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2016 Environ. Res. Lett. 11 124025

(http://iopscience.iop.org/1748-9326/11/12/124025)

Environmental Research Letters

OPEN ACCESS

RECEIVED
24 August 2016

REVISED
10 November 2016

ACCEPTED FOR PUBLICATION
27 November 2016

PUBLISHED
14 December 2016

LETTER

Quantifying the increasing sensitivity of power systems to climate variability

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Keywords: renewable energy, climate variability, power system, electricity, wind power, whole system

Abstract

Large quantities of weather-dependent renewable energy generation are expected in power systems under climate change mitigation policies, yet little attention has been given to the impact of long term climate variability. By combining state-of-the-art multi-decadal meteorological records with a parsimonious representation of a power system, this study characterises the impact of year-to-year climate variability on multiple aspects of the power system of Great Britain (including coal, gas and nuclear generation), demonstrating why multi-decadal approaches are necessary. All aspects of the example system are impacted by inter-annual climate variability, with the impacts being most pronounced for baseload generation. The impacts of inter-annual climate variability increase in a 2025 wind-power scenario, with a 4-fold increase in the inter-annual range of operating hours for baseload such as nuclear. The impacts on peak load and peaking-plant are comparably small. Less than 10 years of power supply and demand data are shown to be insufficient for providing robust power system planning guidance. This suggests renewable integration studies—widely used in policy, investment and system design—should adopt a more robust approach to climate characterisation.

1. Introduction

The growing use of weather-dependent renewable generation is changing the nature of power systems operation. The traditional model, where large plants are controlled to meet electricity demand, is being replaced by a situation in which neither demand nor supply can be fully controlled [1, 2]. While meteorological conditions are well known to affect power demand (e.g., for heating, cooling and lighting [3–7]) they now have an increased impact upon power supply (e.g., wind and solar [8–11]).

Similar challenges face power systems across the world (e.g., Europe [12], US [13–15], Australia [16], and India [17]). Here the power system of Great Britain (GB) is considered as an example of a relatively isolated system with ambitious renewables targets (particularly for wind [2]). Although the time-average signal of anthropogenically forced climate change on renewable resources is perhaps likely to remain modest over GB (and Europe in general) for the coming decades [18–20], many aspects of European power systems are still profoundly affected by strong multi-annual climate variability [21]; estimates suggest that the nationally aggregated annual wind-power capacity factor varies from 25% to 40% ([10]; the capacity factor is the actual wind-power generation as a fraction of total installed capacity).

Despite the demonstrated impact of climate on individual components there has been little research into its impact on the operation of the power system as a whole. The renewables integration literature instead typically relies only on a few years of data (e.g., [22–25] use between one and 13 years). Given these short records, none of these studies is capable of robustly assessing the impact of inter-annual climate variability on the GB power system. This limitation is not peculiar to GB—many other studies internationally adopt the same approach (e.g., [11, 13–15, 26–29] each contain less than a decade of data).

This study therefore seeks to: quantify the sensitivity of the present-day GB power system to inter-annual climate variability; to assess how this sensitivity changes under plausible near-future wind-power scenarios; and to estimate the climate uncertainty that is introduced by relying on shorter meteorological records. To this end, well-validated multi-decadal hourly demand and wind-power time series are constructed for GB and the impact of climate variability assessed using six different power-system metrics (total annual energy requirement, peak load, use of 'peaking', 'mid-merit' and 'baseload' plant, and wind power curtailment). This work therefore extends a growing body of energy-climate literature (e.g., [9, 10, 30–35] for GB) by using multi-decadal meteorological records to provide insight into the operation of an integrated power system for the first time. For simplicity, solar photovoltaics are not included in this present study (in GB the total energy from solar photovoltaic generation in 2014 was less than 15% of that from wind [36]).

The framework used is conceptually simple and combines several well-established methods, yet is sufficient to represent the salient features of both long-term climate and its impact on a nationally integrated power system. By avoiding the computational overheads associated with more complex models (e.g., dynamical meteorological downscaling, power system unit-commitment), the framework is readily adaptable to other national and continental-scale power systems.

2. Methods

Mutually consistent hourly reconstructions of GB-aggregated demand and wind-power are constructed from the MERRA atmospheric reanalysis [37]. The conversion from meteorological (temperature, wind-speed) to power variables (demand, wind-power) uses well-established techniques, trained upon and validated against recent observations of the GB power system. The demand and wind-power conversion models are then applied to the whole MERRA record (1980–2015) to create a 36 year time series assuming a fixed GB power system had existed throughout the period.

A brief overview of the component models is given here and full details are provided in appendix 1 for the demand (section A.1) and wind-power model (section A.2).

Wind-power: four wind-power capacity scenarios are considered: 0, 15, 30 and 45 GW (referred to as NO-WIND, LOW, MED and HIGH respectively). LOW is approximately equivalent to the present GB power system, while the MED and HIGH scenarios are based on National Grid's Gone Green scenarios for 2025 and 2035 respectively [2]. The spatial distribution of wind farms is identical in LOW and MED (corresponding to that observed in 2012, as used by [10]) whereas for the HIGH scenario, the distribution includes many more offshore sites (described in [38]).

