high energy demand, however a two week ahead warning such as this, and continuous updating and refinement of the forecast, would be valuable for mitigating the impact of such extreme stress events on the energy system. During the Beast from the East, wind speeds were, in fact, seen to be above average, characteristic of the strong easterly winds that can occur during very cold conditions, as described by Thornton et al. (2017). This suggests wind power generation may have helped to reduce the severity of this event on the energy system. Specific forecast verification of case studies in which peak residual demand is most severe, i.e. when wind speeds are also below average, do not yet exist.

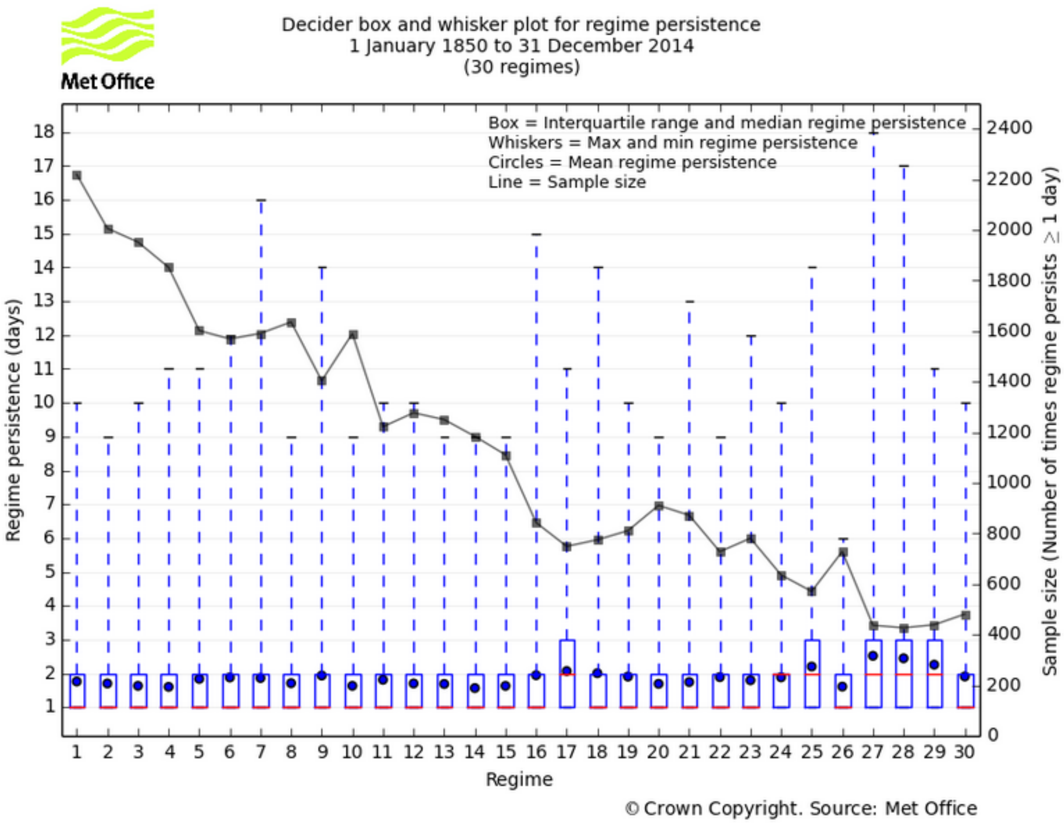


Figure 59: Taken from the Met Office internal Decider website: Box and whisker plots showing the distribution of Regime persistence (in days) for each of the 30 regimes based on daily historic classifications from 1 January 1850 to 31 December 2014.

As an aside, the Decider tool has been used to quantify the distribution of the persistence (in days) of each of the 30 regimes, as shown in Figure 59. These results show how regimes 17, 25, 27 and 28, all identified as potentially characterising peak winter time residual demand events (i.e. very cold and still) persist, on average, for longer than other regimes (2-3 days). Indeed, within the period (1850-2014), regimes 27 and 28 are shown to persist for up to 18 and 17 days respectively. This long period of persistent adverse weather increases the severity of the extreme stress on the energy system, hence an understanding of the forecast skill of predicting the persistence of relevant Decider weather regimes is also important for mitigating energy system stress. Thus far, this forecast verification has not be performed, and would therefore be in interesting area of future exploration.

Summary

- Studies considering the predictability of extreme energy system stress conditions focus on wind ramping events;
- Drew et al. (2017) showed that the Met Office UKV1.5 high resolution forecast model is able to provide valuable information 12 hours ahead of time, to mitigate the impact of a wind ramping event in the Thames on 3$^{\mathrm{rd}}$ November 2014;
- The solar irradiance Nowcast product developed within the National Grid - Met Office collaborative Solar Project outperforms the previously used 'Best Blend' of forecast models for very short-term forecasting of solar irradiance top of atmosphere fraction in cloudy conditions;
- The Met Office qualitatively highlight how both the 'Beast from the East' and summer wind drought of 2018 were identified a month ahead of time by the long-range forecast, providing a great deal of warning for industry and the public;
- Research has shown that NAO-like weather regimes are forecast with greater skill compared to other weather pattern types, due to their stability, and therefore predictability;
- A novel medium-to-long-range forecasting tool has been developed by the Met Office, known as Decider. This tool allocates ensemble forecast members to one of 30 weather regimes allowing for the simple interpretation of future likely weather impacts;
- Temperature, wind speed and cloud cover anomaly maps associated with each of the 30 regimes were examined to identify those that may cause winter and summer time extreme stress on the energy system;
- Forecast skill is good for all relevant regimes, out to 12 days in winter and 10 days in summer. There is an indication that some regimes associated with winter peak residual demand have non-zero forecast skill as far ahead of time as 15 days, and that this form of winter stress event is forecast with greater skill in the medium range than wind ramping conditions;
- The Decider tool was able to forecast the timing and persistence of the Beast from the East (Feb/March 2018) two weeks ahead of time;

- Decider regimes identified as being associated with winter peak residual demand have been observed to persist for up to 18 days within the period 1850-2014, with average persistence of 2-3 days. The forecast skill of predicting the persistence of relevant Decider weather regimes is unknown, and would therefore be in interesting area of future exploration.

4.3 Theme 2 Conclusion

What is missing from the National Infrastructure Assessment?

- The requirement for flexibility in the future renewable energy system will depend not only on the frequency and magnitude of extreme stress conditions, but also the extent to which they can be predicted, and at what lead time;
- The Assessment considers a particular stress event and tests for whether the flexible technologies (e.g. interconnectivity and storage) are adequate for managing the event. In addition, however, the resilience of the energy system and the ability to utilise different flexible technologies may be effected by the length and accuracy of the advance warning given by the weather forecast;
- The predictability of each form of extreme stress event must therefore be considered when planning flexibility and ensuring resilience. This has not been considered thus far in the Assessment.

Does this literature provide any answers?

- Forecast skill is improved by using a high resolution Numerical Weather Prediction (NWP) model in combination with an application relevant statistical bias correction (post-processing) method;
- The literature and results of Met Office verification of weather forecasts identify that temperature is forecast with more skill than other meteorological variables;
- More extreme meteorological conditions are generally less well forecast;
- Large scale, stable meteorological conditions, such as NAO- and NAO+ are predicted with more skill further ahead of time compared to less stable conditions;
- Small scale features such as mixed sky conditions, relevant for solar ramping, are predicted with less skill
- The Met Office UKV1.5 high resolution forecast model was shown to be able to provide valuable wind ramping forecasts 12 hours ahead of time in the Thames Estuary during a case study event in 2014;
- Conditions associated with peak residual demand in both winter and summer are shown to have good forecast skill out to 10 days, with indications of their occurrence identified up to a month in advance in long-range weather forecasts.

What are the remaining gaps in knowledge, not addressed in the literature?

- In most cases, forecast verification is averaged over multiple locations. Further work is needed to verify forecast skill in specific locations most relevant for the energy industry;
- Very few relevant verification case studies exist for energy system extreme stress conditions. Understanding the predictability of these extreme stress conditions through the analysis of further, specific case studies would be of great benefit, e.g. the 2018 summer heatwave;
- Verification of forecast skill in predicting the persistence of extreme stress conditions would also be beneficial;
- Less verification has been carried out for conditions associated with solar ramping.

Which areas addressed within the literature need further analysis to be relevant for the National Infrastructure Commission?

- Verification of the forecast skill of predicting temperature and wind speed above/below thresholds of most importance to energy demand and supply would be of more relevance than those currently used (in Figure 50);
- Further wind ramping verification case studies, similar to Drew et al. (2017), would improve understanding of the predictability of such events;
- The verification methods used in analysing the forecast skill of Decider are relevant, but need to be repeated specifically for the meteorological conditions and locations of most interest.

What does the literature suggest needs to be incorporated within the whole system energy model?

- The predictability of different extreme stress conditions should be quantified and used to inform about the degree to which the energy industry can prepare for, and mitigate against the stress conditions through alternative strategies and flexible technologies.

What methodologies and data sets are available to perform this further analysis and fill these gaps?

- Forecast verification methods, such as those introduced within this section (ROC curve, Brier Skill Score), can be used to assess relevant forecast skill;
- The Decider tool provides a useful way of characterising stress conditions through weather regimes. Specific historical periods in which stress conditions occurred could be identified and used as case studies to assess the forecast skill in predicting the occurrence time and persistence of the associated regimes;
- The ensemble forecasts created by the Met Office and ECMWF (European Centre for Medium-range Weather Forecasting) are used within Decider and are relevant data sets for this analysis;
- The Solar Project solar irradiance forecasts could be used to further verify specific extreme stress conditions associated with surplus solar and solar ramping.

5 Theme 3: Possible techniques and data sets for quantifying rare stress events

The studies discussed within the preceding chapters highlight the importance of quantifying and accounting for rare, extreme stress events associated with adverse weather conditions when planning and exploring the resilience of a future highly renewable energy system.

In particular, these studies identify how the magnitude and duration of all possible forms of stress event must be quantified based on a whole system energy model. That is, a model in which supply and demand are modelled together, estimated from meteorological conditions (as in Staffell and Pfenninger 2018 and Bloomfield et al. 2018). This must be achieved while accounting for: the spatial and temporal dependence in meteorological conditions throughout Europe, based on a long historical period of meteorological data; the effect of climate change on renewable supply and energy demand; future changes in installed renewable capacity, distribution and performance; the future transition away from gas heating and potential uptake in air conditioning; planned interconnectivity with Europe; future planned storage and flexible technologies; and a quantification of the skill and lead time with which adverse meteorological conditions can be forecast.

While many studies address one or some of these requirements, no studies currently exist in which all of these topics are addressed. This highlights where relevant research could be undertaken to facilitate future energy system resilience testing.

5.1 What level of 'extreme' has already been considered in the literature when defining extreme stress events on the energy system?

Many studies aimed at understanding the resilience of the UK energy system to adverse weather, such as Thornton et al. (2016), Thornton et al. (2017), Zachary et al. (2011) and Brayshaw et al. (2012), explore how relevant meteorological conditions, and hence renewable power generation, vary with increasingly extreme levels of energy demand. Commonly, these studies are based on a historical period of meteorological data and the definition of extreme is based on being in the top x% of events within the historical period. For example, Thornton et al. (2017) define high and peak demand days as those in the top 5% and 1% of days in the historical period (1979-2013) respectively, and Brayshaw et al. (2012) define peak demand days as the top 2% of days in their data period.

Other studies focus solely on extremes in renewable power supply, most often associated with extreme high or low wind speeds. In some cases extremity is considered in terms of high or low thresholds in wind speed or wind power generation. For example, Sinden (2007) explore the frequency and spatial extent with which wind speeds fall below or above fixed low or high thresholds (low=4m/s, high=25m/s), while Cannon et al. (2015) quantify the frequency with which a wide variety of extreme wind generation events occur, such as persistent lows, persistent highs and changes in wind capacity factor within varying time windows. Cannon et al. (2015), therefore also define extreme in terms of the duration as well as magnitude of the extreme stress event. Other studies consider extreme events in terms of case study periods within history, for example Leahy and Foley (2012) focus on exploring a single extreme winter (2009/10) during which wind power generation was very low during a prolonged cold spell, and Oswald et al. (2008) explore fluctuations in wind power during a selection of case study months and days during winters 1995-2006.

More recently, studies such as Bloomfield et al. (2018) and Staffell and Pfenninger (2018), quantify stress on the energy system in terms of residual demand, i.e. demand net of renewable power supply. This measure of stress is increasingly relevant with increasing installed renewable capacity and is most suited to quantifying extremity in a whole system energy model in which supply and demand are modelled simultaneously. Similar to Thornton et al. (2017), Bloomfield et al. (2018) define extreme as being the N most extreme events in the data period, for example the 6 highest and lowest years of Total Annual Energy Requirement (TAER) from sources other than renewables, and 10 peak residual demand events.

Within all of these studies a relatively short meteorological record, of no longer than 35 years, is used to quantify the level of 'extreme'. Using a limited historical data set in this way is likely to result in an underestimation of extreme since additional, more extreme events could have occurred, not quantified within the short historical period. In addition, as described by Brown et al. (2018), this empirical approach makes it impossible to estimate the probability of an extreme event of greater magnitude than the maximum value in the data series. As a result, Brown et al. (2018) recommend using statistical Extreme Value Analysis (EVA), a comprehensive and flexible set of tools optimised for analysing the statistical properties of extremes (Brown et al., 2014), to quantify extremes in meteorological variables. The EVA approach involves modelling the most extreme part of the distribution of the meteorological variable (e.g. wind speed) using a mathematical function known as the statistical extreme value distribution (EVD). Common EVDs within the meteorological and climate science community are the generalised extreme value distribution (GEV) and the generalised Pareto distribution (GPD) (Brown et al., 2018). Using an EVD allows for the exploration of statistically plausible extreme events beyond the magnitude of those observed in the limited historical period, and a formal quantification of the recurrence interval (or return period) of extreme events, e.g. an understanding of the magnitude of an event that occurs on average once every 100 years. The EVA approach is used in the Nuclear industry, where safety regulation enforces infrastructure to be resilient to very extreme hot temperatures, equivalent to those that would be observed on average once every 10,000 years. Quantifying this level of extreme temperature would be impossible without using statistical EVA models, since this level of extreme temperature is unlikely to have been observed within the limited historical records. EVA can also be used to represent how extreme levels of a meteorological variable evolve in time, allowing for the quantification of an extreme event in terms of its duration as well as its magnitude. For example, Winter and Tawn (2017) develop a statistical extreme value modelling framework for representing the persistence of heatwaves, and use this model to quantify the probability of a heatwave event lasting as long as the historical devastating heatwave event that occurred in Europe in 2003.

As well as characterising extremity in terms of the magnitude and duration of an event, the skill and lead time with which such an event is forecast by the Numerical Weather Prediction (NWP) model is also relevant. That is, an event that is forecast accurately many days ahead of time will have a less extreme impact on the energy system compared to an event of the same magnitude that is forecast either incorrectly or with less lead time. This characterisation of 'extreme' reflects the Intergovernmental Panel of Climate Change (IPCC) definition of 'risk': as the product of the hazard, exposure and vulnerability (Campos et al., 2014). In this case, the *hazard* is the adverse meteorological condition (e.g. high wind speed), which will only have an extreme impact at a given location if that location is *exposed* (i.e. the high wind speeds occur at that location) and *vulnerable* (i.e. wind turbines are not turned off because the hazard is not forecast with the required warning time).

Finally, the level of 'extreme' can be based on a standard definition, for example the World Meteorological Organization define a heatwave as a period in which the daily maximum temperature exceeds the average maximum temperature (calculated for the period 1961 to 1990) for more than five consecutive days. Alternatively, relevant levels of extreme can be defined based on the requirement of the law or limits in cost. For example ensuring residual demand in the UK energy system meets legal requirements in terms of blackout frequency, and that meeting these requirements through flexible technologies does not exceed an specified level of cost.

Summary

- In the reviewed literature, the level of extreme is defined in terms of the magnitude, variability and duration of peak energy demand, renewable energy supply or a combination of the two as residual/net demand after subtracting renewable supply;
- These studies characterise extreme either by investigating a specific case study period/event, exploring the exceedance of high or low thresholds or focusing on the top x% of events in limited data record;
- Basing the definition of extreme on a limited historical period of data is likely to result in an underestimation of 'extreme', and makes it impossible to estimate the probability of an extreme event of greater magnitude than the maximum value in the data series;
- Statistical Extreme Value Analysis (EVA) is an alternative approach which involves modelling the most extreme part of distribution of the meteorological variable (e.g. wind speed) using a mathematical function known as the statistical extreme value distribution (EVD). EVA allows for the

exploration of statistically plausible extreme events beyond the magnitude of those observed in the limited historical period, and a formal quantification of the return period of extreme events. These techniques have been used in the Nuclear industry to quantify very extreme high air temperatures, and to develop models for the persistence of heatwaves;

- The extremity of a stress event also depends on the skill and lead time with which such an event is forecast. Greater forecast skill at a longer lead time will reduce the vulnerability of the energy system to the hazard, hence reducing the extremity of its impact;
- Extremes can also be characterised in terms of standard definitions for meteorological hazards, e.g. heatwaves, or based on legal requirements or limits in cost.

