



Interannual weather variability and the challenges for Great Britain's electricity market design

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1 **Interannual weather variability and the challenges for Great Britain's** 2 **electricity market design**

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8 **Abstract**

9 Global growth in variable renewable generation has brought significant attention to the challenge of
10 balancing electricity supply and demand. However, inter-annual variability of energy resources has
11 only recently begun to feature in energy system assessments and receives limited recognition in policy
12 discussion, let alone policy design. Meteorological reanalysis datasets that blend modern modelling
13 techniques with historic weather records are seeing increased application in energy system studies.
14 This practice offers insights for market and policy design implications as governments seek to manage
15 the changing energy landscape, as seen with the UK's introduction of the Electricity Market Reform
16 policy package. Here we apply a concise, Load Duration Curve based approach to consider the market
17 and policy implications of increasing variability in the Great Britain (GB) energy system. Our
18 findings emphasise the growing inter-annual variability in operating opportunity for residual mid-
19 merit and even baseload generation, alongside implications for capacity assurance approaches. The
20 growth in wind generation is seen to bring an accompanying opportunity for increased solar
21 generation, with its lower inter-annual variability and largely uncorrelated annual characteristic. The
22 results underscore the need for an increased recognition of inter-annual variability when addressing
23 market design and incentive mechanisms.

24 **Keywords**

25 Wind

26 Solar

27 Renewable variability

28 Reanalysis

29 Curtailment

30 Energy markets

31 **Highlights**

32 Meteorological reanalysis datasets benefit energy system studies

33 Load duration curve approach complements sophisticated system models

34 Inter-annual variability has implications for energy and capacity (power) based markets

35 Blended renewables solutions help mitigate inter-annual variability

36

37

38 **1. Introduction**

39 Global growth in variable renewable energy (VRE, primarily from wind and solar resources) has
40 brought significant attention to the challenge of balancing electricity supply and demand. However,
41 inter-annual variability of energy resources has only recently begun to feature in energy system
42 assessments and receives limited recognition in policy discussion, let alone policy design. This might
43 be considered surprising given the long-standing temperature sensitivity of electricity demand in
44 many regions [1–3] and subsequent year to year variations. Such variability has typically been
45 consigned to a treatment of long-term averages and ‘weather adjusted’ demand, as previously noted
46 by [4,5].

47 As operational experience with renewable generation has increased, so longer time series of power
48 output have become available for energy system studies. For example, the ENTSO-E transparency
49 portal now has generation and load data available for some 35 European Countries at sub-daily
50 resolution for 2014-2018 [6]. Despite this growing experience, meteorological methods are still
51 essential to assess the full range of potential weather impacts. In turn, longer time series of generation
52 output have supported increasing accuracy in synthesising energy generation from weather data.

53 Reanalysis based methods combine historical atmospheric records with state-of-the-art Numerical
54 Weather Prediction (NWP) tools to provide multi-decadal data sets with continuous, gridded, spatial
55 and temporal coverage. Following common use within the meteorological community, reanalysis
56 derived data have seen increasing application for energy-meteorology studies, e.g. [7–16]. Authors
57 have investigated the impact of inter-annual variability on power system aspects including demand
58 [4,5,16], wind power generation [13,14,17] and solar power generation [11]. Both demand and wind
59 power exhibit substantial inter-annual variability, due to their predominant dependence on
60 temperature and wind speed respectively [14]. The inter-annual variability of solar generation is small
61 by comparison, though variability in summer output is still substantial [11]. Reanalysis data is
62 produced by combining a short-range forecast with available observations, within the data
63 assimilation window (typically 6-12 hours, see [18] for further details and [19] for implications of
64 quality and quantity of observations). ‘Modern’ reanalysis datasets cover a relatively recent period, of
65 several decades, where satellite observations are available. The MERRA dataset used in this study is a
66 commonly used example of this type, described further in section 2.2.