Demand: a multiple linear regression model including daily average meteorological and non-meteorological parameters is trained against daily recorded GB demand data from 2006–2015 (following [39]), and downscaled to hourly resolution using a seasonally varying diurnal curve (see appendix, and figure A1 for details). The demand drivers with no meteorological significance (long term economic trends, weekends and public holidays) are then removed. The resulting demand record therefore corresponds to a GB system from the late 2000s, including the effects of seasonality but neglecting the effects of special days.

Load duration curves (LDCcs) are used to combine the demand-and-supply impact of weather and climate on the power system (see, e.g., [24]). in the present context, residual load is the residual power demand once the wind power generation has been removed—that is, it is the power that must be supplied from conventional sources (by conventional here we mean dispatchable sources, i.e. plants that can be directly controlled to adjust their power output). To form an LDC, each year of hourly residual load data is converted to a cumulative frequency curve showing the percentage of the year for which a given residual load threshold is exceeded. By convention these are displayed as in figure 1(a). Any point on the curve shows the percentage of the year (x-axis) for which the residual load required exceeds a threshold (y-axis).

A set of metrics are used to quantify the impact of inter-annual climate variations on the power system. The metrics use the principle of merit order, an indication of operating preference for electricity generation plant which is widely used in power systems analysis [40]. Here baseload refers to plant that operates for a very large percentage of time: this must be cheap to operate but is commonly expensive to build (typified by nuclear generation [41]). Conversely, peaking plant is operated infrequently to satisfy rare peaks in electricity demand; such plant must be cheap to build but is typically expensive to operate (e.g., oil fired plant and open cycle gas turbines [41]). Between these extremes falls a broad range of mid-merit or 'load-following' plant which is neither as cheap to operate as baseload, nor as cheap to build as peaking plant (usually combined cycle gas turbines and coal fired generation in GB).

The metrics discussed below are not exact descriptions of system operation. They are chosen in order to provide simple proxies from which the gross impact of inter-annual climate variability on the components of the power system can be inferred. In reality the impacts of weather and climate on the power system would be much more complex due to the need for,

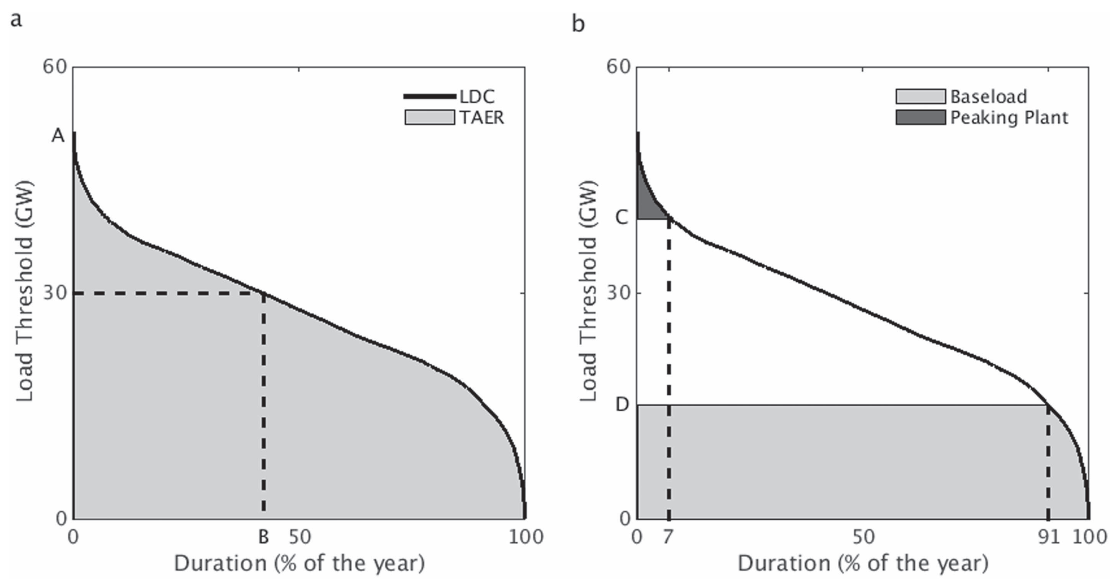

Figure 1. A schematic of power system metrics. In each curve, the solid black line is a single year's LDC (see main text for discussion). Metrics illustrated are: (a) total annual energy requirement (represented by the area under the curve; shaded) with point A marking peak load and point B marking the operating hours of a mid-merit plant (b) peaking plant and baseload total energy requirements (dark and light shading respectively) with points C and D marking the minimum load requirement for peaking plant and maximum load requirement for baseload plant respectively.

increased plant cycling and the requirement for more spinning reserve. For simplicity this study assumes that GB is an isolated system with no interconnectors, and that the operational behaviour of each type of generation is constant throughout these scenarios.The metrics are as follows:

(1) *Total annual energy requirement (TAER):* the total residual load over a calendar year, equivalent to the area under an LDC (see figure 1(a)). Here, TAER represents the total energy requirement from conventional generating plant over the year (units GWh).