5.2 Data requirements to account for climate variability

Climate variability refers to natural fluctuations in the climate on time scales from months to decades, resulting from variation in large scale atmospheric circulation patterns such as the North Atlantic Oscillation (NAO) and the El Niño Southern Oscillation (ENSO). Since fluctuations in these modes of variability can happen over multiple decades, comparatively short data records are unlikely to contain a full representation of this climate variability and hence all possible extreme events. As a result, as noted by Thornton et al. (2017), a number of studies, such as Oswald et al. (2008), Zachary et al. (2011), Brayshaw et al. (2012) and Sinden (2007) emphasize the uncertainty in their results due to the shortage of data considered (often less than 10 years). Thornton et al. (2017) use a longer, 34 year period of demand and wind speed data, but still note how this relatively small number of years limits the estimation of the likelihood of peak demand events. They suggest that an improved estimation could be made by assessing the likelihood of such weather types in a longer historical record or using large ensembles of model simulations.

Staffell and Pfenninger (2018) use 25 years of historical meteorological reanalysis data to estimate wind and solar PV power generation in different future renewable scenarios. Staffell and Pfenninger (2018) describe how using just one historical year is equivalent to drawing a single sample from a large population of widely-distributed weather years. They demonstrate how using just a single year rather than 25 results in estimates of peak demand $\pm 3\%$ from the 25 year mean, minimum demand net of renewables $\pm 13\%$ from the 25 year mean; and the number of hours per year with negative net demand $\pm 23\%$ from the 25 year mean. Staffell and Pfenninger (2018) go on to explain how using a mean weather year or typical meteorological year in scenario modelling studies removes extremes. Fore example steep ramps, peak and minimum demands, and storage and balancing requirements over different time scales, all of which are crucially important for the reliable operation of the power system. They identify that their findings strongly suggest that future work must consider multiple years of data to encompass year-by-year variability in weather, and its influence on both supply and demand, or be of limited significance and validity.

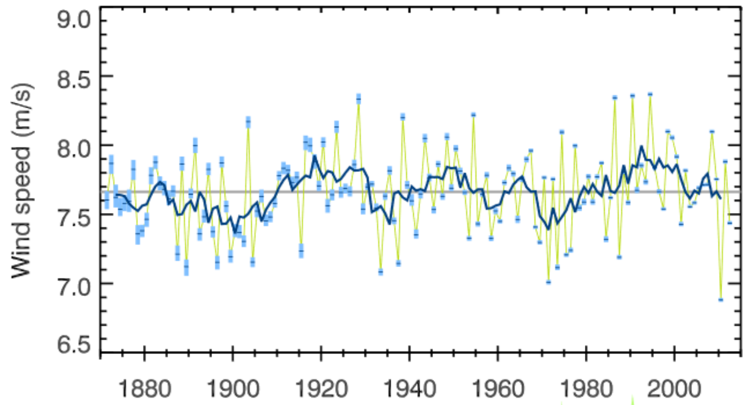


Figure 60: Taken from Bett et al. (2017): Time series of annual average (green) and 5-year moving average (dark blue) wind speed for a region covering 5°W - 1°E and 51°N - 55°N (England and Wales).

Bett et al. (2017) present a study of the variability of wind speeds across Europe over the 142 year period (1871-2012). They show how, for example in England and Wales (as shown in Figure 60), wind speeds over the past ∼20 years are within the range expected from natural climate variability, but do not characterise the full range of variability within the 142-year data set, highlighting how a longer historical period provides a more accurate representation of climate variability.

Bloomfield et al. (2016) explore the impact of year-to-year climate variability on multiple aspects of the UK power system. They highlight how many aspects of the European power systems are profoundly affected by strong multi-annual climate variability, but note how, as previously discussed, many studies of renewable integration into the UK energy system only use a very short data record. Similar to Staffell and Pfenninger (2018), Bloomfield et al. (2016) use historical meteorological data to estimate wind and solar PV power production. Based on a sensitivity study in which 1, 2, 5, 10 or all 36 years of hourly meteorological data are used to calculate the additional power required from non-renewable sources, Bloomfield et al. (2016) show how less than 10 years of data introduces significant levels of uncertainty into the estimated 'mean' characteristics of power system, and is therefore insufficient for providing reliable power system planning guidance. This suggests that future renewable integration studies should aim to adopt more robust approaches for climate characterisation. For example, this could involve developing statistical models for the meteorological variable of interest, using a long historical record periods. In addition, to allow for the quantification of ramping events, appropriate meteorological data must be available at a high temporal resolution (e.g. at least hourly).

Figure 61 presents a table of relevant meteorological data sets. These include observation station data, gridded reanalyses and hindcasts and climate projections (reanalysis and hindcasts are described in Sections 7). These data sets have different merits in terms of the period covered, domain, and spatial and temporal resolution. Many studies in the reviewed literature use the ERA-Interim or MERRA reanalysis data sets due to their free availability and reasonable spatial and temporal coverage.

Dataset	Type	Historical/ Future	Region	Resolution	Period	Time step	Temperature	Wind speed Land	Wind speed Sea	Solar Irradiance
UK observations	Site	Historical	UK	200-300 sites	Good coverage form 1960	Good coverage at 1 hourly	✓	✓		
Global observations	Site	Historical	Global	Good coverage in Europe	Good coverage form 1960	Good coverage at 3 hourly	✓	✓		
Marine observations	Site	Historical	Global	Best coverage in Europe	Good coverage form 1990	Up to half hourly	✓	✓	✓	
SARAH	Satellite	Historical	±65° long and ±65° lat	0.05°x 0.05° (approx. 50km in UK)	1983 to 2015	Half hourly				✓
ERA-Interim	Gridded reanalysis	Historical	Global	80km	1979 to present	3 hourly	✓	✓	✓	✓
ERA-5	Gridded reanalysis	Historical	Global	50km	1979 to present	1 hourly	✓	✓	✓	✓
MERRA	Gridded reanalysis	Historical	Global	40km	1979 to present	1 hourly	✓	✓	✓	✓
UKV	Gridded archived forecast	Historical	UK	1.5km	2012 to present	Up to 1 hourly	✓	✓	✓ (surroun ding UK)	✓
Euro4	Gridded archived forecast	Historical	Europe	4km	2009 to present	1 hourly	✓	✓	✓	✓
	Gridded Hindcast*	Historical	Europe	4km	1979 to June 2015	1 hourly	✓	✓	✓	✓
Twentieth Century Reanalysis	Gridded reanalysis	Historical	Global	2°x 2° (approx. 200km in UK)	1871 to 2010	Daily	✓	✓	✓	
UKCP18	Gridded climate projection	Future	Global	60km	1900 to 2100	Daily	✓	✓	✓	✓
			UK	12km (soon 2.2km)	1981 to 2080	Daily	✓	✓	✓	✓
			UK probabilistic	25km	1961 to 2100	Monthly	✓			✓

Figure 61: Table containing a non-exhaustive list of potential meteorological data sets relevant for whole system energy modelling. *A description of a hindcast is given in the Appendix (Section 7)

In addition to those data sets presented in Figure 61, various freely available data sets have been developed with the aim of facilitating energy resilience research. European Climatic Energy Mixes (ECEM) is a Copernicus Climate Change Services (C3S) activity (Troccoli, A. et al., 2018), from which a demonstrator tool has been developed in which historical and future climate and energy demand and generation data can be explored, compared and downloaded for different countries in Europe (historical period: 1979-2016, future period: to 2100)[14]. In a similar way the Renewables.ninja project, a collaboration between Stefan Pfenninger and Iain Staffell (authors of Staffell and Pfenninger 2018), allows for simulations of download-able hourly power output from wind and solar power plants at a country level or location specific resolution, for the historic period 1979-2018[15]. These tool are both very valuable for validating any whole energy system model developed in which wind and solar power are estimated from meteorological conditions. As well as the Renewables.ninja project, Iain Staffell has developed an additional open source model for European energy demand: The DESSTINEE model (Demand for Energy Services, Supply and Transmission in EuropE)[16]. This model is designed to test assumptions about the technical requirements for energy transport (particularly for electricity), and the scale of the economic challenge to develop the necessary infrastructure, based on forty European countries. Available data

[14] https://ecem.climate.copernicus.eu/demonstrator/
[15] https://www.renewables.ninja/
[16] https://sites.google.com/site/2050desstinee/home

includes projected annual energy demand at country level forward to 2050 and simulated hourly profiles of electricity demand in 2010 and 2050, all based on user specified assumptions for future changes in demand (e.g. projected uptake in electric vehicles). Finally, National Grid publish historical demand data back to 2005 (National Grid, 2019a), relevant for validating demand models.

Summary

- Climate variability is the natural fluctuation in the climate on time scales from months to decades, resulting from variation in large scale ocean and atmospheric circulation patterns such as the North Atlantic Oscillation (NAO);
- Fluctuations in these modes of variability can happen over multiple decades, hence comparatively short data records ($<$10-20 years) are unlikely to contain a full representation of this climate variability and hence the most extreme events possible;
- Less than 10 years of data introduces significant levels of uncertainty into the estimated characteristics of power system, and is therefore insufficient for providing reliable power system planning guidance;
- Wind speeds over the past 20 years are within the range expected from natural climate variability, but do not span the full range of variability of the last 142 years;
- A number of relevant data sets of historical meteorological and future climate conditions exist with varying spatial and temporal extents and resolutions;
- A number of energy projects have developed models and tools for the exploration of downloadable meteorological, power and demand data throughout Europe.

5.3 Methods for quantifying the probability of different extreme stress events occurring, and hence how important they are to consider in the whole energy system

As described by Staffell and Pfenninger (2018), detailed modelling of wind and PV generation with high resolution in space and time is becoming increasingly important for understanding how future highly renewable energy systems vary with meteorological conditions. In addition, as mentioned at the beginning of this Theme, the large number of variables playing a role in the energy system resilience (e.g. interconnectivity with Europe, the volume of installed renewables and uptake in electric vehicles) means these detailed models must represent the whole energy system coherently. That is, a model in which supply and demand are modelled together, estimated from meteorological conditions, and the system is tested for resilience in terms of demand net of renewable supply, supply from Europe and supply from back up and flexible technologies.

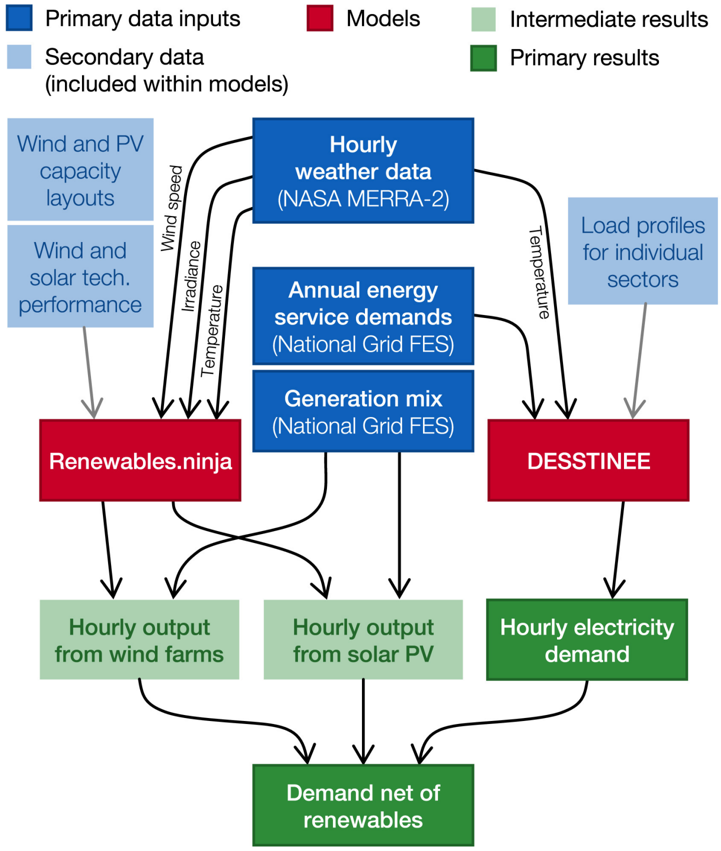


Figure 62: Taken from Staffell and Pfenninger (2018): Schematic of the framework used with the study to assess the impact of weather variability on electricity supply and demand using free and open data and tools (Renewables.ninja and DESSTINEE).

Only one example of a whole energy system model, incorporating adequate meteorological variability and future changes in wind and solar PV capacities as well as demand, exist in the literature, presented in Staffell and Pfenninger (2018). A schematic of this framework is shown in Figure 62. Twenty-five historical years of hourly temperature, wind speed and solar irradiance reanalysis data are combined with installed solar PV and wind capacity maps, a measure of technology performance and the National Grid Two-degrees "Future Energy Scenario" (FES) to estimate hourly wind farm and PV output, based on the Renewables.ninja Virtual Wind Farm Model and PV power output Model as published in Staffell and Pfenninger (2016) and Pfenninger and Staffell (2016) respectively. At the same time, within the framework, the hourly temperature data is used in combination with the FES within the DESSTINEE model to estimate hourly electricity demand. Total supply is then subtracted from demand to give and estimate for hourly demand net of renewables, equivalent to the amount of power required from additional sources. Within such a framework the magnitude and distribution of installed renewable capacity can be varied, and alternative future demand scenarios tested to explore the resilience of residual demand to weather conditions.

This approach of estimating renewable output based on meteorological variables is common in the literature, for example Cannon et al. (2015), Bloomfield et al. (2016), Thornton et al. (2017) and Bloomfield et al. (2018). The wind power is often represented as a function of the cubed wind speed (characteristic

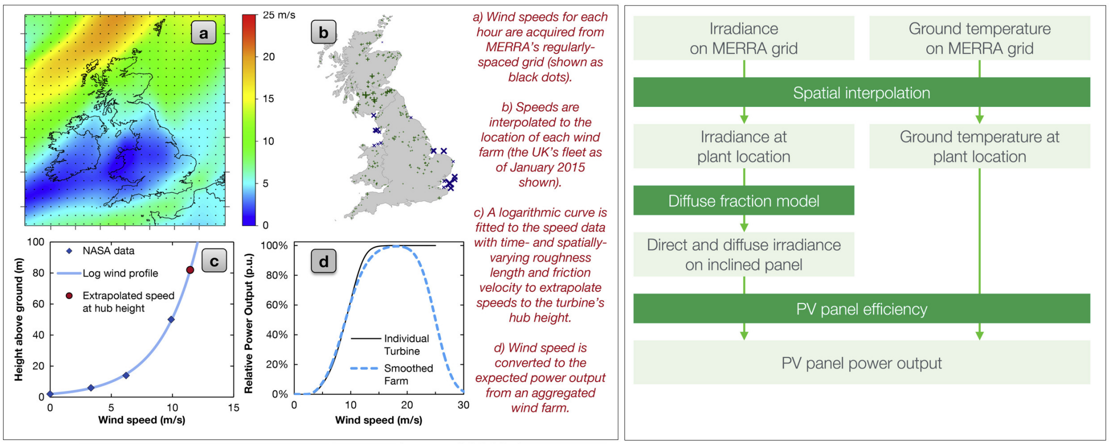


Figure 63: (Left) taken from Staffell and Pfenninger (2016): Overview of the Virtual Wind Farm methodology used in Renewables.ninja. (Right) taken from Pfenninger and Staffell (2016) Overview of the approach used to model PV power output in Renewables.ninja.

of the work done by the wind Thornton 2018) interpolated to the location and height of the wind turbine, while PV power is often a more complex function of solar irradiance, ground temperature, and the inclined angle of the PV panel. Figure 63 presents an overview of the Renewables.ninja[17] Virtual Wind Farm Model (left) and PV power output Model (right) as published in Staffell and Pfenninger (2016) and Pfenninger and Staffell (2016) respectively.

The comprehensive framework employed by Staffell and Pfenninger (2018), allows for two important insights. Firstly, how the electrification of heating and transport causes not just the absolute level of net demand to increase, but also its variability to increase, and secondly, how the addition of PV and wind capacity will result in fundamentally different net demand behaviour by 2030. By 2030, in the future scenario explored by Staffell and Pfenninger (2018) (based on the National Grid Two degree scenario), negative net demand events occur on weekdays and weekends, with expected frequency of occurrence equal to 1.1 and 3.4 days/year, respectively. In addition, net demand drops down to the baseload floor of nuclear power generation regularly during the summer months (24 days/year expected frequency of net demand below nuclear generation). Staffell and Pfenninger (2018) explain how this implies that, by 2030, on half of weekend days curtailment of either nuclear or renewable output would be required unless there were sufficient expansion of storage, interconnection or demand-side response.

Staffell and Pfenninger (2018) note how their results demonstrate the need for smart system elements, which they did not model, but which would enable demand to adapt to changes in supply. Their study adds to the body of evidence that justifies the need for new flexibility options to help balance and harness this output, also reflecting the findings of Huber et al. (2014) and Fattori et al. (2017). Staffell and Pfenninger (2018) describe how demand-side management, fleets of electric vehicles with coordinated charging, and electricity and thermal storage could form a substantial resource for shifting demand, balancing renewables and reducing peak demand, as highlighted by Lund et al. (2015) and Strbac (2008).

[17] https://www.renewables.ninja/

Any future whole system energy models for exploring resilience to adverse weather must therefore incorporate these flexible technologies and strategies to provide a more realistic (and optimistic) picture of the future.