67 Growing interest in high renewable energy systems has been accompanied by increasing
68 sophistication in the variability implications assessed in system level energy studies. Gross et al. have
69 reviewed and revisited the diversity of approaches used to assess the cost impacts of variability
70 [20,21]. Meanwhile, modellers have moved to combine the insights of operational power system
71 models with those from long term investment models [22]. Recently, hybrid modelling approaches
72 have been combined with reanalysis derived data sets, highlighting the sub-optimal implications of
73 planning power systems based on the weather in any one given year [23,24]. Care is needed, though,
74 as such system modelling approaches are highly sensitive to some very uncertain cost assumptions
75 [25]. As illustration, the UK Climate Change Committee [26] note cost estimates of onshore wind
76 falling from above 80 to below 50 £/MWh in some three years (compares latest 2020 cost estimates
77 with previous 2030 estimates used to inform the UK’s fifth carbon budget in 2015). Such financial
78 uncertainties bring a risk that weather sensitivities can be obscured and weather implications only
79 partly appreciated.

80 The low marginal cost and non-dispatchable nature of VRE can bring a threat to the economic
81 viability of other generating plant competing for market opportunity. This contributes to uncertainty
82 regarding the most effective market design to assure policy aims. Hirth et al emphasise the
83 significance of the ‘utilisation effect’ on residual plant, noting this as one aspect of ‘profile costs’, a
84 sub-set of the integration costs of VRE. Wind profile costs are estimated to be around 15-25 €/MWh
85 at 30-40% market share [27]. This disruption can be amplified for other power plant with extended
86 start-up and cool down periods (typified by nuclear plant, but also seen to some extent with coal
87 generators and high efficiency CCGT) and exacerbated by the capital-intensive nature common to
88 most low carbon generation options (especially nuclear and Carbon Capture & Storage). As a result,

89 debate continues whether energy only markets can ensure supply adequacy, or supplementary
90 capacity assurance mechanisms are needed [28].

91 In response to these challenges, alongside the imperatives for decarbonisation, energy security and
92 energy affordability, many countries have re-evaluated energy market design and / or introduced
93 incentive mechanisms. The UK has introduced a package of legislative measures, under the Electricity
94 Market Reform project. Experience from the early years operation of these collective measures is
95 under close international scrutiny, given the shared global nature of the challenges reflected [29]. Two
96 measures are of particular significance here:

97 - Contracts for Difference (CFD) provide an energy price mechanism to support new low carbon
98 generation. 15 year CFD contracts have been awarded to renewables schemes including wind and
99 solar generation, while a 40 year contract has been agreed for the new-build Hinkley Point nuclear
100 scheme. This process has been accompanied by an increased openness in cost assumptions [30],
101 including indicative load factor figures for generating plant, notably 93% for CCGT and 90% for
102 nuclear. These are stated as ‘maximum potential’ values while levelised costs will be higher when
103 plant is required to operate at lower load factors.

104 - The Capacity Mechanism¹ seeks to assure security of supply through a capacity (power) based
105 contribution. Contracts are available to all technologies that are not receiving other government
106 incentives, including demand side solutions. The level of capacity procured for any given year is
107 decided by the government, following a recommendation from National Grid. To determine this level,
108 a reliability standard traditionally known as ‘Loss of Load Expectation’ (LOLE) has been set as no
109 more than three hours per year [31]. (For a description of LOLE derivation see [32].) In practice, this
110 standard typically translates to periods where the System Operator must take exceptional actions
111 rather than direct supply interruption.

112 Interannual variability of energy and peak load have implications for the practical and economic
113 effectiveness of such market mechanisms. Within the CFD design, strike prices are agreed based on a
114 single long-term average capacity factor. Variability in actual, annual wind levels has the potential to
115 lead to over or underpayments as a result. Within Capacity Mechanism implementation, close
116 attention has been paid to long-term variability in establishing a target capacity margin; however with
117 this target margin set in advance there is no provision to adjust for actual weather influence each year.
118 With annual variations in peak, temperature sensitive electricity demand and wind contribution at the
119 moment of peak demand this can result in seemingly unnecessary generation being funded some
120 years, while shortfall of generation could still be expected during others.