(2) *Peaking plant:* peaking plant is assumed to be economically efficient when operating for less than 7% of the year [42, 43]. It is therefore possible to identify (a) the threshold residual load beyond which peaking plant becomes economically efficient (units GW; figure 1(b), point C), and (b) the volume of energy for which peaking plant is the most economically efficient generation type (hereafter 'peaking energy'; units GWh; figure 1(b) dark shading).

(3) *Baseload plant:* baseload plant is assumed to be economically efficient when operating in excess of 91% of the year (based on a general expectation for new GB nuclear build [42, 43]). The maximum residual load that is available for baseload plant to operate at economically efficient levels (units GW; figure 1(b) point D) and the volume of energy provided by plant operating at and above this point (hereafter 'baseload energy'; units GWh; figure 1(b) light shading) are therefore calculated.

(4) *Peak load:* the highest hourly residual load recorded on the system in any given year (figure 1(a) point A, units GW).

(5) *Curtailment of wind-power:* curtailment is assumed to occur when wind-power production exceeds the ability of the power system to use it. For simplicity, curtailment is considered to occur only when wind-power instantaneously exceeds 70% of the total demand (due to system stability issues it is unlikely to be allowed to exceed this level [44]). The volume of energy curtailed is then calculated (units GWh).

(6) *Operating hours of a mid-merit plant:* a typical mid-merit plant in the current GB power system might expect to operate when residual load exceeds 30 GW (i.e., there are cheaper options for 29 GW of generation and the 31st GW requires a more expensive generator to be used). The number of hours per year for which this plant would operate is calculated (figure 1(a), point B).

It is emphasised that the operating points chosen for peaking plant, mid-merit and baseload plant metrics are indicative values that relate to preferred operating levels for an economically optimal power system. Power plants are planned and built over multiple years. Once constructed an individual

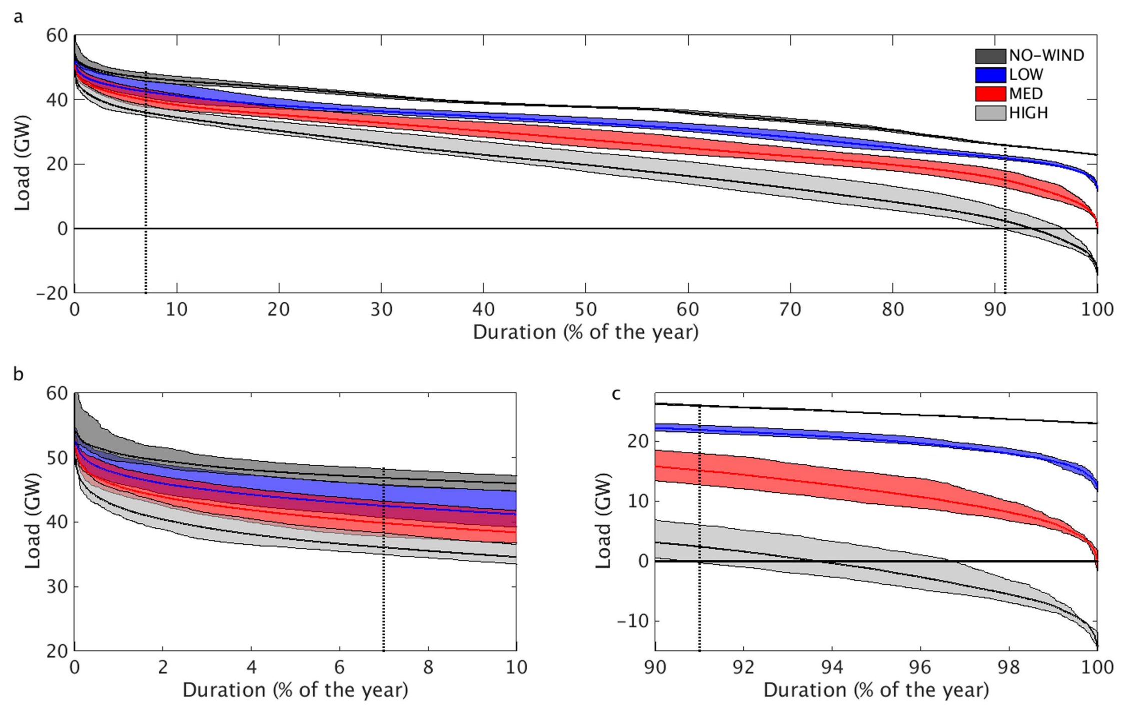

Figure 2. LDCs for NO-WIND LOW, MED and HIGH wind-power scenarios (dark grey, blue, red and light grey, respectively). The multi-year mean LDC in each scenario is a solid line, with the edges of the shaded area marking the two extreme years from the set of 36 LDCs within each scenario (1990 and 2010, respectively). Vertical dashed lines show the percentage of time that baseload-plant (91%) and peaking plant (7%) are required to operate as defined in [42]. (a) shows the full range of operating durations. (b) and (c) are identical to (a) but highlight only the low- and high-duration parts of the curves respectively.

Table 1. Mean and inter-annual range of the 36 years total annual energy requirement (TAER), the total energy required from Peaking and Baseload plant (in TWh) under four different wind-farm installation scenarios (see section 2 for detailed discussion). The range is the difference between the highest and lowest of the 36 values of each metric. For convenience of comparison, the maximum range of values are also expressed in brackets as a percentage (normalised by the mean value from the NO-WIND scenario).