In addition, Staffell and Pfenninger (2018) do not incorporate interconnectivity with Europe within their whole system energy model. This interconnectivity is highlighted in the literature as a potential approach for mitigating extreme stress conditions, as discussed in Section 3.2, and shown to be an important way of coping with the extreme stress event included in the Aurora analysis conducted for the Assessment (see slides 75-76 in Aurora Final Report[18]). Including interconnectivity with Europe within future analyses is therefore also important for quantifying the probability of different extreme stress events.

The modelling framework presented by Staffell and Pfenninger (2018) is also limited in its representation of potential meteorological conditions in two ways. Firstly, Staffell and Pfenninger (2018) argue that robust climate change signals occur on a longer time horizon than renewable energy investments, and therefore only consider historical meteorological conditions (the period 1991-2015). While the effect of climate change on wind speed and solar irradiance is less clear, there is a strong indication that temperatures will increase throughout the UK by 2050 which will have a significant impact on energy demand, potentially reducing demand for heating in winter, but increasing demand for cooling in summer. It will be very important to take this into account when aiming to quantify the probability of different extreme stress events in the coming decades. Secondly, as discussed in Section 5.1, Staffell and Pfenninger (2018) using the limited historical data set is likely to result in the underestimation of extremes, and Extreme Value Analysis (EVA) techniques should be used to statistically model, and extrapolate beyond, the observed meteorological data.

Figure 64 demonstrates how an Extreme Value Distribution (EVD), known as the Generalised Pareto Distribution (GPD), can be fit to the extremes of a meteorological variable (here temperature), and then used to extrapolate beyond the range of the observed meteorological data. The GPD model can be used to create a return level plot, as shown in Figure 64 (d). This plot estimates the return period (or recurrence interval) of different levels of extreme temperature, calculated as a function of the number of years in the data set and the number of occurrences of the event in the period. While the maximum temperature in the (synthetic) observation record is approximately 23°C, having a return period of 30 years (since 30 years of observations are used), the GPD model allows for higher return period temperatures to be estimated (with a quantification of uncertainty). For example, based on this synthetic time series of temperature data, the most likely estimate of the temperature expected to occur on average once every 100 years is approximately 25°C (i.e. the top right corner of Figure 64 d).

This EVA approach is commonly used in the natural hazards literature for quantifying extreme, rare

[18] https://www.nic.org.uk/wp-content/uploads/Power-sector-modelling-final-report-1-Aurora-Energy-Research.pdf

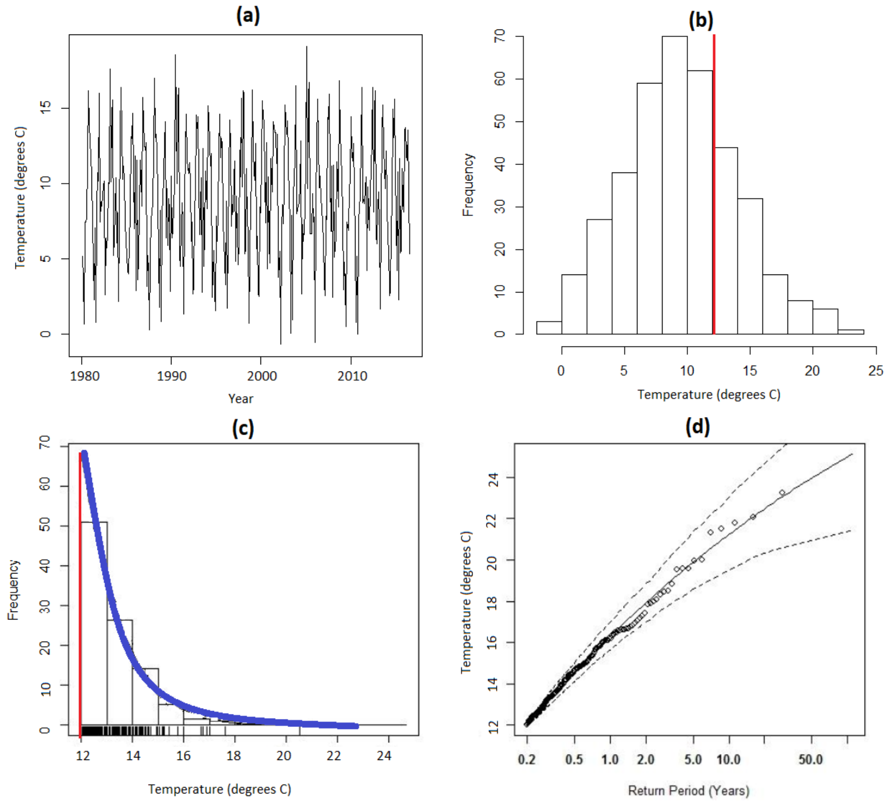


Figure 64: A demonstration of how statistical Extreme Value Analysis (EVA) techniques allow for extrapolation beyond the range of the observed meteorological data. (a) A synthetic time series of daily air temperature (1980-2019), (b) a histogram of the daily air temperature data in (a), showing the distribution of observed temperatures in the period, with a high threshold (12°C) shown in red, (c) the same histogram as shown in (b) but for temperatures above the high threshold [red line], with a mathematical function known as the Generalised Pareto extreme value Distribution (GPD) fitted to this extreme part of the data [blue line], (d) a return level plot of the fitted GPD model for extreme temperature. The solid line shows the most likely estimate while the dashed lines show the 95% confidence interval (a quantification of uncertainty), and the synthetic observed temperature data are shown as circles.

events. For example Youngman and Stephenson (2016) develop a framework for modelling extreme natural hazards in space and time using the GPD model, applied to model European windstorms; Maposa et al. (2017) develop a GPD model for extreme flood heights in the lower Limpopo River basin of Mozambique; and Tawn et al. (2018) show how EVA modelling approaches can be used to quantify extreme wave heights in the North Sea, important for the design of offshore structures. Further, a recent initiative funded by the Energy Technologies Institute and delivered by EDF Energy, the Met Office and Mott Macdonald, has delivered a set of technical volumes summarising the state of the art in the characterisation for a variety of natural hazards, supported by a set of case studies (ETI Natural Hazards Project, 2019). These technical volumes and case studies focus on specific hazardous meteorological variables, e.g. temperature, wind speed and flooding, and demonstrate how EVA can be applied in each situation to model the data and quantify the probability of extreme events. In addition, as introduced in Section 5.1, the Nuclear power industry infrastructure is required to be resilient to extreme hot temperatures, equivalent to those expected to be observed on average once every 10,000 years. The Met Office have recently completed a piece of work to identify this extreme temperature at the location of a proposed Nuclear Power station to ensure build safety (peer reviewed paper in preparation). An approach similar to that presented in Figure 64 was used to achieve this, with additional methodological steps to account for climate change and reduce uncertainty (discussed in later parts of this Theme).

An additional benefit of developing a statistical model to represent the meteorological variables of relevance to the energy system, is that it can be used to simulate many thousands of years of synthetic, physically plausible weather data. This can be used to improve the quantification of the frequency and magnitude of extreme events. Synthetic weather data can also be simulated from climate models, however these take a long time to run and require very high-performance super computers. Statistical models, on the other hand, are very quick to run and require minimal computing expense. Statistical weather models are frequently developed and used in this way for weather and climate resilience testing, for example Serinaldi and Kilsby (2012) developed a statistical monthly rainfall model for water resource management and impact studies, and the Intergovernmental Panel on Climate Change (IPCC) use statistical weather models to assess climate change impacts on extreme natural hazards such as droughts[19].

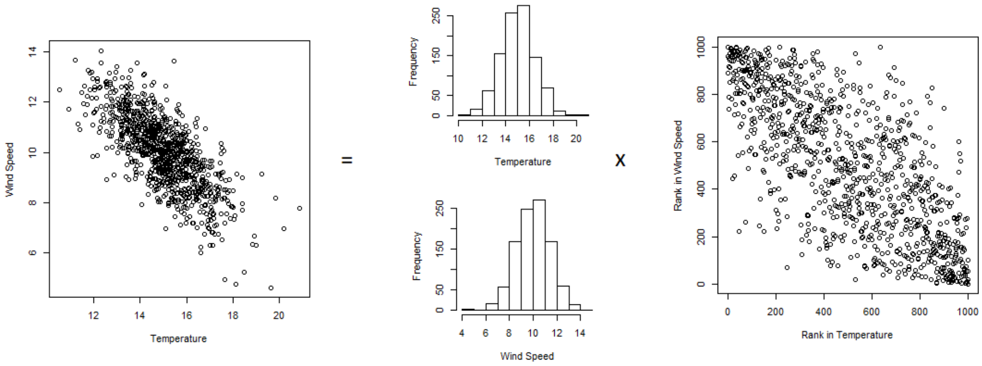


Figure 65: A demonstration of the copula approach for modelling multiple meteorological variables. The joint distribution of two (or more) meteorological variables (left) can be decomposed into (1) the magnitude of each variable separately (middle) and (2) their mutual dependence (right) which can be modelled using a copula.

Rather than just modelling one meteorological variable at a single location, developing a statistical model for the meteorological conditions relevant for the whole UK energy system would require the representation of all three important meteorological variables (temperature, wind speed and solar irradiance) over their full range (not just the extremes), simultaneously and coherently in space and time. As described by Sanderson and Winter (2018), an approach for statistically modelling multiple meteorological variables simultaneously is to use a 'copula'. As demonstrated in Figure 65 (formally proved by Sklar's Theorem, Sklar 1959) the copula approach allows for the joint distribution of two (or more) meteorological variables (left) to be decomposed into two parts: the magnitude of each variable separately (middle) and their mutual dependence (right). The magnitude part of the data is modelled using a statistical distribution, while the dependence part is modelled using a copula. Sanderson and Winter (2018) show how such an approach can be used to model temperature and rainfall simultaneously for the quantification of the probability of extreme warm and dry conditions at a location in the UK.

[19] https://www.ipcc-data.org/guidelines/pages/weather_generators.html

This approach can be easily extended to incorporate all three meteorological variables and multiple locations/regions throughout Europe. In doing so the dependence between meteorological conditions at different locations is modelled, ensuring realistic, physically plausible meteorological conditions are simulated over the spatial domain of interest.

Realistic temporal evolution of the meteorological variables is also very important for the energy system

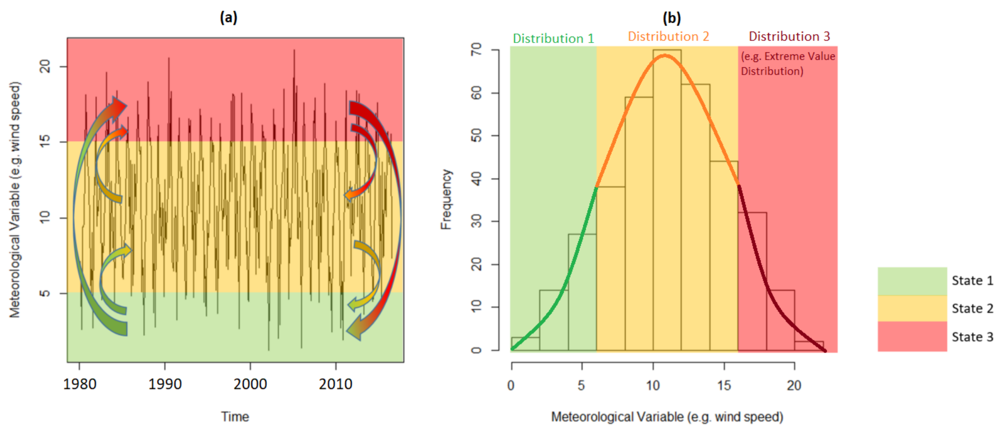


Figure 66: A demonstration of the Hidden Markov Modelling (HMM) approach. (a) a synthetic time series of a meteorological variable (e.g. wind speed) with three HMM states superimposed and transition arrows from one state to another added. (b) the corresponding histogram of the meteorological variable with the three HMM states superimposed and a demonstration of how different statistical distributions are used to model the variable within each state, including an Extreme Value Distribution (e.g. the GPD) for the highest part of the data.

model. In particular it is vital that the temporal resolution is fine enough to explore ramping events (e.g. at least hourly), and that the persistence of extreme high or low meteorological conditions are accurately represented. To achieve this, a Hidden Markov Model (HMM) can be used to represent the magnitude and temporal evolution of each meteorological variable (in each location/region). A HMM represents a time series of data as being in a series of 'states'. For example, as shown in Figure 66 (a), wind speeds could be represented as being in one of three states: state 1 - extremely low wind speed, state 2 - normal wind speed, state 3 - extremely high wind speed. The evolution of the time series from one time step to the next is represented by a transition matrix which characterises the probability of evolving from one state to another. For example, suppose at time step t the model is in state 2 (normal winds), then the transition matrix characterises the probabilities of either remaining in state 2, transitioning to state 1 (low winds) or transitioning to state 3 (high winds) at time step $t + 1$. In the HMM, the data within each 'state' is then modelled using a different statistical distribution, depending on the characteristic of the data in that state, as demonstrated in Figure 66 (b). For example, the data in state 3 can be modelled using an extreme value distribution (EVD), as previously introduced, to allow for the correct representation of the extremes. The HMM has been found to be particularly successful at modelling the temporal persistence of different states, very relevant for accurately representing extreme stress conditions on the energy system (e.g. extreme high and low winds).

Hence, as time evolves, for a given meteorological variable and location/region, the HMM transition matrix determines the state in which the process is located and simulates a value for the meteorological variable from the distribution that characterises that state (e.g. from the Extreme Value distribution for state 3 representing extreme high wind speeds). Further, the relationship between meteorological variables and locations/regions is modelled using a copula, as explained in the previous paragraph. Therefore, in this way the statistical model is able to accurately represent all relevant meteorological variables over their full range, simultaneously and coherently in space and time, and can be used to quickly simulate plausible synthetic weather for quantifying the probability of different extreme stress events on the energy system.

Further, the future effect of climate change on the meteorological variables can be incorporated within the statistical model. This could be achieved in one of two ways. One approach involves fitting the statistical model to future climate projections of the relevant meteorological variables. However, characterising extreme meteorological phenomena using climate models is very challenging given the need for high spatial resolution to accurately model the relevant atmospheric processes (Brown et al., 2014). As a result, climate model projections of extremes of meteorological variables are highly uncertain. The release of the latest Met Office UK climate projections (UKCP18) will soon include 2.2km projections over the UK. This very high spatial resolution will allow for improved representation of fine scale atmospheric processes, and may therefore reduce this uncertainty. However, an alternative approach has been developed by Brown et al. (2014) to improve the representation of extremes in future climates. This approach involves incorporating the relationship between global mean temperature, a variable which is known to be well represented by climate models, and the meteorological variable of interest (e.g. wind speed) within the statistical model. The global mean temperature can then be projected into the future climate and this relationship then used to project the meteorological variable of interest into the future climate. This approach was used in the recent nuclear safety work carried out by the Met Office, as introduced earlier in this Section. Nuclear infrastructure has a life span of approximately 70 years, therefore the infrastructure is required to be resilient to, not the current 1 in 10,000 year hot temperature event, but the 1 in 10,000 year hot temperature event in the future climate. The relationship between global mean temperature and extreme temperatures at the location of interest was used to project the local temperatures into the future and give a more accurate estimate of this very extreme future temperature, used within the nuclear build.

Based on these ideas and the elements of the future energy system that have been highlighted as important, Figure 67 shows a schematic of a potential approach from modelling the whole UK energy system to allow for the exploration and quantification of extreme stress conditions, now and in the future. Initially the UK and Europe are divided into regions based on their variability/co-variability in meteorological conditions (i.e. the results presented in Section 3.2, National and Europe Wide). Different and/or more regions could be explored based on the requirements of the analysis. The current or future scenario of interest is then specified by setting the parameters shown in the green circles. That is, the climate change scenario and year; the demand profile in terms of the uptake in electric vehicles and air

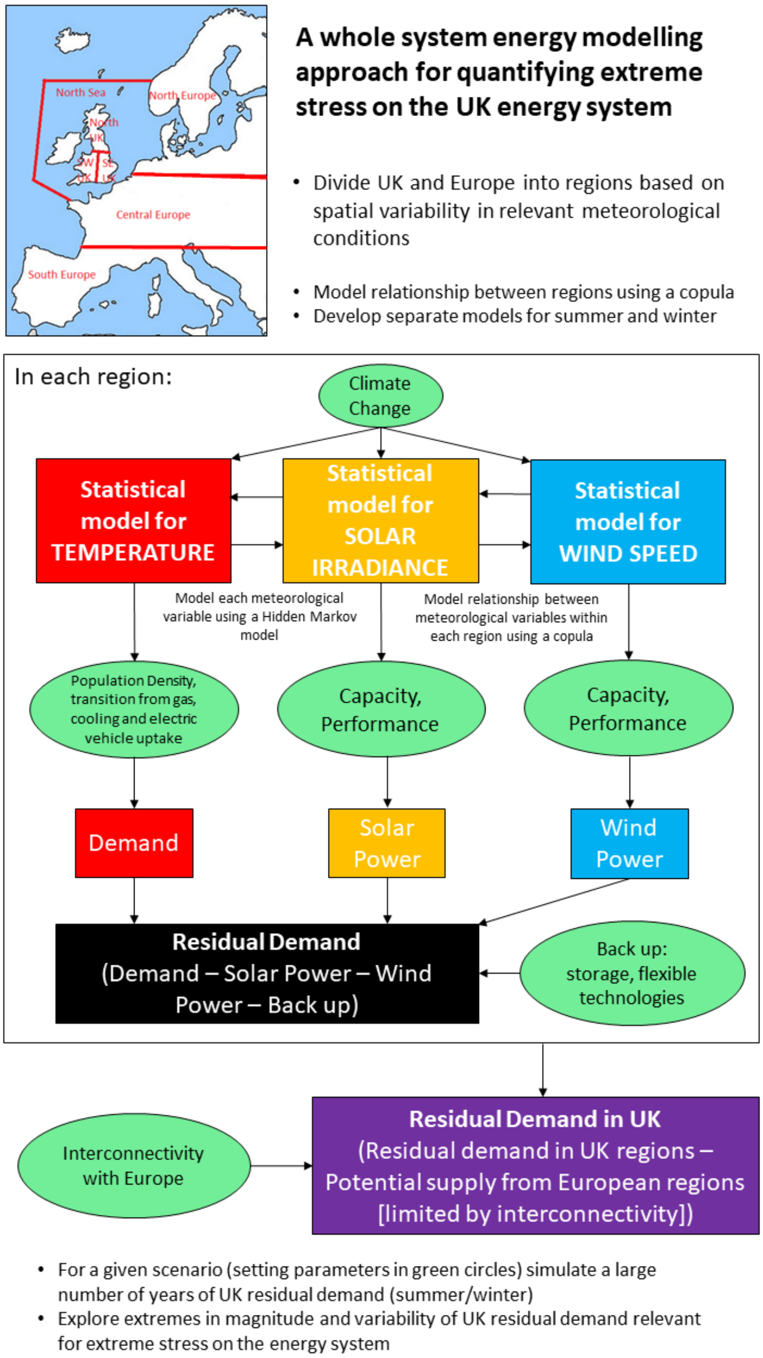


Figure 67: Schematic showing a potential approach from modelling the whole UK energy system to allow for the exploration of extreme stress conditions, incorporating statistical models for meteorological variables, climate change, changes in renewable capacities, transitions in demand, flexible technologies and interconnectivity with Europe.

conditioning, the transition away from gas and changes in population density; the quantity, location and performance of installed renewable capacity; the quantity of back up and flexible technologies; and the interconnectivity with Europe.