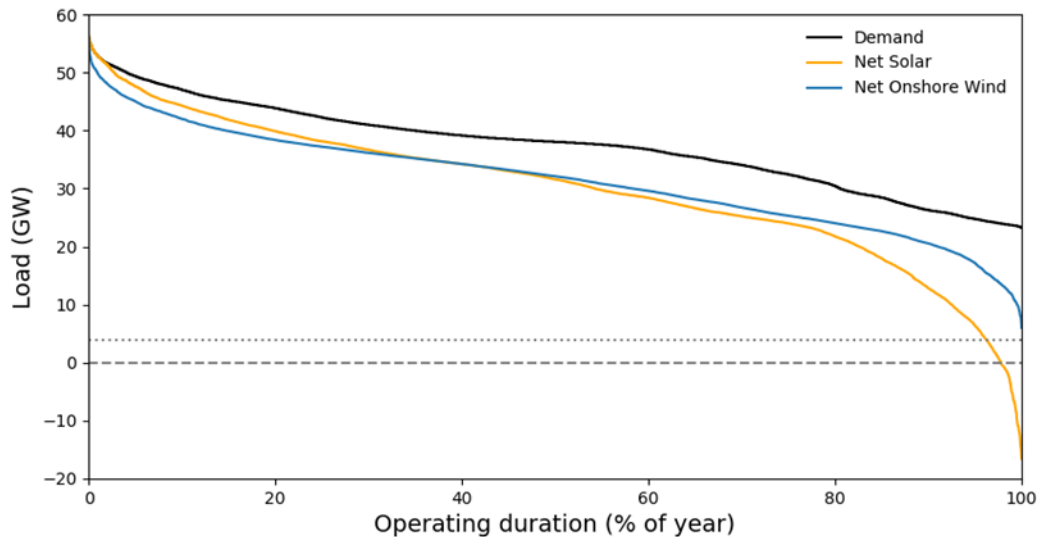
121 In this paper, we combine reanalysis derived, multi-decadal time series of historic UK weather data
122 with a Load Duration Curve (LDC) technique to explore the system implications of weather
123 sensitivity, especially the inter-annual variability in wind, solar and temperature influence. The LDC
124 approach entails certain simplifications but brings the advantage of isolating weather-based effects
125 from other economic and technical uncertainties. It also allows simultaneous assessment of energy
126 and power concerns. The challenge of long-term energy availability is quite distinct from the
127 challenge of peaks in instantaneous energy transfer rate (power). Further, the LDC approach allows
128 ready exploration of multiple years and extreme weather influences. We argue that the merits of this
129 framework justify parallel use to complement the application of more sophisticated energy system
130 models.

¹ During preparation of this paper, a standstill was imposed on the UK Capacity Mechanism following a judgment concerning State Aid interpretation at the General Court of the Court of Justice of the European Union. Although payments are not being made, the mechanism is still in operation, anticipating a full restoration of the scheme as soon as possible. See <https://www.gov.uk/government/collections/electricity-market-reform-capacity-market>.

131 **2. Method**

132 *2.1. The Load Duration Curve technique*

133 LDCs are a long-established analytical technique used by energy practitioners to assess the preferred
134 generating mix in a given power system, e.g. as used by [33], described by [34] and revisited in [35].
135 Often applied for a single year, an LDC shows the power level that is exceeded for each incremental
136 duration of the year. Figure 1 gives an example with a synthesised demand curve. Descriptors of
137 electricity generation roles vary. In this paper, we adopt the terms *peaking*, *load following* and
138 *baseload*, which can be broadly inferred as corresponding to horizontal areas on the left, middle and
139 right of the plot, respectively. Figure 1 has also adopted a common approach to VRE, by subtracting
140 generation in each hour from the demand requirement. This assumes a preference for renewable
141 energy, reflecting the low marginal cost and low carbon credentials of such plant, and results in
142 demand net renewable curves that show the operating opportunity available for other generating plant.
143 We follow previous authors in adopting the term *residual generation* to collectively describe plant
144 other than VRE.