	TAER (TWh)		Peaking plant energy (TWh)		Baseload plant energy (TWh)	
Scenario	Mean	Range	Mean	Range	Mean	Range
NO-WIND	326	10.17 (3%)	1.3	0.7 (54%)	227	3.8 (2%)
LOW	283	23.8 (7%)	1.7	0.9 (69%)	190	11.8 (5%)
MED	240	39.8 (12%)	1.9	1.0 (77%)	128	45.9 (20%)
HIGH	170	48.7 (15%)	2.0	1.2 (92%)	18	55.0 (24%)

Table 2. The mean and inter-annual range of peak load, Peaking threshold power load requirement and Baseload maximum load requirement under the four different installed wind-power scenarios. See section 2 for definition of the scenarios and metrics.

	Mean (GW)				Inter-annual range (GW)			
	NO-WIND	LOW	MED	HIGH	NO-WIND	LOW	MED	HIGH
Peak load	55.0	52.9	51.8	50.1	8.4	6.1	6.0	8.2
Peaking plant threshold Load requirement	47.1	42.6	39.9	36.2	3.3	5.3	5.5	4.2
Baseload plant max. Load requirement	26.0	22.0	15.1	2.5	0.4	1.3	5.3	6.4

plant's operating hours may vary from one year to the next, affecting revenues; plant will not be swapped out instantaneously. The varying power and energy values that follow represent a measure of investment uncertainty that should be considered by system planners.

3. Results

Figure 2 shows the maximum, minimum and mean annual LDCs derived from each of the four wind-power capacity scenarios. The key metrics are summarised in tables 1 and 2.

3.1. Exacerbation of climate sensitivity in the present day

The impact of the current installed wind-farm capacity on the power system is first considered by contrasting the LOW and NO-WIND scenarios. For the NO-WIND scenario there is a 3% (10.2 TWh) difference in the TAER from conventional plant between the highest and lowest years in the record (1986 and 2007 respectively). The spread between the LDCs is largest at higher residual loads, indicating that inter-annual variations in climate have a greater impact on peaking- rather than baseload-plant (an inter-annual range of 54% of mean peaking energy compared to 2% for baseload energy; table 1). Table 2 shows that in terms of residual load requirements, the inter-annual range of plant operation is also greatest at higher residual loads (8.4 GW for peak demand compared to 0.4 GW for the maximum residual load from baseload-plant). Under this scenario the mid-merit plant is called upon for approximately 7050 h yr^{-1} with an inter-annual range of 251 h $yr^{-1}$and there is no wind power curtailment.

In the LOW scenario, the TAER is always reduced compared to NO-WIND (figure 2). Consistent with [45], this reduction preferentially occurs for low merit order plant (the mean baseload energy *decreases* by 16%, while the mean peaking plant energy actually *increases* by 30%; table 1). There is also an increase in the inter-annual variability of TAER (doubling compared to the NO-WIND scenario; table 1), particularly affecting the baseload *energy* and peaking *power* requirements (tables 1 and 2 respectively). The two most extreme years in the record are now 1990 and 2010—as opposed to 1986 and 2007 in the NO-WIND scenario—indicating that different conditions are now dominating the inter-annual variability in TAER. The operating hours of a mid-merit plant both decrease on average, and become substantially more variable (5600 h yr^{-1} with an inter-annual range of 880 h yr^{-1}, a 3-fold increase in variability). No curtailment is seen in the LOW scenario.

More positively the inter-annual range in peak load decreases (from approximately 8.4 GW in NO-WIND to 6.1 GW in LOW; table 2).This indicates some compensation between wind-power availability and extreme demand peaks, which was implied by [30] and will be returned to in subsequent publications.

The installed wind-power in the present-day GB power system therefore already substantially exacerbates the inter-annual variability in the operation of conventional power plant, particularly for mid-merit and baseload generators. In many cases, this exacerbation is on the order of several hundreds of percent of the baseline variability in the NO-WIND scenario.

3.2. The impact of increasing wind-power generation

The changing climate sensitivity under future wind capacity scenarios (MED and HIGH) relative to the current day scenario (LOW) is now considered. As the installed wind-power capacity increases there is a reduction in the mean TAER (from 283 TWh in LOW to 170 TWh in HIGH) but a significant increase in its inter-annual range (doubled between the LOW and HIGH scenarios, table 1).

As before, increasing wind-power capacity *reduces* the use of baseload generation while *increasing* the use of peaking plant (mean 90% decrease and 15% increase from the LOW to the HIGH scenarios respectively, table 1). Figure 2, however, also suggests that the inter-annual range increases across the scenarios, particularly for baseload plant. The impact of moving across the wind-capacity scenarios (from LOW to HIGH unless noted) is therefore discussed for each power system metric individually:

Peak load: increasing wind-power capacity reduces the mean peak-load (from 52.9 to 50.1 GW; table 2) but increases its year-to-year variability (from 6 to 8 GW).