Using these scenario specifications, within each of the regions, the energy system is modelled in a similar way to Staffell and Pfenninger (2018) (as in Figure 62). However, rather than using a fixed historical period of meteorological data, the statistical approach described above is used to allow for a greater range of plausible events and the incorporation of climate change. This statistical model is used to simulate a large number of years of plausible, synthetic, spatially and temporally coherent temperature, solar irradiance and wind speed data. These are combined with the specified installed capacity and demand profiles and wind/solar farm power models to estimate demand and power generation at each time step and in each region. These are then combined with a measure of the power supplied by back up and flexible technologies to give a residual demand. The residual demand in the UK at a given time step is then calculated by summing over UK regions and subtracting an estimate of the supply available from the European regions, limited by the specified interconnectivity. This approach will result in a long time series of UK residual demand, characteristic of the specified scenario. Extremes in magnitude and variability of this output can then be explored to quantify the frequency, duration and severity of extreme stress on the energy system associated with that scenario. Multiple different scenarios could be investigated to identify the optimal energy system in terms of minimising the impact of weather and climate. In addition, the meteorological conditions associated with extreme stress events could be related back to the Decider weather pattern regimes, allowing for an estimate of the predictability of such conditions.

Summary

- Detailed modelling of wind and PV generation with high resolution in space and time is becoming increasingly important for understanding how future highly renewable energy systems vary with meteorological conditions;
- The large number of variables playing a role in the energy system resilience (e.g. interconnectivity with Europe, the volume of installed renewables and uptake in electric vehicles) means these detailed models must represent the whole energy system coherently;
- Staffell and Pfenninger (2018) present such a framework, highlighting the importance of incorporating flexible technologies and interconnectivity to give a more realistic (and optimistic) picture of the future energy system;
- All previous similar studies use a limited historical data set of meteorological conditions. Rather, Extreme Value Analysis (EVA) techniques should be used to statistically model, and extrapolate beyond, the observed meteorological data to give a more complete representation of potential extreme conditions;
- A statistical model for meteorological variables, relevant for the whole energy system model, must be spatially and temporally coherent throughout Europe. To achieve this the temporal evolution and magnitude of a meteorological variable at a given location/region can be modelled using a Hidden Markov Model (HMM) with an extreme value distribution for the extremes, and the dependence between meteorological variables and spatial locations/regions modelled using a copula;
- The effect of climate change can be incorporated within the statistical model, either by fitting

the model to future meteorological conditions rather historical, or to reduce uncertainty, by modelling the relationship between the relevant meteorological variables and global mean temperature, known to be well represented by climate models;

- Such a statistical model can be used to quickly generate many thousands of years of spatially and temporally plausible synthetic weather for a given climate change scenario and year, with minimal computational cost;

- This synthetic weather can then be used within a whole energy system model, similar to Staffell and Pfenninger (2018), to estimate UK residual demand given a specified future scenario for: demand profile (e.g. uptake in electric vehicles and air conditioning, the transition away from gas, and changes in population density); the capacity and performance of solar and wind power infrastructure; the quantity of back up and flexible technologies; and the interconnectivity with Europe. Extremes in magnitude and variability of this output can then be explored to quantify the frequency, duration and severity of extreme stress on the energy system associated with that scenario. Multiple difference scenarios could be investigated to identify the optimal energy system in terms of minimising the impact of weather and climate;

- The meteorological conditions associated with extreme stress events could be related back to the Decider weather pattern regimes, allowing for an estimate of the predictability of such conditions.

5.4 Methods for reducing uncertainty when quantifying extremes

When representing weather, climate and power generation in the energy system using mathematical models, it is very important to quantify the many sources of potential uncertainty, and if possible take measures to reduce these uncertainties. In the mathematical modelling disciplines uncertainties are often categorised as either *Epistemic* or *Aleatoric*. Epistemic uncertainty, also known as systematic uncertainty, is caused by things that could be known in principle but are unknown in practise. For example because a measurement is not accurate, or because the model neglects a certain effect. These uncertainties can therefore be reduced if more is understood about the process being modelled. Aleatoric uncertainty, also known as statistical uncertainty, is due to the randomness inherent to the natural process, for example the atmosphere. Aleatoric uncertainty is therefore non-reducible and must instead be quantified using statistical techniques.

Approaches for reducing uncertainty therefore focus on gaining a better understanding of the modelled system or process. A large source of Epistemic uncertainty originates from the limited sample of data upon which the model is based. This is particularly true for rare extreme events. To help to over come this, Thompson et al. (2017) developed the 'UNSEEN' method - UNprecidented Simulated Extremes using ENsembles - which involved using the Met Office supercomputer and the decadal numerical climate prediction system to simulate a very large ensemble of possible weather scenarios, creating a considerable body of virtual observations ($\sim$ 1,000 years). The risk of a previously unobserved extreme event is then quantified as the frequency with which it occurs within the large data set of virtual observations. In practise, this approach has been used by The National Flood Resilience Review (HM Government, 2016) to assess the risk of unprecedented monthly winter rainfall. The UNSEEN approach, however, relies on the assumption that the climate model is able to realistically represent the distribution of extreme events. In addition, since the occurrence of extreme events are based on counts within the simulated data sets (rather than statistical extreme value models), the approach is limited to assessing return levels up to the length of the data set (1,000 years). Indeed, since simulating synthetic weather from a NWP or climate model is very computationally expensive, running further years of the model would require a great deal of time and computational expense (unlike a statistical model), hence the UNSEEN approach is limited to just these 1,000 years.

The nuclear safety project, previously introduced in earlier sections of this theme, acknowledged these limitations of the UNSEEN approach, and, since the project required the estimation of the 1 in 10,000 year hot temperature event at a given location, proposed an alternative approach for reducing uncertainty. This approach involved fitting a statistical Extreme Value (EV) model to a combination of data sets: observations and hindcasts (see Section 7 for a description of a hindcast). Incorporating the climate model hindcasts in this way greatly reduced the uncertainty in the estimated extreme event (compared to using the observations only), allowed for the quantification of the very extreme 1 in 10,000 year hot temperature event (using the EV model), and accounted for the potential bias in the climate model generated hindcasts by allowing for differences in the EV model parameters. A paper documenting this approach is currently in preparation.

As well as using statistical models to reduce uncertainty by combining data sources, as in the nuclear project, a specific branch of statistical theory, known as *Bayesian statistics*[20], allows for further reductions in uncertainty through the specification of prior beliefs and the borrowing of information across a hierarchical statistical model structure. That is, in a Bayesian statistical model, rather then estimating the model parameters using data only, the statistician is able to incorporate any prior beliefs they may have about the parameters, for example any known physical upper bounds (O'Hagan, 2004). This helps to constrain the statistical model and hence reduces the uncertainty in model estimates. Further, Bayesian statistical models allow for hierarchical structures, in which different groups/regions within the data can be modelled separately, but as coming from statistical distributions with a common parameter. This allows for the borrowing of information across groups/regions, reducing the uncertainty compared to modelling each group/region in isolation. This benefit is discussed by Sharkey and Winter (2018), who develop a Bayesian hierarchical model for extreme precipitation in Great Britain.

Summary

[20] https://www.analyticsvidhya.com/blog/2016/06/bayesian-statistics-beginners-simple-english/

- Mathematical model uncertainty can be characterised as either Epistemic, i.e. caused by things that could be known in principle but are unknown in practise, and hence can be reduced by further understanding of the process being modelled; or Aleatoric, i.e. caused by the natural randomness of the physical process being modelled, and hence cannot be reduced;
- A large source of Epistemic uncertainty originates from the limited sample of data upon which the model is based, particularly true for rare extreme events. Approaches for reducing uncertainty when quantifying extreme therefore often focus on increasing the sample of extreme events;
- The UNSEEN approach used the Met Office supercomputer and decadal climate prediction system to simulate a very large ensemble of possible weather scenarios, and quantified the risk of previously unobserved extreme events as the frequency with which they occur within the large data set of virtual observations. This approach, however, has limitations in terms of climate model representation of extreme events and the inability to quantify extreme events beyond the length of the simulated data (1,000 years);
- To overcome this, the nuclear safety project recently completed by the Met Office to estimate the 1 in 10,000 year hot temperature event at a specific location in the UK, developed an alternative approach for reducing uncertainty in which multiple data sources were combined within an Extreme Value statistical model;
- Bayesian statistical modelling approaches provide further methods for reducing statistical model uncertainty through the specification of prior beliefs and the borrowing of information across a hierarchical statistical model structure.

5.5 Theme 3 Conclusion

What is missing from the National Infrastructure Assessment?

- The Assessment is based on an average year of weather, removing extremes which must be explored for energy system resilience. Rather, a statistical Extreme Value model based on a long period of data must be used to accurately represent all possible extreme meteorological conditions;
- The Assessment considers a single extreme stress condition, based on increasing demand and capping on-shore wind capacity. Without a comprehensive representation of meteorological conditions it is impossible to quantify how extreme this tested extreme event is, i.e. how frequently it might be expected to occur, and hence whether an alternative more/less extreme event is more relevant;
- The extreme stress event in the Assessment is based on a single day/snapshot in time. The temporal, hour-to-hour variability if the energy system is also important, therefore the modelling

approach developed for testing the energy system resilience to adverse weather must have a fine temporal resolution and evolve realistically in time;

- Many different future scenarios and extreme stress conditions should be explored in relation to adverse weather conditions;
- The results of the literature highlight how meteorological condtions in Europe might effect supply from interconnectivity, hence the modelling approach developed for testing the energy system resilience to adverse weather should also include European weather conditions;
- The Assessment does not incorporate climate change or the subsequent potential uptake in air conditioning.

Does this literature provide any answers?

- Studies identify how the magnitude and duration of all possible forms of stress event must be quantified based on a whole system energy model. That is, a model in which supply and demand are modelled together, estimated from meteorological conditions. This must be achieved while accounting for: the spatial and temporal dependence in meteorological conditions throughout Europe, based on a long historical period of meteorological data; the effect of climate change on renewable supply and energy demand; future changes in installed renewable capacity, distribution and performance; the future transition away from gas heating and potential uptake in air conditioning; planned interconnectivity with Europe; future planned storage and flexible technologies; and a quantification of the skill and lead time with which adverse meteorological conditions can be forecast;
- Statistical Extreme Value Analysis (EVA) should be used to model the most extreme part of the distributions of relevant meteorological variables. This will allow for the exploration of statistically plausible extreme events beyond the magnitude of those observed in the limited historical period, and a formal quantification of the return period of extreme events;
- A statistical model for meteorological variables, relevant for the whole energy system model, must be spatially and temporally coherent throughout Europe. To achieve this the temporal evolution and magnitude of a meteorological variable at a given location/region can be modelled using a Hidden Markov Model (HMM) with an extreme value distribution for the extremes, and the dependence between meteorological variables and spatial locations/regions modelled using a copula;
- Such a statistical model can be used to quickly generate many thousands of years of spatially and temporally coherent and physically plausible synthetic weather for a given climate change scenario and year, with minimal computational cost. This synthetic weather can then be used within a whole energy system model, similar to Staffell and Pfenninger (2018), to estimate UK residual demand given a specified future scenario. Extremes in magnitude and variability of this output can then be explored to quantify the frequency, duration and severity of extreme stress on

the energy system associated with that scenario. Multiple different scenarios could be investigated to identify the optimal energy system in terms of minimising the impact of weather and climate;

- The extremity of a stress event also depends on the skill and lead time with which such an event is forecast. Greater forecast skill at a longer lead time will reduce the vulnerability of the energy system to the hazard, hence reducing the extremity of its impact;
- Approaches for reducing uncertainty when quantifying extremes often focus on increasing the sample of extreme events. The Nuclear safety project recently completed by the Met Office developed an approach for reducing uncertainty, in which multiple data sources were combined within an Extreme Value statistical model;
- Bayesian statistical model approaches provide further approaches for reducing statistical model uncertainty through the specification of prior beliefs and the borrowing of information across a hierarchical statistical model structure.

What are the remaining gaps in knowledge, not addressed in the literature?

- No studies in the literature incorporate all of the energy system elements described above. Specifically, no studies include a statistical (extreme value) model for the relevant meteorological conditions, climate change, the potential uptake in summer time air conditioning, flexible technologies or interconnectivity with Europe;
- Therefore, thus far, there is no understanding of how a realistic future highly renewable, flexible energy system will perform in adverse weather conditions;
- The whole energy system models in the literature and proposed here do not consider energy transmission and distribution. A great deal more research is required to understand and incorporated these elements of the energy system.

Which areas addressed within the literature need further analysis to be relevant for the National Infrastructure Commission?

- A whole system energy modelling approach should be developed which incorporates all of the important elements described above, for example the approach presented in Figure 67.
- This model should be designed to specifically address the questions and aims of the Commission, and test relevant future scenarios in terms of installed capacity, interconnectivity and flexibility.

What does the literature suggest needs to be incorporated within the whole system energy model?

- Interconnectivity with Europe, and hence an estimate of weather dependent energy demand and supply in Europe;
- The potential supply of energy from flexible technologies and back up storage;

- Changes in renewable capacities and performance;
- Changes in future demand, taking into account population density, transition for gas heating, and the uptake in air conditioning and electric vehicles;
- A Bayesian statistical model for meteorological conditions, using copulas, Hidden Markov Models and Extreme Value Analysis techniques, allowing for better representation of very extreme conditions and hence reducing uncertainty in quantification of extreme events;
- A quantification of the predictability of the extreme stress conditions by matching those identified as being a challenge for the energy system to the Decider weather pattern regimes.

What methodologies and data sets are available to perform this further analysis and fill these gaps?

- Appropriate statistical modelling methodologies could include, Bayesian statistical approaches, Extreme Value Analysis, Hidden Markov Models and Copula dependence models;
- The effect of climate change on the relevant meteorological variables could be incorporated within the statistical model using the approach developed by Brown et al. (2014);
- Renewable power generations such as those used by Renewables.ninja[21], are available for converting meteorological conditions to power;
- A non-exhaustive table of potentially relevant data sets is presented in Figure 61

[21] https://www.renewables.ninja/

6 Theme 4: Sensitivity of the energy system to climate variability and change

As previously introduced in Section 5.2, climate variability refers to natural (i.e. non-man made) fluctuations in the climate on time scales from months to decades, resulting from variation in large scale atmospheric circulation patterns such as the North Atlantic Oscillation (NAO) and the El Niño Southern Oscillation (ENSO). Conversely, climate change refers to alterations in the earths atmosphere that occur over much longer periods, such as multiple decades to millennia. Climate change can be caused by natural processes, such as volcanic activity or shifts in the Earths orbit, however recent changes in climate (i.e. since the mid-20$^{\mathrm{th}}$ century) have been predominantly attributed to human activity (IPCC, 2013b), resulting from increased concentrations of heat-trapping greenhouse gases in the atmosphere.

The energy system is sensitive to both climate variability and climate change. As decribed by Bonjean Stanton et al. (2016), understanding the impacts of climate variability and change on the energy system is increasingly important not only for the electricity companies providing such critical services, but also for policy-makers in charge of ensuring the security of a country's electricity supply.