145
146 *Figure 1. Example Load Duration Curve (LDC) – modelled energy timeseries for 2011. The dotted line indicates a reference*
147 *level of non-variable baseload plant, reflecting anticipated nuclear new build (see 2.4 below).*

148
149 *2.2. Data approaches and energy simulation*

150 This paper presents modelled electricity demand and supply for the Great Britain (GB) power system,
151 derived from long term weather data sets. This allows combinations of weather from a known year
152 with differing assumptions for the installed generating capacity cases. The reanalysis based models
153 and subsequent LDC framework are readily adaptable to any country-scale power system, given the
154 global nature of reanalysis data. In addition, information is required on installed renewable capacities
155 and a minimum of one year of metered energy data to train the regression models (as is available from
156 the ENTSOe transparency platform [6]).

157 The primary data source for the results presented below is the MERRA reanalysis [18]. MERRA data
158 starts from the beginning of the modern satellite era, covering the period from January 1979 -
159 February 2016. An updated product, MERRA2 is now available [36]; however, all results below
160 derive from MERRA following the extensive validation work completed to date for energy
161 simulation.

162 Consistent hourly, GB-aggregated, reanalysis derived time series have been prepared for the period
163 1980 – 2015, covering simulated wind generation, solar generation and electricity demand. This
164 follows work developed through a series of studies and extensively documented in previous papers.

165 The data used in this study are freely available for download from the University of Reading Research
166 Data Archive [37].

167 For the wind power model, 2 m, 10 m, and 50 m wind speeds on each horizontal level are bi-linearly
168 interpolated to each wind farm's location. The wind speed is then vertically extrapolated to the turbine
169 hub height, assuming a logarithmic change in wind speed with altitude. Hub-height winds are
170 converted to wind farm normalised power output using a non-linear transform function and multiplied
171 by the installed capacity to produce an estimate of farm output. Finally, the power output is summed
172 over all the wind farms in Great Britain (GB) to produce an hourly time-series of GB-aggregated wind
173 power generation. Extensive discussion of the model's validation is provided in [17]. Further
174 development to better distinguish between onshore and offshore resource is covered in [9].

175 The solar power model assumes the GB distribution of solar panels as of June 2017 (when some 12.5
176 GW was installed). The model divides Great Britain into 9 regions, determining the spatially-
177 averaged, hourly mean surface shortwave irradiance and 2m air temperature for each region.
178 Modelled data was compared with observations from Met Office weather stations and, consistent with
179 the findings of Boilley and Wald [38], seen to overestimate irradiance. A quantile-quantile bias
180 correction has therefore been applied to the regional irradiance data. No temperature correction was
181 required. A multi-linear regression approach is used to determine solar PV generation from the
182 meteorological variables. Model derivation is described in greater detail in [39].

183 Daily mean demand is determined using a multiple linear regression with daily average parameters
184 trained against recorded demand data from 2006-2015. The daily mean 2m temperature from MERRA
185 is spatially averaged over Great Britain and used to create an effective temperature. Non-
186 meteorological demand drivers include the weekly cycle of demand, national holidays and long-term
187 fluctuations due to changes in GDP, population growth and energy efficiency. The daily-mean
188 demand data is downscaled to hourly resolution using a linear combination of four prescribed
189 seasonal diurnal cycles. Full details of the model including the regression coefficients and its
190 validation are given in [4].

191 2.3. Capacity assumptions

192 The analysis below assesses demand and supply combinations for two sets of assumed generation
193 capacities. The capacity sets have been designed to ensure clarity of the role of VRE in the energy
194 mix.

- 195 • *Energy Equal* – Capacities that would result in an equal annual, average energy contribution
196 from each renewable resource. The blended case offers a total contribution from all resources
197 with a combined output equal to the energy from the individual resources. To achieve this an
198 extreme solar assumption is required, deemed unlikely until 2050 at the earliest. Meanwhile
199 wind capacities for the blended case must be held slightly below current levels.
- 200 • *2030 Plausible* – Here each case represents a plausible maximum, with individual resource
201 capacities drawn from different National Grid scenarios and a blend drawn from the scenario
202 with the highest overall renewable contribution. 2030 falls within the timeframe of influence
203 of current energy policy.