Peaking plant: peaking plant energy slightly increases as the installed wind capacity increases (from a mean value of 1.7–2.0 TWh; table 1), while the inter-annual range slightly increases (from 0.9 to 1.2 TWh). The mean minimum load at which peaking plant becomes economically efficient reduces (42.6 to 36.2 GW; table 2), while its inter-annual range is approximately constant (circa 4 GW).

Baseload-plant: baseload energy decreases dramatically (from a mean value of 190–18 TWh; table 1) while the inter-annual range increases (12–55 TWh). Similarly, the mean maximum baseload requirement decreases (from 22.0 to 2.5 GW; table 2) while its inter-annual range increases (1.3 to 6.4 GW). Much of this change occurs between the LOW and MED scenarios with a weaker change between MED and HIGH. As shown in figure 3, this is attributable to increasing deployment of offshore wind-power capacity in the HIGH scenario which provide a much steadier power output than further increasing the installed capacity at onshore sites (consistent with [38]). The inter-annual range here represents a challenge for system planners indicating that the economic preference for baseload plant (such as nuclear) will vary depending on each year's weather. In practice, nuclear plant, once built, is expected to remain operational for decades and is unlikely to be operated to give absolute priority for wind. Years where baseload energy is seen to reduce should be taken to imply some combination of

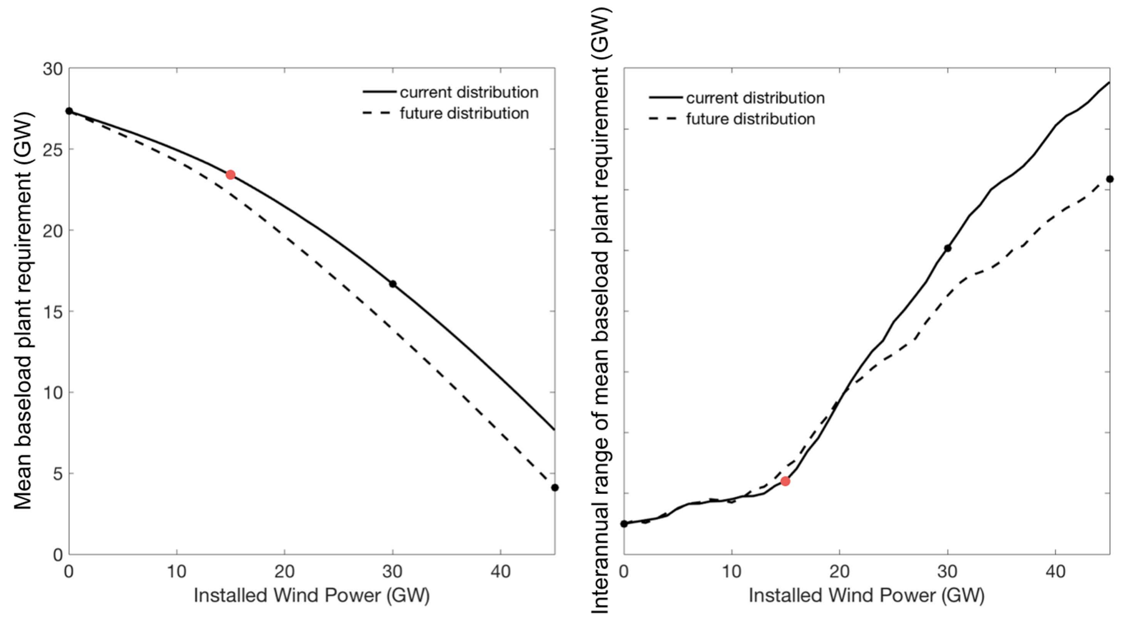

Figure 3. The impact of increasing installed wind farm capacity on the baseload energy requirement assuming different spatial wind-farm distributions. The solid line indicates the current-day spatial wind-farm distribution (as used in the LOW and MED scenarios), whereas the dashed line indicates a plausible 'future' spatial wind farm distribution (with more offshore turbines, as used in the HIGH scenario). Red dots show the approximate current scenario. (a) Mean baseload energy requirement and (b) inter-annual range of baseload energy requirement. The four main scenarios used in this paper (NO-WIND, LOW, MED and HIGH) are marked as dots on the relevant curves for reference.

reduced operating hours for nuclear and increased wind curtailment.

Mid-merit plant: the mean operating hours for a mid-merit plant decreases substantially (from 5600 to 1870 h yr^{-1}). The inter-annual variability increases significantly (from 880 to 1350 h yr^{-1}).

Curtailment of wind-power: curtailment become increasingly significant as wind-power capacity increases (from 0 TWh yr^{-1} in the NO-WIND and LOW scenarios to a mean value of 0.3 TWh yr^{-1} in the MED scenario, and 13.2 TWh yr^{-1} in the HIGH scenario). The inter-annual range of curtailment also increases (from 0.4 TWh yr^{-1} in the MED scenario to 12 TWh yr^{-1} in the HIGH scenario).

Inter-annual variability therefore becomes increasingly important across the whole power system as wind-power capacity increases, but with the effects being most pronounced for baseload generators. These changes are large (e.g., the inter-annual range of energy production from baseload increases 5-fold between the 'present day' and most extreme future scenario).