6.1 Previous work incorporating climate variability and/or change in a whole system energy model

Climate Variability

As described in Section 5.2, research has shown that a long period ($>$20 years) of meteorological data is required to represent the natural variability of the climate within energy system models. Indeed, Bett et al. (2017) show that, while the last 20 years of wind speeds in eastern England are within the range expected from natural climate variability, they do not span the full range of variability of the entire 142-year data set used within the study. Since data sets with long historical records often have low spatial resolution, studies aiming to incorporate climate variability within energy system models commonly use higher spatially resolved reanalysis data sets such as MERRA and ERA-Interim (see Table in Figure 61) which typically cover the past 35-40 years (back to 1979).

Examples of some such studies include Bloomfield et al. (2016), who use 36 years (1980-2015) of MERRA reanalysis temperature and wind speed data within a parsimonious representation of a power system, characterising demand and wind power, to study the impact of year-to-year climate variability on the UK power system with increasing installed wind capacity. Bloomfield et al. (2018) follow on from this, using the same data and power system model to explore the changing sensitivity of the UK power system to different meteorological drivers as increased wind capacity is added to the system (as discussed in detail in Section 3). Thornton et al. (2016) explore the co-variability of temperature, electricity demand

and gas demand in the UK from 1975 to 2013, using historical temperature and demand observations. Pfenninger and Staffell (2016) use 30 years of reanalysis and satellite data within a solar PV power model to investigate long-term patterns in European PV generation, while Pfenninger (2017) explore 25 years of simulated wind and PV generation from the Calliope energy modelling framework, presented in Pfenninger and Keirstead (2015), and Bett and Thornton (2016) investigate the co-variability of wind and solar power in the UK using ERA-Interim reanalysis data and power system models.

None of the aforementioned studies, however, study a whole system energy model in which demand, wind and solar PV power generation are considered simultaneously. The only example of such a study is Staffell and Pfenninger (2018), introduced in detail in Section 5.3. Staffell and Pfenninger (2018) incorporate climate variability within a whole system energy model by utilising 25 years of historical meteorological reanalysis and satellite data within models for renewable energy supply[22], and demand[23], and explore the increasing impact of weather on electricity supply and demand in future systems with increased renewable capacity, electric vehicles and electrified heating.

Climate Change

Bonjean Stanton et al. (2016) present a systematic literature review of the impacts of climate change on electricity systems. Those papers reviewed include Burnett et al. (2014), how explore the impact of climate change on UK solar energy resource, Cradden et al. (2012) and Harrison et al. (2008), who focus on understanding how climate change will impact wind power in the UK, and McColl et al. (2012) how assess the potential impact of climate change on the UKs electricity transmission and distribution network.

Further, researchers from the University College London (UCL) Energy Institute present a similar literature review of the trend and gaps in knowledge associated with climate change impacts on the energy system (Cronin et al., 2018). They highlight how most studies on this topic are focused on wind power in Europe. Specifically, Pryor and Barthelmie (2010), Tobin et al. (2015), Davy et al. (2017) and Carvalho et al. (2017) all assess the potential impacts of climate change on European wind energy resource. Cronin et al. (2018) highlight further studies focused on the effect of climate change on solar energy generation in Europe: Patt et al. (2013), Crook et al. (2011) and Gaetani et al. (2014), and the transmission/distribution network: Cradden and Harrison (2013). Hence, similar to Bonjean Stanton et al. (2016), none of the identified studies consider the effect of climate change on the energy system as a whole.

A very limited number of studies were identified investigating the effect of climate change on energy demand, only two of which include the UK: Wood et al. (2015) and the 2012 UK Climate Change Risk

[22] https://www.renewables.ninja
[23] https://sites.google.com/site/2050desstinee/home

Assessment (Capon, R. and Oakley, G., 2012). As well as published articles, National Grid describe the potential challenges that will arise from increased demand for cooling in a hotter UK climate (National Grid, 2017).

The results of the studies referenced in this section will be presented as part of Section 6.3.

Summary

- Studies that aim to represent and explore the effect of climate variability on the energy system demonstrate the importance of using a long period of historical meteorological data (>20 years);
- Many such studies use 25-35 years of spatially and temporally complete reanalysis data, predominantly to explore part of the energy system, with one example doing so in a whole energy system model setting;
- A number of studies explore the effect of climate change on either wind power generation, solar power generation or the energy transmission/distribution network;
- No studies have been identified in which climate change is incorporated within a whole system energy model.

6.2 Which meteorological variables effect each part of the energy system (demand, supply, transmission, distribution)?

Demand

Referring back to Section 3.1, temperature is identified as being the most important meteorological variable for determining demand (electricity and gas) in the UK. In the current climate, this relationship is strongest in winter and weakest in summer (see Figure 1). For example Thornton et al. (2016) identify that during the period 1975-2013, a 1^{o}C decrease in daily temperature in winter resulted in a 1% increase in daily electricity demand, and a 3%-4% increase in gas demand. Therefore, the electrification of gas heating could greatly increase the sensitivity of electricity demand to temperature. Climate change is likely to cause an increase in UK summer temperatures, potentially increasing the uptake in air conditioning. This would create a new inverse relationship where by increasing temperatures cause increased electricity demand during summer months, as currently seen in Southern European countries. On the other hand, this warming my help to reduce demand in winter months.

Supply

In the future, highly renewable energy system, energy supply would be sourced predominantly from wind and solar power. As a result, the meteorological variables that will have the most effect on supply are wind speed (for wind power) and solar irradiance for (solar power). The performance of solar PV panels is also a function of wind speed and temperature, hence these meteorological variables will also effect solar power supply.

As described in previous Themes, an important parameter of the whole energy system is the *residual demand*, or the demand net of renewable supply that is required to be met by other sources (e.g. fossil fuels). This output is a combination of energy demand, wind and solar power supply, and is therefore effected by temperature, wind speed and solar irradiance. In addition, in a complete model of the future energy system this residual demand will also depend on storage and flexible technologies, as well as how effectively the power is transmitted from where it is generated and distributed to where it is needed.

Transmission and Distribution

All identified studies investigating the effect of meteorological conditions on energy transmission and distribution are focused on extreme weather events and the damage they caused to energy system infrastructure. Extreme weather conditions most often highlighted within the literature include windstorms, flooding, and thunderstorms.

Küfeoglu et al. (2014) summarise the effect of a number of the recent extreme weather events on the energy system. For example these included, the excessive rain experienced along the northern Alps from May to early June 2013, resulting in severe flooding in Germany, Czech Republic, Austria, Switzerland and Hungary. During this period energy substations were flooded causing long lasting black outs. In addition, Küfeoglu et al. (2014) describe the effect of multiple extreme windstorms experienced in the UK in the winter of 2013/14, whose strong winds and extreme rainfall caused extensive power outages, affecting around 750,000 energy customers. Extreme windstorms cause trees to fall on the power lines, as experienced in Finland in October 2013 (Küfeoglu et al., 2014), and in very cold conditions can freeze the power lines, as experienced during an extreme windstorm in Northern Ireland in March 2013 (Küfeoglu et al., 2014). Küfeoglu et al. (2014) go on to discuss how the future planning of energy transmission and distribution infrastructure must consider natural hazard maps to avoid areas with hazard risk. In addition, they describe how existing infrastructure should be strengthened to better withstand very strong winds.

Similarly, Panteli and Mancarella (2015) describe how various forms of extreme weather effect energy transmission and distribution: *Heat waves* can limit the transfer capability of transmission lines, and increase the energy losses and the line sagging; *High winds* during storms can lead to faults and damage to overhead transmission and distribution lines, most often by debris being blown against the lines; *Cold spells and heavy snow and ice* can cause failures in overhead lines and towers; *Lightning* *strikes* on or near overhead conductors can cause short-circuit faults, which can trigger the disconnection of the lines, and the voltage surge caused by the strike transferred along the line can cause damage to equipment; and *Heavy rain and floods* pose a danger to substation equipment. Specifically, Ward (2013) identify that high wind speeds have the most significant effect of the grid systems in Europe.

Summary

- Temperature is the most important meteorological variable for determining energy demand (electricity and gas). In the current climate this relationship is strongest in winter, while in a warmer future climate, this relationship may become stronger in summer due to the uptake in air conditioning;
- The meteorological variables that have the most effect on power supply are wind speed (for wind power) and solar irradiance, wind speed and temperature (for solar power);
- All identified studies investigating the effect of meteorological conditions on energy transmission and distribution are focused on extreme weather events and the damage they caused to energy system infrastructure. These extreme weather events include high winds during windstorms, cold spells causing heavy snow and ice, heavy rain causing flooding, lightening strikes, and heat waves.

6.3 How do climate variability and climate change effect relevant meteorological variables, and hence which (variability or change) has most impact on each part of the energy system?

Climate variability

Thornton et al. (2016) explore the historical relationship between temperature, electricity demand and gas demand in the UK. In doing so they present the variability in each over a number of historical years. Thornton et al. (2016) use a Fourier analysis approach to isolate the climate related variability in demand and remove the low frequency variability resulting from socio-economic changes (e.g. GDP, increase in embedded generation, and the UK's move away from heavy industry). This detrended data is shown in Figure 68 (a) and (b). Similarly, the long term trend in Central England Temperature (CET) observations is removed using the same approach to isolate climate variability and remove the effect of climate change. This detrended temperature data is shown in Figure 68 (c).

As described by Thornton et al. (2016), the time series shown in Figure 68 effectively retained the high frequency variability and the climatological annual cycle, while removing long term variations in the annual mean. For example the demand spike in winter 1986-1987 and the anomalously high demand throughout winter 1978-1979 are still present in the detrended electricity demand time series. As noted by Thornton et al. (2016), gas has a larger annual cycle compared to electricity, explained by the greater

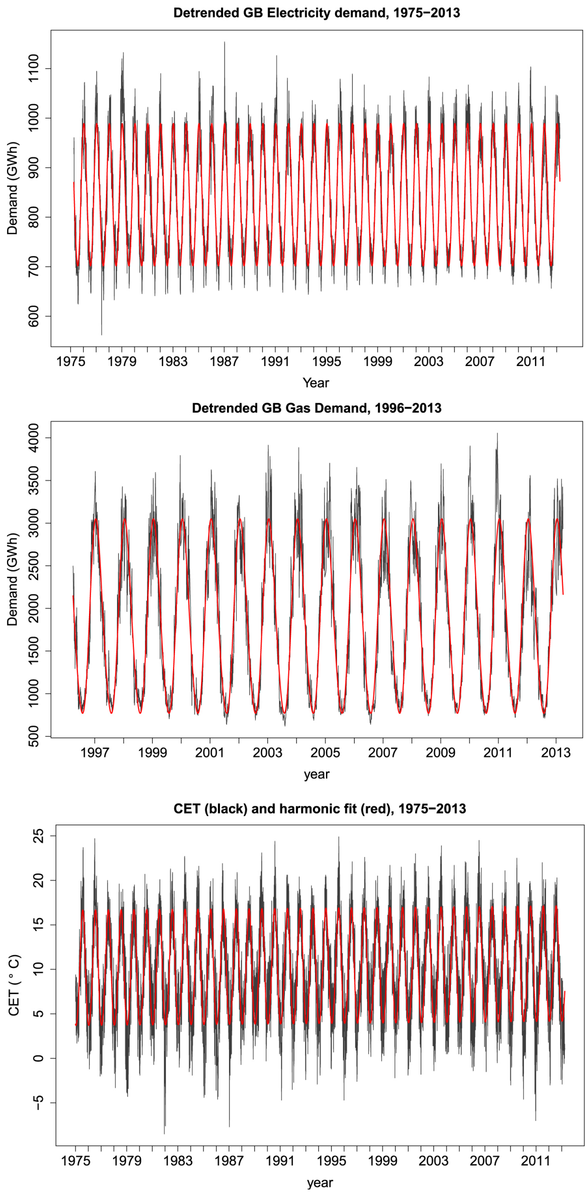


Figure 68: Taken from Thornton et al. (2016): (a) Detrended GB electricity demand time series (GWh, black) and climatological annual cycle (red), April 1975-March 2013, (b) detrended GB gas demand time series (GWh, black) and climatological annual cycle (red), January 1996-March 2013, (c) Central England Temperature (CET) time series (°C, black) with harmonic fit (red), for the period January 1975-March 2013 (the period for which demand observations are available).

sensitivity of gas consumption (for space heating) to changes in temperature. This also results in a larger degree of variability in gas demand during winter. The annual cycle of gas demand remains relatively constant throughout the period, while the annual cycle of electricity demand reduces by approximately a third over the 38 year period. Thornton et al. (2016), however, hypothesise that this change is driven by non-meteorological changes, since the same reduction in the seasonal cycle of temperature is not seen (Figure 68 (c)). Finally, Thornton et al. (2016) note that the variability in temperature associated with both the annual cycle and daily fluctuations is much greater than the lower frequency climate variability.

Staffell and Pfenninger (2018) also present the inter-annual (year-to-year) variability of temperature by plotting the average temperature across each day of the year and including the variability across 25

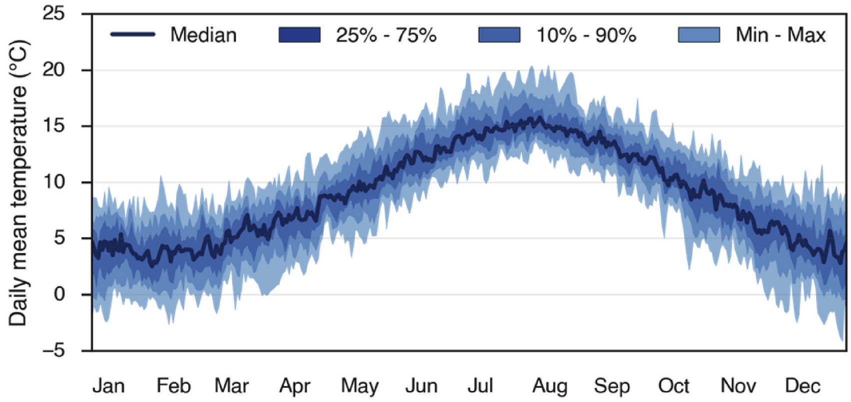


Figure 69: Taken from Staffell and Pfenninger (2018): Inter-annual variability of daily average British mainland temperature during 19912015.

weather years as shaded regions. In doing so, Staffell and Pfenninger (2018) show that the inter-annual variability in temperature (represented by the width of the shaded region) is lower in summer compared to winter, with variability highest in November and December.

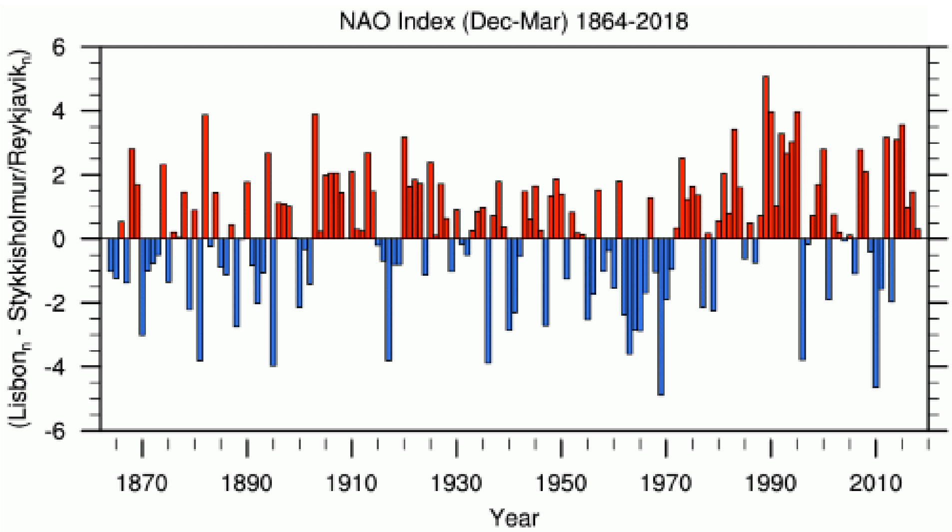


Figure 70: Taken from Climate Data Guide (2019): Winter (December - March) index of the NAO based on the difference of normalised sea level pressure (SLP) between Lisbon, Portugal and Reykjavik, Iceland since 1864.

As introduced in Section 5.2, Bett et al. (2017) explore the variability in wind speed across Europe over a long 142 year historical period (1871-2012). Referring back to Figure 60, Bett et al. (2017) show how the annual and 5-yearly mean wind speeds in England vary over this period. Specifically Bett et al. (2017) note how there is a clear increasing trend from around 1970 to a peak in the mid-1990s, followed by a return to near-average values after 2000. Figure 70 presents the index of the North Atlantic Oscillation (NAO) mode of climate variability over the same 140 year period studied by Bett et al. (2017). A similar period of anomalously high NAO is observed from the late-1980s to 2000, highlighting the close link between UK meteorological conditions and the NAO. In addition Figure 9, shows how this large degree of inter-annual variability in wind speed is seen consistently throughout the UK (large standard deviation of daily wind speeds during the period), particularly in Scotland and the North Sea.