204 Table 1 presents *weighting factors* used in this paper to establish the installed generation assumptions.
205 Long-term average capacity factors² are calculated from the wind and solar power models (described
206 in section 2.2). The weighting factor is calculated as the long-term capacity factor for solar divided by
207 the relevant long-term wind capacity factor. These weighting factors are then applied as a ratio in
208 calculating the Energy Equal capacity assumptions presented in Table 2.

209 Table 2 presents the two sets of four capacity assumptions that are used throughout. Each set
210 comprises one value for each of the three individual resources and a single blend of all three. Relevant

² *Capacity factor* is a common usage, though often substituted with *load factor*, to describe 'Energy that can be produced by a generator as a percentage of that which would be achieved if the generator were to operate at maximum output 100% of the time' [21]. This source also includes an extensive glossary of other energy system terminology.

211 reference generation capacities have been selected from National Grid’s 2018 Future Energy
 212 Scenarios (FES) [40]. The FES scenarios, from the UK electricity system operator, reflect extensive
 213 stakeholder consultation adding credibility to their use in studies of this type. These scenarios include
 214 capacity projections for each year through to 2050, with particular attention given to 2030 and 2050.
 215 Values have been taken from the National Grid scenario which provides the most relevant figure for
 216 each of our capacity assumptions. The source scenario and year is stated where appropriate.

217

218 *Table 1 Long term capacity factors, from hourly reanalysis derived energy timeseries from 1980-2015*

	Capacity Factor (36 year mean)	Weighting factor
Onshore wind	28.80	0.389
Offshore wind	37.65	0.297
Solar	11.20	1

219

220 *Table 2 Capacity case assumptions. Installed capacities (GW), with National Grid scenario indicated in parenthesis where
 221 relevant.*

222 *(CR – Community Renewables, 2D – Two Degrees, SP – Steady Progression. 20, 30, 50 indicate projected years – 2020 etc)*

	Current capacities	Capacity set 1. Energy Equal		Capacity set 2. 2030 Plausible	
		Individual resource	Blend	Individual resource	Blend
Offshore wind	10.0 (SP20)	19.7	6.57	29.9 (2D30)	29.9 (2D30)
Onshore wind	12.8 (SP20)	25.8	8.60	23.4 (CR30)	19.5 (2D30)
Solar	13.7 (SP20)	66.2 (CR50)	22.1	33.0 (CR30)	24.3 (2D30)

223

224 *2.4. Other considerations*

225 By drawing on modern reanalysis data, the results below emphasise inter-annual variability inherent
 226 to the current climate system and note related energy market policy risk and uncertainties. The
 227 analysis does not include the additional uncertainty which could arise with a changing climate. New
 228 generations of high resolution climate models can also be used to understand potential impacts of
 229 climate change on weather-dependent power system components, such as demand [41] renewable
 230 generation [42–47] and power system operation [48,49]. As energy policy evolves to better reflect
 231 inter-annual variability, consideration will also be needed to such growing understanding of longer-
 232 term changes.

233 The demand model is based on the recent system demand characteristic and is exposed to uncertainty
 234 with changes in electricity using technologies, which can be expected to increase with growing
 235 electrification of heat and transport. Such trends have the potential to both increase and fundamentally
 236 alter the timing of electricity demand. The daily aggregation of data, presented in section 3.1.3,
 237 addresses this to an extent. (Aggregation assumes a midnight to midnight day). Daily aggregation
 238 indicates the maximum potential benefit that could be achieved with in-day storage or comparable
 239 flexibility approaches. Global energy systems are seeing rapid development of demand response,
 240 energy storage and alternative flexibility approaches such as controlled two-way connection of

241 electric vehicles (V2G or vehicle to grid). The greatest attention is being directed at in-day balancing
242 or daily peak reduction [27] which ensures high utilisation of the capital invested.