3.3. Implications of record length for power system modelling

A common objective in power system planning is to identify the economically optimal mix of generation to satisfy a set of policy or technological choices. Here, this is interpreted as identifying the capacity of each generation type (peaking, mid-merit and baseload) required to minimise the long-run economic cost for a particular wind capacity scenario. As discussed previously, most previous studies rely on short data records—often just a single year—and it is therefore useful to estimate the size of the error this may introduce.

Five different sampling period experiments are performed. For each experiment, the n years are selected randomly from the 36 year MERRA record where $n = 1$, 2, 5, 10 or 36 (each year of climate data is assumed serially independent; the same year may also be selected multiple times in a particular sample). The selected years are processed to produce two time-average annual LDCs—one for each of the LOW and MED scenarios—and estimates of the maximum baseload plant requirement are calculated for each scenario. These two estimates are differenced (i.e., LOW–MED) to estimate the *mean reduction* in baseload capacity between the scenarios. This process is repeated 1000 times for each sampling-length experiment.

Figures 4 summarises the range of possible simulated changes in mean baseload capacity as a function of sample length. Single-year samples lead to differences in the projected change by 50% or 3 GW (similar experiments for peaking plant show a range of 100% or 2 GW for peaking capacity, not shown). The range drops rapidly with increasing sample size to about 15% (1 GW) for 10-year samples and less than 10% (0.5 GW) for 36 year samples. The size of the potential error introduced by using short records (less than 5–10 years) is perhaps significant as it is comparable to, for example, the changes in nuclear capacity stated in National Grid's Gone Green scenario (a 2.3 GW or 25% increase between 2020 and 2030, [2]). Sampling

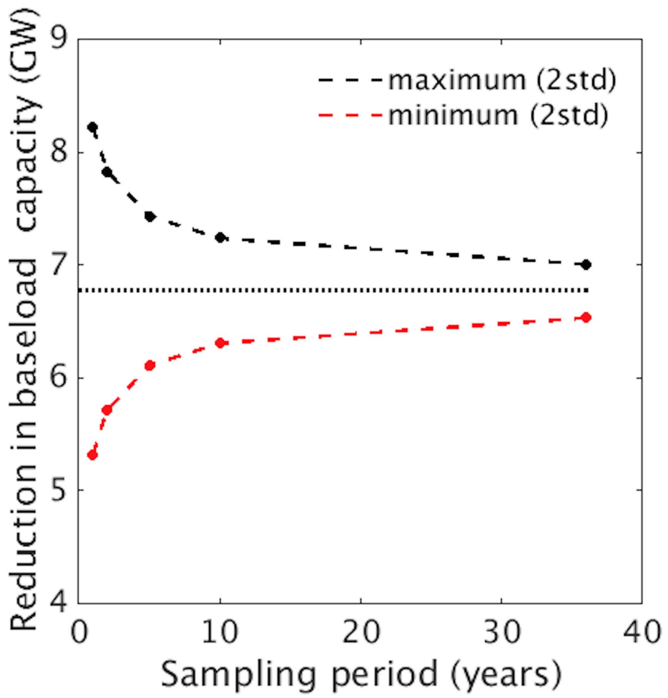

Figure 4. Simulated reduction in the optimal baseload plant capacity between MED and LOW wind-power scenarios as a function of climate-data sample length (see main text for discussion). Dotted lines indicate the bounds for which 95% of the distribution of data fall within as calculated using a bootstrap method (+/−2 standard deviations from the 1000-sample average change). For reference, the mean value over the continuous period from 1980–2016 is plotted as a black dotted line.

periods of less than 10 years therefore introduce significant levels of uncertainty into the estimated 'mean' characteristics of power system planning projections in the present framework.

It is, however, emphasised that the results presented here do not imply that 10 or even 36 samples are sufficient for fully characterising climate uncertainty. The sampling uncertainties identified here are likely to be underestimates of the full climate uncertainty: 36 years is a relatively short window for quantifying climate extremes and the role of anthropogenic climate change and multi-decadal natural variability (e.g., NAO trends [21]) have not been considered. It is also noted that many planning studies use consecutive years of climate observations (rather than random sampling) and are therefore are more likely to underestimate the role of serial correlations on inter-annual timescales.

3.4. Comparison to previous studies

To emphasise the importance of long meteorological datasets to power system modelling the study by [23] is reviewed. In that paper, weather data from the period 2000–2007 was used as an input to a complex simulation of the GB power system. The authors found a 13% difference (approximately) in the total wind-power generation between the best and worst wind years.

If that same period is now re-evaluated using the reanalysis-based methodology described here then a similar inter-annual range in wind-power generation is found (11%). However, if the period is extended to cover the whole of the 1980–2015 record, the inter-annual range increases to 32%, i.e., an almost three-fold increase on the original study. The impact of inter-annual climate variability is therefore likely to be substantially underestimated by the earlier study [23] and again emphasises the importance of accounting for decadal climate variability when modelling power systems with high levels of renewable generation.