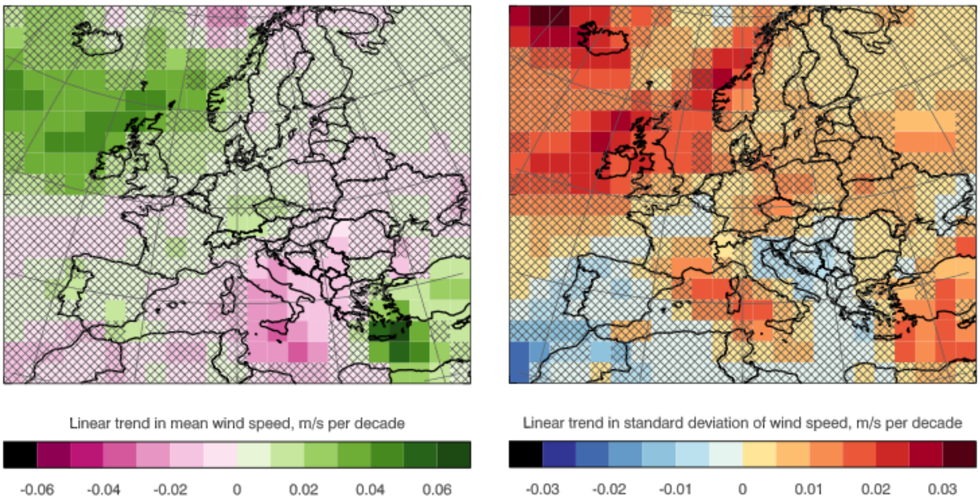


Figure 71: Taken from Bett et al. (2017): Map of the linear trend in the time series of ensemble-annual-mean wind speeds in each grid cell (left), and the ensemble-mean of the annual standard deviation of daily wind speeds (right), over 18712012. Cross hatched areas indicate where the trend is not significant at the 0.1% level.

Bett et al. (2017) note how in Figure 60, there is no clear long-term trend in wind speed throughout the 142 year period in east England. Bett et al. (2017) further demonstrate this lack of long term trend throughout Europe by performing a linear regression on the time series of 5-yr means and standard deviations of the wind speeds in each grid cell. As described by Bett et al. (2017), the existence of any trend (i.e. whether the gradient of the linear fit was significantly different from zero) was assessed using a statistical significance test at the 0.1% level, as presented in figure 71. Bett et al. (2017) describe how, while most areas over Europe show no significant trend, the area of the Atlantic surrounding the north and west coasts of Ireland and Scotland shows a significant positive trend in the magnitude and variability of wind speeds during the period (with the mean wind speed increasing at a rate of approximately 0.03 m/s per decade). However, while this trend is statistically significant, it is extremely small (0.5 m/s over the 142 years). However, Bett et al. (2017) go on to explain how the uncertainties in their data make it extremely difficult to separate decadal climate variability, systematic errors, and genuine long-term trend, hence these significant trends may not be associated with long-term changes, e.g. climate change. These results indicate that historical climate change has not had a significant effect on wind speeds in most of Europe, and rather climate variability (e.g. the NAO) is the dominant driver of wind speed (and hence wind power) variability.

Bett and Thornton (2016) explore the variability and co-variability of wind speed, surface clearness and solar irradiance in the UK during the period 1979-2013, using the ERA-Interim reanalysis data set. As shown in Figure 72 (a), Bett and Thornton (2016) present the annual cycle of variability in these three meteorological variables by plotting the monthly standard deviations of daily meteorological data over the period, scaled by their all-time average. Figure 72 demonstrates how, over the 34 year period, wind speed and surface clearness exhibit greater variability in winter, while irradiance varies most in summer.

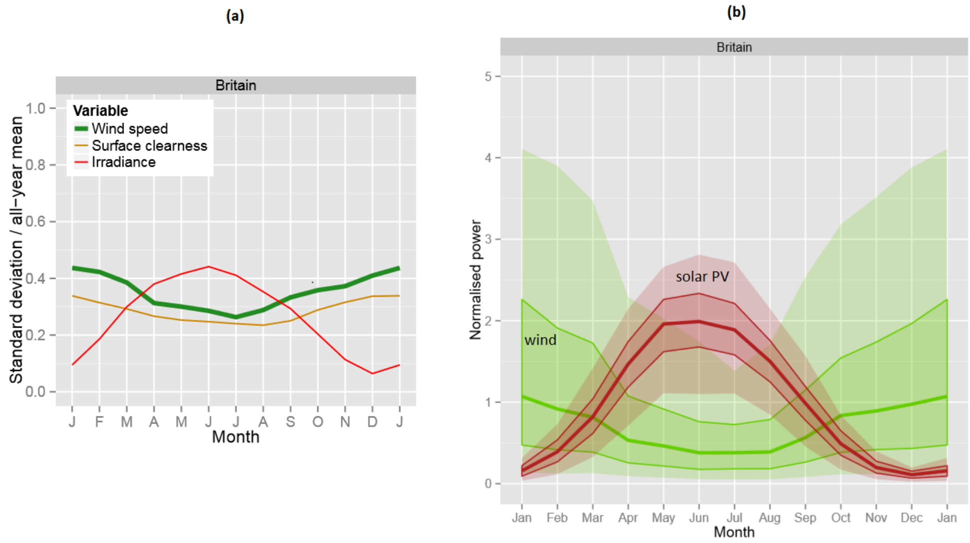


Figure 72: Taken from Bett and Thornton (2016): (a) Annual cycle of monthly variability (standard deviation of daily data) compared to the all-year mean value, for the variables indicated, (b) The distribution of daily-mean wind (green) and solar PV (red) power output each month, both scaled by their long-term all year average. The lines and shading indicate the medians, 25$^{\mathrm{th}}$ and 75$^{\mathrm{th}}$ percentiles, and 5$^{\mathrm{th}}$ and 95$^{\mathrm{th}}$ percentiles of the daily data.

In addition, wind speed and surface clearness variability remains consistently high throughout the year, while the variability in solar irradiance is much lower in winter compared to summer. This is further reflected in Figure 72 (b), which shows the distribution of daily mean wind and solar PV power output, based on applying simple wind and solar power models to meteorological conditions throughout the study period. As noted by Bett and Thornton (2016), Figure 72 (b) characterises many of the features of Figure 72 (a), such as the strong variability of the wind speeds across all seasons, and the larger seasonal variation in solar irradiance. In addition, the wind power distribution (green) is very wide, and skewed with a longer tail towards higher values, reflecting the cubic relationship between wind speed and wind power (Bett and Thornton, 2016). Bett and Thornton (2016) go on to describe how these features have important implications for energy balancing: specifically how during the summer, solar power is at its strongest and most variable, while wind power retains a large degree of variability. Therefore, increasing the relative capacity of solar PV to compensate for low wind in winter would greatly increase the total variability in summer. These results highlight the profound effect that climate variability has on meteorological conditions relevant for energy supply.

In a similar way, Pfenninger (2017) use solar PV and wind power models, in combination with reanalysis and satellite data to explore the inter-annual variability in solar PV and off-shore wind power generation in the UK during the period 1990-2014, presented in Figure 73 (a) and (b) respectively. These figures show the mean daily capacity factor for each day of the year across the 25 years of power simulations for the UK. Pfenninger (2017) highlight how, while there are seasonal trends for both wind and PV generation, there is also considerable inter-annual variability. For example, Figure 73 (a) shows how, within the 25 year period, there have been sunny days in winter with almost as much PV generation across the UK as observed cloudy days in summer. In addition. similar to Bett and Thornton (2016), Figure 73(b)

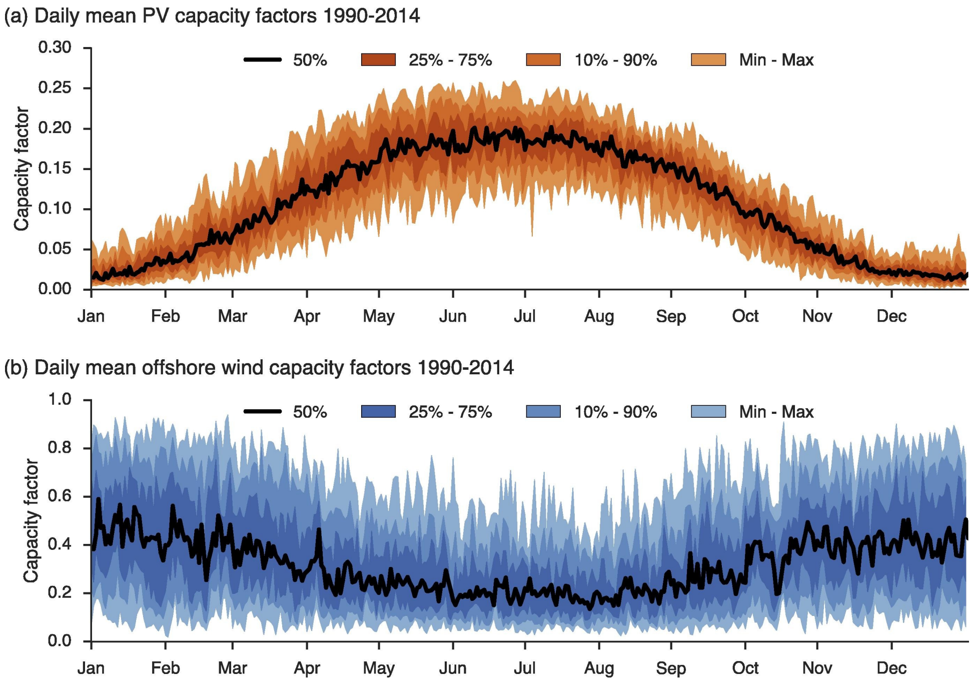


Figure 73: Taken from Pfenninger (2017): Inter-annual variability of daily capacity factors from 1990 to 2014. (a) PV, and (b) Offshore wind. The black line shows median daily capacity factors for each day of year from the 25 years of hourly data used in this study, while the shaded areas indicate their possible range over those 25 years.

shows how wind capacity factor exhibits a great deal of inter-annual variability, with the UK average wind capacity factor ranging from close to zero to almost one on the same calendar day throughout October-April across the 25 years. Pfenninger (2017) conclude that, despite this inter-annual variability in the renewable resource, power systems with high shares of variable renewables will likely become a reality, hence energy modellers must propose solutions for their stable operation.

This large degree of inter-annual climate variability in wind speed and solar irradiance has a profound impact on the variability of the energy system as a whole, particularly with increasing installed renewable capacities and the potential electrification of space heating. As a result, a number of studies explore the variability in residual demand (demand net of renewable generation) to fully understand the impact of climate variability on the energy system. For example, referring back to Figure 7 (b), Pfenninger and Staffell (2016) present the variability in demand net of PV power supply for different levels of installed PV capacity, based on demand in 2014 and 30 years (1985-2014) of hourly PV capacity factors estimated from meteorological data. Figure 7 (b) shows how the within year and inter-annual variability in solar meteorological conditions results in large variations in residual demand for a given installed PV capacity, with this variability increasing with increasing installed PV.

In a similar way, Bloomfield et al. (2016) quantify the increasing sensitivity of the power system to climate variability as a result of increasing wind power capacity in the energy system. Specifically, Figure 74 explores the effect of climate variability on baseload energy requirement. Bloomfield et al. (2016) specify a baseload plant as being a plant that is economically efficient when operating in excess of 91%

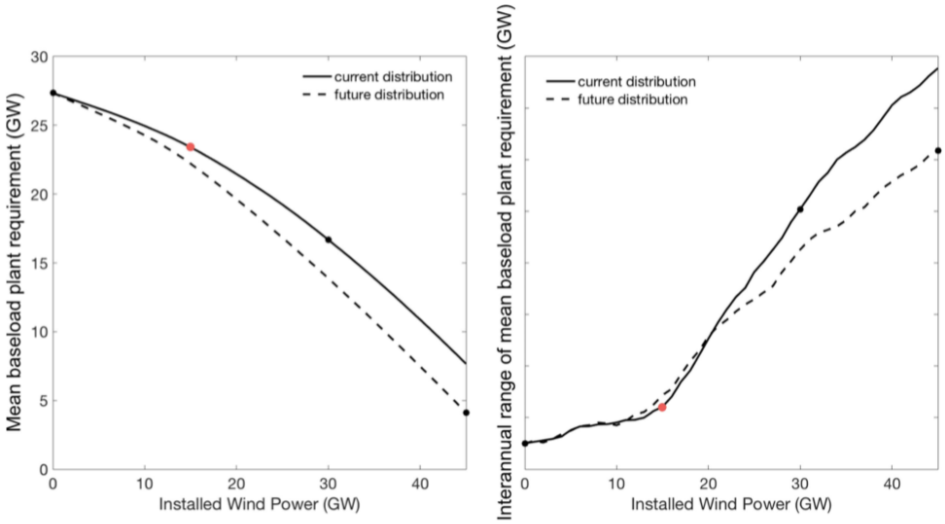


Figure 74: Taken from Bloomfield et al. (2016): The impact of increasing installed wind farm capacity on the baseload energy requirement assuming different spatial wind farm distributions. The solid line indicates the current-day spatial wind-farm distribution (as used in the LOW and MED scenarios), whereas the dashed line indicates a plausible 'future' spatial wind farm distribution (with more off shore turbines, as used in the HIGH scenario). Red dots show the approximate current scenario. (a) Mean base load energy requirement and (b) inter-annual range of baseload energy requirement. The four main scenarios used in this paper (NO-WIND, LOW: 15GM, MED: 30GW and HIGH: 45W) are marked as dots on the relevant curves for reference.

of the year (typically characteristic of nuclear generation). Baseload energy is subsequently defined as the volume of energy provided by plants operating at and above this point (Bloomfield et al., 2016). As described by Bloomfield et al. (2016), Figure 74 shows that baseload energy requirement dramatically decreases with increasing installed wind capacity, while the inter-annual variability dramatically increases. Bloomfield et al. (2016) highlight how the largest change in inter-annual variability occurs between the LOW and MED scenarios, with a smaller increase between MED and HIGH. Bloomfield et al. (2016) attribute this to the increasing deployment of off-shore wind capacity in the HIGH scenario which provides a much steadier power output compared to further increases in the install capacity at existing onshore sites, as a result of increasing spatial diversification. Bloomfield et al. (2016) discuss how this large inter-annual range in the future highly renewable energy system will pose a challenge for system planners since the economic preference of baseload plants (such as nuclear) will vary depending on each years weather. Bloomfield et al. (2016) suggest that, in practice, in the years where baseload energy is reduced, a combination of reduced operating hours for nuclear and increased wind curtailment should be applied.

As introduced in Section 3.2 (seasonal) and Figure 34, Bloomfield et al. (2018) show how the magnitude and inter-annual variability in total seasonal residual demand changes with increasing installed wind capacity, based on 34 years of historical wind speed data. Figure 34 shows how inter-annual variability is always greatest in winter and increases dramatically with increasing wind capacity, resulting in a very large inter-annual standard deviation bar for winters (December-January-February) in the HIGH wind capacity scenario.

Staffell and Pfenninger (2018) bring all three meteorological variables - temperature, wind speed

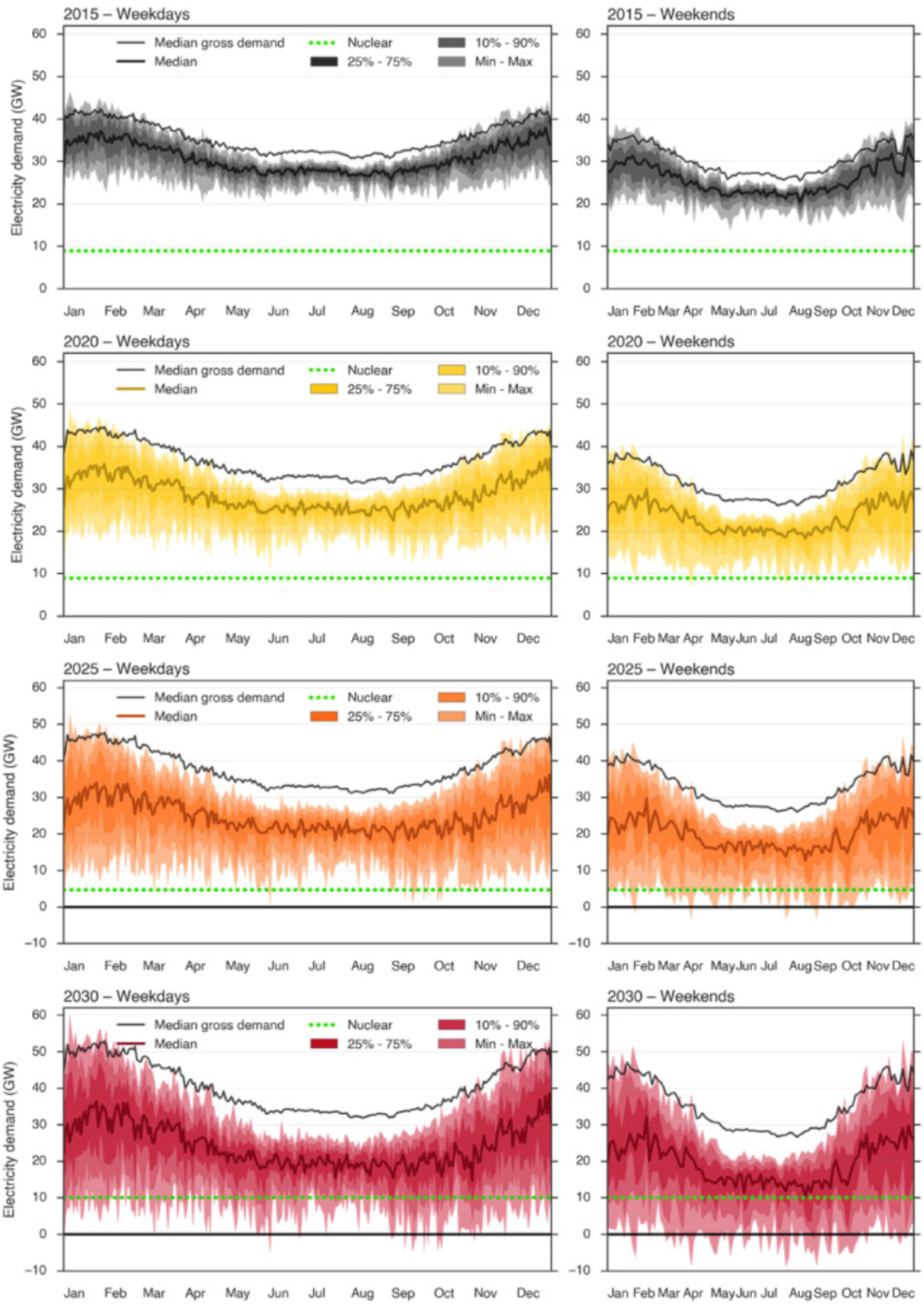


Figure 75: Taken from Staffell and Pfenninger (2018): Inter-annual/Year-to-year variability of hourly average net demand across 25 historical weather years for the current (2015) system and the 2020, 2025 and 2030 scenarios. The green dotted line shows the capacity (and expected firm output) from nuclear generation based on National Grid's projection (National Grid, 2019b). The spread in each plot represents the expected frequency of occurrence over the period of 19912015.