243 It is not currently known how market and operational preferences will discriminate between nuclear
244 and renewables as higher combined instantaneous system penetrations are reached. The system
245 operator might wish to maintain nuclear generation for stability contribution increasing short-term
246 curtailment of renewables. By contrast, an idealised market basis would give preference to renewables
247 with their even lower marginal generation costs (as indicated by [32]). In turn, higher CFD
248 agreements for new build nuclear could motivate higher negative price bidding and preferential
249 operation. Accordingly, certain graphs show a 4.2GW threshold, representing the capacity of new
250 nuclear operating under a CFD contract, expected to be operational by 2030.

251 The LDC approach brings value through illustrating a range of variability implications at a glance,
252 however results are best interpreted as the limiting case, especially when considering curtailment. The
253 approach neglects operational factors [50] which can contribute to relatively low levels of curtailment
254 with current and near future renewables penetrations. More sophisticated modelling is needed to
255 address plant start-up costs and ramping rate limits, as well as geographical power flow restrictions
256 which are currently leading to renewable generation curtailment in the UK. In contrast, the net-load
257 limits revealed by the LDC approach become increasingly significant as renewables deployment
258 increases towards the capacity levels in our test cases.

259 **3. Results**

260 *3.1. Resource comparisons, Energy Equal contributions*

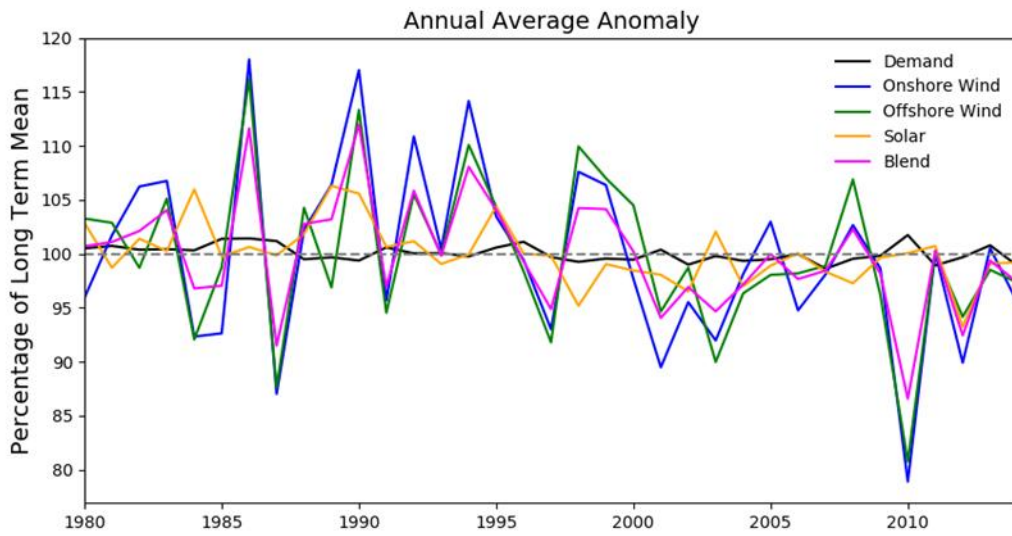
261 In this section we present results from the *Energy Equal* case described in section 2.3, with capacities
262 detailed in Table 2. These capacities ensure that the long-term energy supplied by VRE is equal in
263 each case. This allows the truest possible comparison of the influence of underlying variability.

264 Figure 2 shows the variation in annual resource capacity factors for the 36 year data range. Wind is
265 seen to exhibit a striking inter-annual variability, notably greater than solar, or weather sensitive
266 demand. The greatest wind energy is seen in 1986, while wind generation is lowest in 2010 alongside
267 high demand. It is curious to note rare years, 1982, 1988 and 2005, where onshore and offshore wind
268 anomalies show opposite signs.