4. Conclusions

Multi-decadal meteorological data at hourly resolution have been used to determine the impact of inter-annual climate variability on the nationally-integrated GB power system. A parsimonious and transparent modelling framework is established by combining several well-established physical-statistical-economic techniques. Four different wind-power installation scenarios are examined, broadly corresponding to no-wind-power, present-day, and National Grid's Gone Green 2025 and 2035 scenarios. The impact is summarised in table 3: as the amount of installed wind-power capacity increases, the total amount of energy required from other generators (coal, gas, nuclear) is reduced. Wind therefore contributes to decarbonising the power system but, consistent with [45, 46], the reduction is particularly pronounced for power plants expecting to operate as baseload rather than peaking (i.e., for long periods of the year rather than in short bursts). The introduction of additional

Table 3. A summary description of the changes in mean and inter-annual range for the power system metrics. Difference is taken between the MED and NO-WIND scenarios and expressed as a percentage of the NO-WIND value. Units on each underlying quantity used to calculate the percentage are provided for convenience.

Metric	Mean	Inter-annual range
Total annual energy requirement (TWh)	−26%	+290%
Peak load (GW)	−6%	−28%
Peaking plant energy (TWh)	+46%	+30%
Marginal mid merit plant (h)	−50%	+560%
Baseload plant energy (TWh)	−44%	+1100%

wind-power capacity also greatly exacerbates the year-to-year variability in operating opportunity for conventional generators, particularly for baseload type plant (e.g., a 2035 scenario leads to a several-fold increase in the year-to-year variability). The impact of inter-annual climate variations across the power system are non-trivial, and changes due to increasing wind capacity represent a several-fold increase on historic experience. Indeed, even the present-day level of wind-farm installation has approximately doubled the exposure of the GB power sector to inter-annual climate variability.

Climate variability therefore has significant implications for the operation of the power system and this variability is likely to become increasingly important under many plausible near-future wind power scenarios. Moreover, although this study addresses only wind-integration in the GB power system in detail, it is likely that qualitatively similar results would be found for many other power systems seeking to integrate high shares of renewables in regions of strong climate variability (e.g., Western Europe). This study adds to a growing body of evidence which suggests that the power system modelling community should begin to take a more robust approach to its treatment of weather and climate data and, crucially, incorporate a wider range of climate variability (see section 3.4).

The modelling approach presented provides a tractable, efficient and transparent framework for identifying and understanding the impact of inter-annual climate variability on the power system as an integrated whole. It is therefore an advance on previous climate impact studies that have addressed power system components only in isolation, yet its simplicity should enable it to be readily applied to a wide range of climate datasets and other large-scale power systems. This modelling approach would likely be particularly useful for countries which have limited demand and supply data and have future plans to incorporate large quantities of wind power generation. The reliance on meteorological re-analysis data rather than complex power system modelling tools allows for the impacts of climate variability to be quickly identified. We do not claim that this methodology reduces the need to use more sophisticated models of the power system—either to address questions of long run economic investment or short run operational dispatch—but we do claim that the results presented here raise some concerns about the robustness of power systems planning studies which have relied on crude or short representations of climate. We conclude that the detailed nonlinear processes through which long-term climate variability and change effects the power system deserves much more attention from the community than it has received to date. Given this, system planners should treat the results of previous studies using sparse weather data with caution.

Acknowledgments

This research is funded by the Natural Environmental Research Council (NERC) under Grant 1362178.

Appendix

A.1. Demand model

The demand model takes two parts. Firstly, the daily-mean demand is estimated using a regression-based technique. This is then downscaled to hourly resolution using a set of fixed diurnal cycles, shown in figure A1.

The daily-mean component uses land-only daily-mean 2 m temperatures, T, spatially averaged over the GB region (11.3W−2.7E, 50N−59N) taken from the MERRA reanalysis (available from: https://gmao.gsfc.nasa.gov/reanalysis/MERRA/). Land-only grid boxes are defined as those within MERRA with a land fraction of greater than 50%. A multiple linear regression model in the style of [39] is created, for day t, of the form:

$$\begin{aligned}\mathrm{Demand}(t) &= \alpha_1 + \alpha_2(t) + \alpha_3\sin(\omega t) \\ &+ \alpha_4\cos(\omega t) + \alpha_5\mathrm{Te}(t) + \alpha_6\mathrm{Te}^2(t) \\ &+ \sum_{k=7}^{8}\alpha_k\mathrm{WE}(t) + \sum_{l=9}^{12}\alpha_l\mathrm{WD}(t) + \alpha_{13}\mathrm{HOL}(t),\end{aligned} \tag{1}$$

where the 'effective temperature' is $\mathrm{Te}(t) = \frac{1}{2}T(t) + \frac{1}{2}\mathrm{Te}(t-1)$. The α's are regression coefficients. α_2 represents an exogenous time-trend (e.g., changes in GDP, population, energy efficiency, and embedded wind-power generation [47]). α_3 and α_4 correspond to the mean annual cycle of exogenous demand drivers (e.g., human behavioural patterns and use of lighting). α_5 and α_6 correspond to the weather drivers of demand. α_7 to α_{13} are binary values accounting for exogenous behavioural factors, with WE, WD and HOL respectively corresponding to weekends, weekdays and major national holidays (Christmas, Easter and Bank Holidays). Only four weekdays have been included in the model as no statistically significant change was found for fridays (p value was found to be greater than 0.1).