and solar irradiance, together into a whole system energy model for temperature driven demand and weather driven renewable supply. They explore the inter-annual variability in demand net of renewable supply, based on 25 years of historical meteorological data, and present how this variability changes with increasing installed wind and solar PV capacities and future changes in demand due to electrified heating and electric vehicles (as in the National Grid Two degree future scenario (National Grid, 2019b)). This future change in inter-annual variability for 2015, 2020, 2025 and 2030 is presented in

Figure 75, showing how the variability dramatically increases every 5 years in this future energy system scenario. As described by Staffell and Pfenninger (2018), while the current situation (2015) is manageable, by 2020 net demand is starting to reach down to the region of firm nuclear generation on weekends (albeit with a low frequency of occurrence, of 1 day in 4 years). Staffell and Pfenninger (2018) note how even though by 2025 nuclear capacity is lower, since some existing reactors retire before a new build is expected to be on-line, the energy system situation still worsens with a weekend frequency of 4.8 days/year below the lower nuclear generation level. Further, by 2025, on weekends net negative demand (i.e. overproduction by PV and wind generation alone) may occur. Staffell and Pfenninger (2018) further identify how, by 2030, such negative net demand events occur on both weekdays and weekends with higher expected frequency of occurrence, and net demand regularly hits the baseload floor of nuclear generation, suggesting that on half of weekend days curtailment of either nuclear or renewable output would be required unless there were sufficient expansion of storage, interconnection or demand-side response. At the other extreme, as identified by Staffell and Pfenninger (2018), this increased inter-annual variability is associated with increasing peak net demand, gradual between 2015 and 2025, and more rapid after 2025.

In addition, referring back to Figure 19, Staffell and Pfenninger (2018) explore how the inter-annual variability in ramping events changes in the National Grid future energy system scenario (National Grid, 2019b). Specifically, Figure 19 shows how the width of the distribution of the magnitude of 1-hourly ramping events increases in future years. Again this indicates how the future energy system, with increased renewable capacity, will become increasingly sensitive to climate variability.

As previously described, the transmission and distribution networks are most sensitive to meteorological conditions characterising natural hazards such as windstorms, floods and thunder storms. As introduced in Section 3.1 (and others), large scale climatic modes of variability such as the North Atlantic Oscillation (NAO), East Atlantic pattern (EA) and the El Niño Southern Oscillation (ENSO) affect the weather in the UK and Europe. Indeed, a number of studies document the link between these modes of climate variability and natural hazards in Europe. For example, Guimarães Nobre et al. (2017) explore the role of climate variability in extreme flooding in Europe, and identify that positive and negative phases of NAO and EA are associated with significant differences in the intensity of extreme rainfall in Europe; that ENSO has a much smaller influence compared to the NAO and EA; and how during summer NAO+ periods flood occurrence and flood damage are on average 170% and 136% greater respectively. Dawkins et al. (2016) identify a decline in the intensity of winter-time European windstorms in the 21st century, and show how this decline is strongly related to the changing phase of the NAO; from more years of NAO+ in the period 1979-1999, to more years of NAO- in the period 2000-2014, as presented in Figure 76. Dawkins et al. (2016) note, however, how windstorms from the winters 1989/1990 and 2013/2014 occur during similar NAO conditions (as shown in Figure 76) but have very different spatial characteristics, and therefore suggest that additional modes of climate variability are

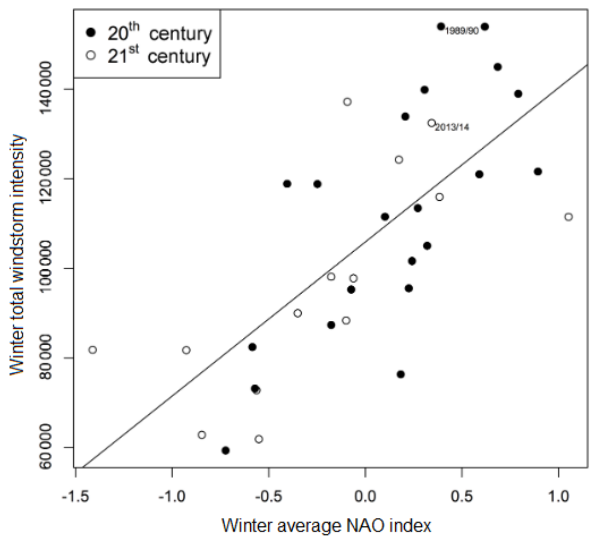


Figure 76: Taken from Dawkins et al. (2016): The relationship between winter total windstorm intensity and winter-averaged NAO index for October-March winters 1979/1980-2013/2014. The linear fit (yx) is shown (solid line). The two comparative periods, winters in the 20$^{\mathrm{th}}$ century and winters in the 21$^{\mathrm{st}}$ century, are indicated. The points associated with winters 1989/1990 and 2013/2014 are labelled.

likely to play a role in the variation of European windstorm intensity. Similarly, Piper and Kunz (2017) highlight the substantial impact of the NAO on lightning activity in Europe; Beniston (2019) show how extreme high and low NAO indices cause European temperatures to exhibit large positive or negative departures from their mean values, causing heatwaves and cold spells; and Spencer and Essery (2016) identify a strong link between the NAO and the number of days of snow cover in Scotland in winters 1875-2013.

Climate Change

This section relates closely to Section 3.6, completed as part of Theme 1. While Section 3.6 focused on the effect of climate change on meteorological conditions associated with extreme stress on the energy system, this section will aim to give further understanding of the effect of climate change on the general operation of the energy system, in all meteorological conditions.

The effect of climate change on UK energy demand is most closely related to changes in regional temperature. As part of their study into the historical relationship between temperature and energy demand, Thornton et al. (2016) present the annual mean Central England Temperature (CET) over a long historical period (1772-2013), shown in Figure 77.

Thornton et al. (2016) fit a third order polynomial function to the annual mean CET shown in Figure 77, demonstrating how the time series exhibits a general increasing trend since approximately 1900. As shown in Figure 45, this increase in UK temperature is expected to continue into the future, with the magnitude of the upward trend greatly depending on the specified future climate change scenario, e.g.

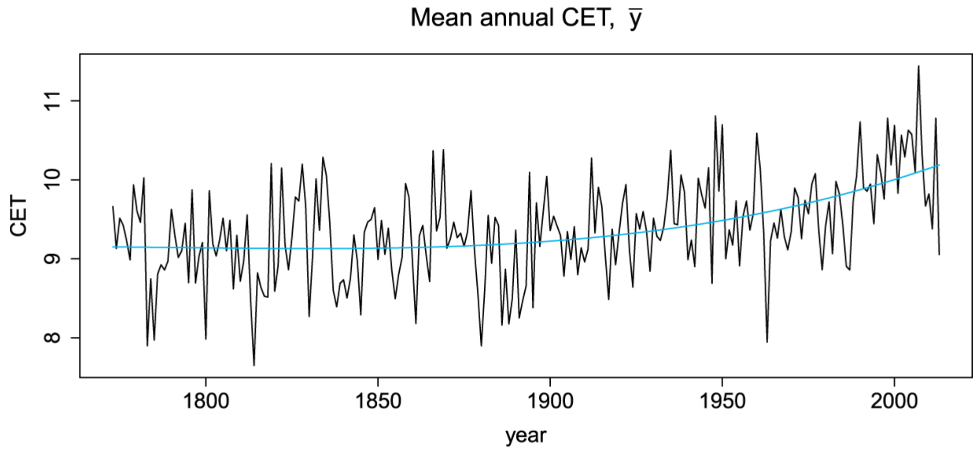


Figure 77: Taken from Thornton et al. (2016): Annual mean Central England Temperature CET (°C, black) and a third order polynomial fit (blue).

Representative Concentration Pathway (RCP) 2.6 or 8.5 (see Section 6.4 for more information about climate change scenarios and how they should be interpreted and incorporated).

Few studies explore the impact of climate change on energy demand, with only Wood et al. (2015) and part of the 2012 UK Climate Change Risk Assessment (Capon, R. and Oakley, G., 2012) focusing on energy demand in the UK. Both identify how cooling demand in summer is likely to experience a marked increase, posing an important issue for managing the future energy system. In addition, National Grid discuss the challenges associated with the future uptake in air conditioning (National Grid, 2017), and research groups are developing approaches for greener and more efficient cooling, for example the department of 'Cold Economy' within the University of Birmingham Energy Institute[24].

The effect of climate change on wind speed and wind power generation has been initially reviewed in Section 3.6. Further studies focused on this topic include: Cradden et al. (2012), who identify relatively minor changes in wind and hence wind power production in the UK; and Harrison et al. (2008), who show a general increase in winter production and decrease in summer production in the UK. As noted by Bonjean Stanton et al. (2016) and Cronin et al. (2018), these studies in combination with those reviewed in Section 3.6, highlight the substantial uncertainty associated with assessing projected changes in wind. Bonjean Stanton et al. (2016) acknowledge this uncertainty but conclude there is greater evidence that wind power generation is likely to increase in the UK, in agreement with Hosking et al. (2018) (Section 3.6), particularly in the second half of the 21st century.

Similarly, Section 3.6 provides an initial review of the effect of climate change on solar irrandiance and solar power generation. As seen for wind power, there is substantial uncertainty in the effect of climate change on European solar PV generation, with studies suggesting contradicting trends. As described in Section 3.6, Burnett et al. (2014) identify a significant increase in solar irradiance in south-west UK, with the increase becoming less significant further north, while Jerez et al. (2015b) show a negative change

[24] https://www.birmingham.ac.uk/research/activity/energy/policy/cold/cold-energy.aspx

in potential solar PV production in the UK and over the whole of Europe in a future climate. As noted by Cronin et al. (2018), Patt et al. (2013) show how climate change is more likely to decrease cloud cover in the mid-latitudes (including Europe), but also decrease PV efficiency due to rising temperatures. As a results, regional studies identify very small changes in western European and UK solar generation of no more than 10% by the end of the century (Crook et al. 2011; Gaetani et al. 2014).

As described by Cronin et al. (2018), the effect of climate change on the transmission and distribution network is expected to be relatively low in the UK compared to other regions of the world. Specifically, Cradden and Harrison (2013) show how the risk associated with the effect of rising temperatures on the transmission capacity of overhead lines is expected to be low in the UK, while McColl et al. (2012) show that there is no clear signal associated with the future frequency of wind and gale faults in the UK. McColl et al. (2012) do, however, show that snow, sleet and blizzard faults are likely to decrease in the future due to rising temperatures and hence a reduction in the number of snow days. In addition, the Energy Networks Association (ENA) took part in the second round of the Climate Change Adaptation Reporting Program in 2015 (Energy Network Association, 2015), and will be releasing a further report as part of the third round later this year (2019). The second round report concluded that there was no evidence to support the adjustment of network design standards due to climate change. It did, however, acknowledge how future rising temperatures may effect the operation of thermal power stations, and hence suggested that this should be considered when designing new builds of this infrastructure.

Rather than focusing specifically on the effect of climate change on the transmission and distribution network, a number of studies explore the effect of climate change on natural hazards themselves. For example, Mölter et al. (2016) review the results of multiple previous published climate modelling studies on future changes in storminess over the North Atlantic and European region, and find that a majority of studies suggest a projected increase in the frequency and intensity of storms in western Europe, and a decrease in the north and south of Europe. In addition, there is a well established signal that future extreme rainfall will increase due to the warming of the atmosphere (which can therefore hold more moisture) (Fischer and Knutti, 2016).

Bonjean Stanton et al. (2016) and Cronin et al. (2018) highlight how there are a number of gaps in our understanding of the effect of climate change on the energy system. In particular, Cronin et al. (2018) note how there are relatively few studies on other forms of renewable energy (e.g. tidal power), and no studies which consider the energy system as a whole. In addition, they note how the changing impacts of extreme weather events has been less extensively studied, and suggest that significant work should be undertaken to understand the changing frequency of resulting potential power outages.

Cronin et al. (2018) identify an additional interesting area of research, also requiring further exploration, around understanding the effect of climate change on climate variability. Research on this topic encompassing the UK is limited to wind power and shows contradictory results: Pryor et al. (2012) identify a slight decline in inter-annual variability of wind energy potential in northern Europe, while Hueging et al. (2013) indicate a significant intensification of both inter-annual and intra-annual variability of wind energy over parts of western and central Europe. Further, as shown in Section 3.6, different climate models show different future changes in the North Atlantic Oscillation (NAO), known to be an important mode of climate variability in the UK and Europe.

As noted by Cronin et al. (2018), the identified uncertainty in the effect of climate change on the energy system as a result of contradictory study results is most likely due to the use of differing climate models and climate change scenarios. For example, studies prior to 2011, such as Pryor and Barthelmie (2010) and Harrison et al. (2008), pre-date the release of the Coupled Model Inter-comparison Project Phase 5 (CMIP5), and are therefore based on relatively outdated climate models with less advanced science. Conversely, more recent studies such as Burnett et al. (2014) and Carvalho et al. (2017) are based on the CMIP5 models, while the latest UK climate projections (UKCP18) are based on CMIP5 models as well as results from the more advanced Met Office climate models. Further, Hosking et al. (2018) use an alternative climate model data set from the Half a degree Additional warming, Prognosis and Projected Impacts (HAPPI) project, which is thought to advance understanding beyond CMIP5 (Hosking et al., 2018). In addition, greenhouse gas emissions scenarios have changed over time, with studies prior to the release of the new Representative Concentration Pathways (RCPs) in 2010 (as described in detail in the Appendix - Section 7) being based on alternative, less sophisticated scenarios which did not adequately represent crucial possibilities, such as climate change mitigation and adaptation (Moss et al., 2010). Improved understanding about the effect of climate change on the energy system will therefore require the careful selection of the most appropriate climate model data and informed interpretation and incorporation of the most appropriate climate change scenarios (see Section 6.4).

Based on the studies reviewed in this section it is apparent that climate variability plays a very important role in modulating meteorological conditions relevant for the energy system in the UK and Europe. In particular, the NAO is a very important mode of climate variability in the region, particularly for predicting when extreme meteorological conditions may occur, effecting energy demand, supply and the transmission and distribution networks. Conversely, the effect of climate change on the energy system is less clear, with the projected trend in wind speed and solar irradiance varying from study to study. There is however, a clear upward trend in UK and European temperature which will have profound effects on energy demand - reducing heating demand in winter and increasing cooling demand in summer. Hence climate variability has most impact on energy supply and the hazards that effect the transmission and distribution networks, while climate change is likely to have the most impact on energy demand.

Summary

- Gas demand has a larger annual cycle and larger degree of winter-time variability compared to electricity, explained by the greater sensitivity of gas consumption (for space heating) to changes in temperature;

- Variability in temperature associated with both the annual cycle and daily fluctuations, is much greater than the lower frequency climate variability;
- Inter-annual variability is lower in summer compared to winter, with variability particularly high in November and December;
- Most areas over Europe show no significant trend in wind speed intensity and variability (1871-2010);
- From year-to-year, wind speed and surface clearness exhibit greater variability in winter, while solar irradiance varies most in summer. Further, inter-annual variability in wind speed and surface clearness is consistently moderately high throughout the year, while the inter-annual variability in solar irradiance is much lower in winter compared to summer;
- The high level of inter-annual variability in wind speed and solar irradiance is such that, over the 25 year period 1990-2014, there have been sunny days in winter with almost as much PV generation across the UK as on cloudy days in summer, and UK average wind capacity factor ranges from close to zero to almost one on the same calendar day across the 25 years throughout October-April;
- The inter-annual variability in baseload energy requirement (e.g. nuclear power) increases dramatically when onshore installed wind capacity is increased from 15-30GW;
- In the future energy system following the National Grid Two Degree future scenario, inter-annual variability in demand net of renewable supply increases substantially every 5 years 2015-2030. By 2030 negative net demand events occur on both weekdays and weekends, while winter-time peak net demand increases;
- The transmission and distribution networks are most sensitive to meteorological conditions characterising natural hazards such as windstorms, floods and thunderstorms. The NAO and East Atlantic pattern (EA) are associated with significant differences in the intensity of extreme rainfall in Europe. The NAO also shown to modulate windstorm intensity, extreme temperature, lightning activity and snow fall in Europe;
- UK temperature has been increasing since approximately the mid 20$^{\mathrm{th}}$ century due to man-made climate change. This increase is projected to continue, with the magnitude of the upward trend greatly depending on the specified future climate change scenario (i.e. the level of greenhouse gas emissions and mitigation). Hence, cooling demand in summer is likely to experience a marked increase, and the development of clean cooling technologies will be important in the future;

- The effect of climate change on wind and solar power generation and natural hazards effecting the transmission and distribution network in the UK and Europe is less certain, with results depending on the climate model, climate scenario and spatial region studied. Improved understand will therefore require the careful selection of the most appropriate climate model data and region, and informed interpretation and incorporation of the most appropriate climate change scenarios;
- Hence, climate variability has most impact on energy supply and the hazards that effect the transmission and distribution networks, while climate change is likely to have the most impact on energy demand.