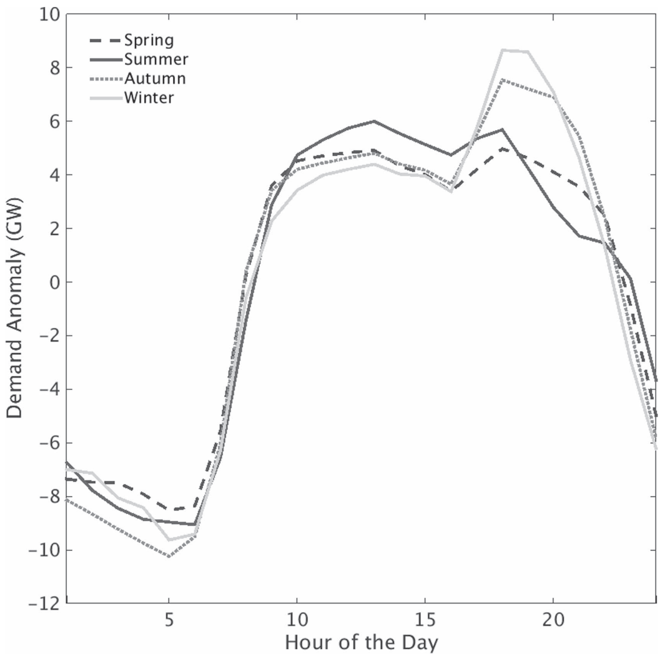

Figure A1. Composite diurnal demand cycles for each meteorological season of the year, expressed as an anomaly from the mean daily demand. Seasons are defined as Spring (March–May), Summer (June–August), autumn (September–November) and winter (December–February.) created from the average of the 2005–2012 demand data.

Table A1. Demand model regression coefficients for the training period from 2006–2015. The terms are described as in equation (1). Weather dependent terms are shown in bold.

Regression parameter	Value
α_1	1409 (GW)
α_2	−0.68 (GW yr^{-1})
α_3	**0.28** (GW d^{-1})
α_4	**2.86** (GW d^{-1})
α_5	**−112.50** (GW K^{-1})
α_6	**48.69** (GW K^{-1})
α_7	−4.03 (GW)
α_8	−4.93 (GW)
α_9	0.33 (GW)
α_{10}	0.58 (GW)
α_{11}	0.65 (GW)
α_{12}	0.63 (GW)
α_{13}	−5.58 (GW)

The regression model is trained against metered daily demand data from 2006–2015 (source, [48]). The parameters derived are given in table A1. Regression parameters are found to be insensitive to the training period used. The model performs well compared to others of similar type (see [49]) with an R^2 of 0.95 and an RMSE of 1.09 GW (approximately 25% of the standard deviation in the recorded daily demand values).

The daily-mean demand data is downscaled to hourly resolution using a prescribed diurnal cycle. A different diurnal cycle is determined for each meteorological season based on the recorded 2006–2015 hourly demand data (figure A1). Examining individual years seasonal average diurnal cycles shows that the prescribed diurnal cycles are robust to the choice of year used in their creation from 00:00–16:00 and 22:00–23:59. There are some minor discrepancies between the shape of each years average diurnal cycles from 16:00–22:00 in Spring and Autumn, however, sensitivity analysis has shown that the shape of these cycles does not cause qualitative differences to the cumulative frequency distribution of hourly demand (not shown).

Each daily demand value (derived from equation (1)) is then downscaled to hourly resolution using a linear combination of relevant diurnal curves (e.g., the daily-mean demand for 1st December is downscaled using a 50%–50% weighting of the diurnal curves derived from the SON and DJF hourly data). At hourly resolution the resulting demand model performs well with R^2 of 0.78 and an RMSE of 3.55 GW (corresponding to 45% of the standard deviation in the recorded hourly demand values) for a validation period 2011–2012.

As the primary aim of this study is to isolate the impact of *weather and climate variability* on the power system it is advantageous to remove the variability due to trends, weekends and holidays (as these have no meteorological significance). In the remainder of this paper, the daily demand model is therefore reduced to equation (2) and is then downscaled to hourly resolution as before.

$$\text{Demand} = \alpha_1 + \alpha_3 \sin(\omega t) + \alpha_4 \cos(\omega t) + \alpha_5 T(t) + \alpha_6 T^2(t). \quad (2)$$

A.2. Wind-power model

Hourly time series of GB aggregated wind-power capacity factor from 1980–2015 are generated based on hourly 2, 10, and 50 m wind-speed data from the MERRA reanalysis, closely following the approach described in [10, 38], model available from: www.met.reading.ac.uk/~energymet/data/Cannon2015/Model.php.

Wind speeds are spatially interpolated to the locations of the 2012 GB wind farm distribution, then vertically interpolated using a logarithmic profile to approximate turbine hub height (80 m). Wind speeds are converted at each site into wind-power using a standardised wind-power curve and aggregated across GB to produce the hourly capacity factor (see [10, 38] for further details on the methodology and power curve used). This capacity factor can be converted into total wind-power generation by multiplying by the total installed wind-power capacity. As discussed in [10], the model reproduces the recorded 2012 wind-power output well with a correlation coefficient of 0.96.

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