6.4 How should different climate change scenarios be interpreted and incorporated?

As shown in Figure 78, the global climate is warming, characterised by an increase in global mean temperature since the beginning of the 20$^{\mathrm{th}}$ century. There is overwhelming and growing evidence that this warming is due to vastly increased, and still increasing, quantities of greenhouse gases in the atmosphere (IPCC, 2013b). These are heat-trapping gases, which absorb thermal infra-red radiation emitted by the Earths surface, the atmosphere and clouds. Consequently, this changes the radiative forcing in the atmosphere, defined as the difference between insulation (sunlight) absorbed by the Earth and energy radiated back to space.

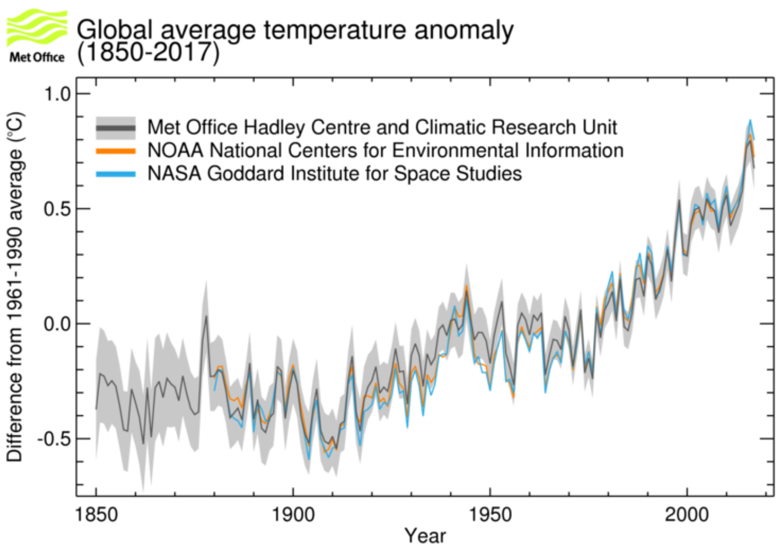


Figure 78: Global average temperature anomaly (difference from 1960-1990 average) [https://www.metoffice.gov.uk/research/monitoring/climate/surface-temperature].

The amount of future climate change and its implications for the environment and society will depend on future emissions of greenhouse gases, the response of the Earth's system to these subsequent changes in radiative forcings, and humankind's respond through changes in technology, economics, lifestyle and policy (Moss et al., 2010). As described by Moss et al. (2010), these extensive uncertainties in the future trajectory necessitate the use of *scenarios* to explore the range of potential consequences of different response options.

As described in the Appendix (Section 7), the latest UK climate projections delivered by the Met Office (UKCP18) and the Intergovernmental Panel on Climate Change (IPCC) fifth assessment report (IPCC, 2013a) consider four potential Representative Concentration Pathways (RCPs), namely RCP2.6, RCP4.5, RCP6.0 and RCP8.5. Each of these RCPs has an associated narrative, explained in the Appendix (Section 7). A comparison of these four RCPs is presented graphically in Figure 79.

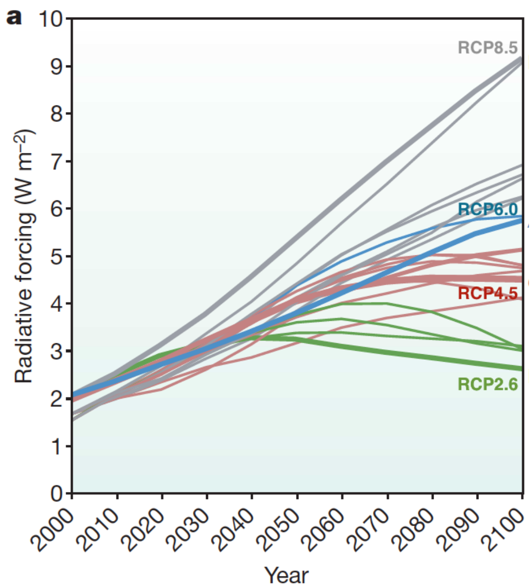


Figure 79: Taken from Moss et al. (2010): Changes in radiative forcing relative to pre-industrial conditions. Bold coloured lines show the four RCPs selected to represent the four radiative forcing targets at 2100; thin lines show approximately 30 alternative candidates scenarios in the peer-reviewed literature.

As can be seen in Figure 79, the four RCPs do not noticeably diverge until 2020 and the three lower pathways remain roughly overlapping until 2040. It is therefore possible that we are currently on any one of these trajectories (or indeed a completely different one). Moreover, the UKCP18 overview report (Lowe, J. A. et al., 2018) describes how the scientific community can not reliably place probabilities on alternative scenarios, and hence can not say which scenario is most likely. The report goes on to guide that, when considering their vulnerability to future weather and climate, users should consider all scenarios, with adaptation to the climate response of an RCP8.5 future representing a more precautionary view of future for emissions.

As time evolves the most likely trajectory will become more clear, based on the implementation and development of further emission reduction pledges. An assessment of the emission and temperature trajectory being followed should therefore be completed periodically (e.g. every 5 years) to incorporate new information on recent emissions, development in international climate agreements, progress in physical climate science and observations, and updated assumptions regarding key technologies and other assumptions. Towards mid-century this update could become less frequent if there is a robust shift to a low carbon economy and stabilisation of global temperatures.

Summary

- The global climate is warming, characterised by an increase in global mean temperature since the mid-20$^{\mathrm{th}}$ century, due to vastly increased emissions of greenhouse gases in the atmosphere;
- There are extensive uncertainties in the future trajectory of the global climate, due to unknown future emissions of greenhouse gases, the unknown response of the Earth system to these subsequent changes in radiative forcings, and the unknown human respond in terms of technology, economics, lifestyle and policy. This necessitates the use of scenarios to explore the range of potential consequences of different response options;
- The latest UK climate projections (UKCP18) consider four potential Representative Concentration Pathways (RCPs): RCP2.6, RCP4.5, RCP6.0 and RCP8.5;
- The four RCPs do not noticeably diverge until 2020 and the three lower pathways remain roughly overlapping until 2040. Hence, currently the scientific community can not reliably say which scenario is most likely, and all scenarios should therefore be included in climate change adaptation plans;
- As time evolves our most likely trajectory will become more clear. An assessment of the emission and temperature trajectory being followed should therefore be completed periodically (e.g. every 5 years) to incorporate new information.

6.5 Theme 4 Conclusion

What is missing from the National Infrastructure Assessment?

- The Assessment does not consider either climate variability or climate change by only using an average year of weather;
- Rather, a long historical or simulated set of meteorological conditions (historical or future) would need to be incorporated to quantify the effect of climate variability and change and hence understand the full range of possible scenarios and ensure energy system resilience

Does this literature provide any answers?

- A number of studies use 25-35 years of historical meteorological data to explore parts of the energy system, one of which aims to understand the energy system as a whole (although does not include interconnectivity with Europe or flexible technologies). A number of studies explore the effect of climate change on either wind power generation, solar power generation or the energy transmission and distribution network, but none include multiple parts of the energy system within these studies;

- The effect of climate variability and change on energy demand is associated with temperature, energy supply is associated with wind speed and solar irradiance, and the transmission and distribution network is associated with natural hazards, such as windstorms, flooding, snow and lightning;
- Inter-annual climate variability of temperature is moderate compared to the annual cycle and daily fluctuations in temperature;
- Wind speed and surface clearness exhibit greater inter-annual variability in winter, while solar irradiance varies most in summer. Further, inter-annual variability in wind speed and surface clearness is consistently moderately high throughout the year, while the inter-annual variability in solar irradiance is much lower in winter compared to summer;
- This inter-annual variability has produced sunny days in winter with almost as much PV generation across the UK as on cloudy days in summer (1990-2014), and UK average wind capacity factors range from close to zero to almost one on the same calendar day throughout October-April across the 25 years;
- This large inter-annual variability in meteorological conditions relevant for energy supply results in a dramatic increase in demand net of renewable supply in future energy systems within increased installed wind and solar capacities;
- The North Atlantic Oscillation (NAO), a large scale mode of winter climate variability effecting European weather, is shown to modulate wind speeds, windstorm intensity, extreme temperatures, lightening activity and snow fall in Europe;
- UK and European temperatures are consistently projected to increase due to man-made climate change with the magnitude of the upward trend depending on the specified future climate change scenario. This increase in temperature is expected to greatly increase cooling demand in summer, necessitating new technologies for clean cooling;
- The effect of climate change on wind and solar power generation and natural hazards effecting the transmission and distribution network in the UK and Europe is less certain, with results depending on the climate model, climate scenario and spatial region studied;
- Climate variability has most impact on energy supply and the hazards that effect the transmission and distribution networks, while climate change is likely to have the most impact on energy demand;
- Improved understanding of the effect of climate change on the energy system will require the careful selection of the most appropriate climate model data and region, and informed interpretation and incorporation of the most appropriate climate change scenarios;

- The latest UK climate projections (UKCP18) consider four potential Representative Concentration Pathways (RCPs): RCP2.6, RCP4.5, RCP6.0 and RCP8.5;
- Currently, the scientific community can not reliably say which scenario is most likely, hence all scenarios should therefore be included in climate change adaptation plans;
- An assessment of the emission and temperature trajectory being followed should be completed periodically (e.g. every 5 years) to incorporate new information.

What are the remaining gaps in knowledge, not addressed in the literature?

- An understanding of the effect of climate variability and climate change on a whole system energy model, including all relevant elements such as interconnectivity and flexible technologies;
- An improved understanding of the regional effect of climate change on all relevant meteorological conditions, explored using a consistent data set, based on the best current understanding of the future climate;
- More work is needed to understand the effect of climate change on climate variability, since in combination these two elements have an impact on all parts of the energy system;
- A better understanding of the effect of climate variability and change on the transmission and distribution network, to better understand the current and future risks of damage causing power outages.

Which areas addressed within the literature need further analysis to be relevant for the Commission?

- The effect of climate variability on an evolving future energy system (as in Staffell and Pfenninger 2018) could be repeated for a whole energy system model incorporating the future scenarios within the Assessment analysis;
- Climate change studies could be repeated using the most up-to-date and relevant data sets.

What does the literature suggest needs to be incorporated within the whole system energy model?

- A long historical period of meteorological data must be used (either directly on to develop a statistical model for weather) to represent the identified large climate variability in wind speed and solar irradiance, relevant for energy supply;
- The effect of climate change on temperature should be incorporated to accurately represent changes in demand as a result of the potential uptake in air conditioning.

What methodologies and data sets are available to perform this further analysis and fill these gaps?

- A table of relevant data sets is given in Figure 61. These include reanalysis and hindcast data sets which cover the last ~ 40 years, and the UKCP18 climate projections which provide reasonable global spatial resolution (60km) and high UK resolution (12km), incorporate the most up-to-date scientific understanding about the global atmosphere, and implement the latest and most comprehensive representative concentration pathways;
- In addition, as introduced in Section 5.3, statistical modelling techniques can be used to model how extreme meteorological conditions change with climate change by incorporating the relationship between global mean temperature, a variable which is known to be well represented by climate models, into the statistical model for the meteorological variable of interest (e.g. wind speed). The global mean temperature could then be projected into the future climate and this relationship then used to project the meteorological variable of interest into the future climate.

7 Appendix

7.1 Atmospheric Pressure

As described in the Learning pages of the Met Office website (`https://www.metoffice.gov.uk/learning/atmosphere/high-and-low-pressure`), atmospheric pressure is the force exerted by the weight of the air in the lower atmosphere, measured in hectoPascals (hPa). Warm air at the equator rises and spreads towards the poles while cold air at the poles sinks towards the equator. Zones of rising air lead to areas of low pressure at the surface, while sinking air leads to high pressure at the surface. As a result, zones of high and low pressure cover the globe. These zones have a significant role in the evolution of weather. Air naturally flows from high to low pressure, creating winds, which are stronger the greater the pressure difference between the high and low zones. In high pressure zones, the descending air suppresses weather development often leading to calm, clear conditions, while in zones of low pressure, winds circulate rapidly inward and upward (due to the Coriolis force of the spinning Earth), cooling the air to form clouds and precipitation.

7.2 Reanalysis Data

As described by Brown et al. (2018), creating a reanalysis data set involves using historical observations, retrospectively, to drive a numerical weather prediction (NWP) model, i.e. a model that is normally used for forecasting the weather in real time. Rather than being allowed to evolve freely, the model is systematically constrained at reasonable intervals (e.g. every 6 hours) by the assimilation of further historical observations at each such interval. The advantage of this process is that it produces a gridded data set of potentially many variables, and potentially spanning several decades and large geographical areas (even global). There are some limitations; mainly these relate to the limitations of the chosen NWP model (i.e. how well it performs in terms of modelling key weather parameters) and to any deficiencies in the quality of the observations ingested into the process.

7.3 Hindcast Data

Hindcast data is similar to Reanalysis data (see above), however the weather of climate model is allowed to evolve freely for a longer period of time between the assimilation of historical observations. For example, in the Euro4 hindcast data set, this happens every 24 hours. This can lead to jumps in the model output at each observation assimilation time step.

7.4 Climate Change Scenarios

The amount of future climate change and its implications for the environment and society will depend on future emissions of greenhouse gases, the response of the Earth's system to these subsequent changes in radiative forcings, and humankind's respond through changes in technology, economics, lifestyle and policy (Moss et al., 2010). As described by Moss et al. (2010), these extensive uncertainties in the future trajectory necessitate the use of *scenarios* to explore the range of potential consequences of different response options. These scenarios are not predictions of the future, rather plausible realisations made under a particular set of assumptions. Hence, these plausible futures reflect expert judgements regarding socio-economic, environmental, and technological trends (Moss et al., 2010). Potential future scenarios are developed by modelling these assumptions simultaneously and minimising the costs of mitigation actions using an 'integrated assessment model'.

The latest UK climate projections delivered by the Met Office (UKCP18) and the Intergovernmental Panel on Climate Change (IPCC) fifth assessment report (IPCC, 2013a) consider four potential Representative Concentration Pathways (RCPs), namely RCP2.6, RCP4.5, RCP6.0 and RCP8.5. These pathways characterise four future radiative forcing targets at 2100, of 2.6, 4.5, 6.0 and 8.5 W/m^2. Moss et al. (2010) present the development of these four RCPs, describing how a novel parallel approach was employed, beginning with the identification of the four 2100 radiative forcing targets, each of which could be reached by multiple possible trajectories of different combinations of economic, technological, demographic, policy and institutional futures. The research community then went on to identify specific emissions scenarios from the peer-reviewed literature as plausible pathways towards reaching each target radiative forcing trajectory (Moss et al., 2010). These were labelled the Representative Concentration Pathways (RCPs), where 'Representative' reflects the fact that each RCP provides only one of many possible scenarios that would lead to that specific radiative forcing characteristic.

Moss et al. (2010) go on to describe how these four specific radiative forcing targets were identified based on a number of criteria. Specifically, to include the full range of stabilisation, mitigation, and reference emissions scenarios available in the current literature; to provide a manageable and even number of scenarios, to avoid the inclination of using the central case in an odd set of scenarios as the 'best estimate'; to give an adequate separation between pathways in the long term; and ensuring the availability of existing models to represent all relevant variables. Much of the selection process was based on the IPCC Fourth Assessment Report (Fisher et al., 2007), with final selection based on discussions at an IPCC expert meeting in September 2007, and a subsequent open review involving many modelling teams and users (Moss et al., 2010).

RCP2.6, also known as the ‘Peak and decline’ pathway, represents a future in which the world aims for, and is able to implement sizeable reductions in emissions of greenhouse gases, meeting the long-term target specified in the UK Climate Change Act (2008). This would require further targets to be set, beyond those currently being implemented. This is the most optimistic of the four RCPs. RCP8.5, also known as the ‘Rising’ pathway, is the most pessimistic scenario in which global greenhouse gas emissions continue to rise because nations of the world choose not to switch to a low-carbon future. RCPs 4.5 and 6.0 represent alternative futures in which implementation and completion of emission pledges vary. Specifically, many studies have shown that, if after reaching emission reduction targets at 2030, emissions remain constant then RCP4.5 may be the most likely, while if emissions increase again after 2030, RCP6.0 is most likely.

It is possible that we are currently on any one of these trajectories (or indeed a completely different one). As a result, the scientific community can not reliably place probabilities on alternative scenarios, and hence can not say which scenario is most likely.

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