269 Figure 3 examines the implications of the annual reference frame. When comparing years, it is
270 common practice for energy researchers to adopt a calendar year basis, e.g. [4,11,15,23,24]. However,
271 meteorologists would often group months into four seasons of three full months where weather is
272 most typically consistent within each season – DJF, MAM, JJA, SON (December, January, February
273 etc.) A calendar basis effectively splits each winter season across two separate years. Alongside the
274 calendar year, we present a UK financial year (April to March) and an astronomical year (February to
275 January). Of these, the UK financial year has the benefit of including a consistent meteorological
276 winter (DJF) and summer (JJA). This reveals some notable differences, especially for wind
277 generation, where the absolute inter-annual range is slightly reduced and 1986 is no longer a peak
278 wind year; closer examination reveals that a 1986 calendar year combines contribution from two high-
279 wind winters. A new peak year of 1992 is seen for wind with both financial and astronomical
280 framings. Other peaks are seen to shift years, dependent on the framing used. Whilst not influencing
281 long term mean or variance, the alternate framings do reduce extremes, most significantly for wind
282 power with max-min range reducing from 11.3% (calendar year) to 9.6% (financial year).

283 On this basis, we adopt a UK financial year for the remainder of analysis in this paper, unless
284 otherwise stated. Each year therefore incorporates the full winter season from the end of that year.
285 The implications of the chosen year frame are examined in more detail in section 3.1.2.

286

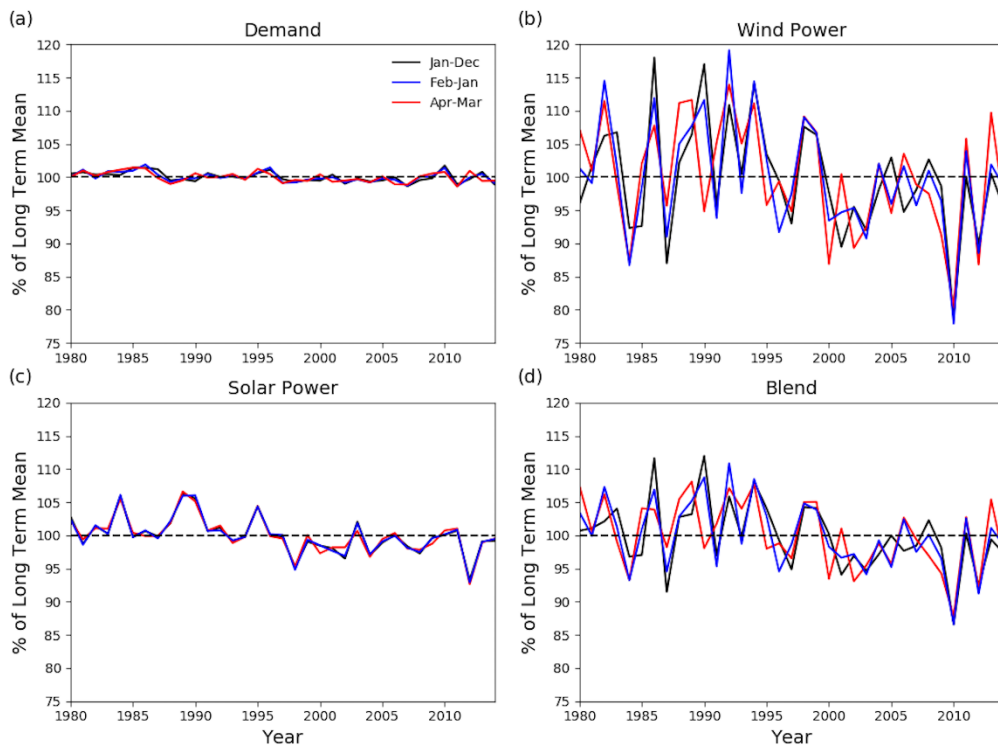


287

288 *Figure 2, Variation in annual capacity factors, given calendar year basis*

289

290



291

292 *Figure 3, Variability in annual energy output, given three annual framings (year commencing in each case). Offshore and*
293 *onshore wind are shown combined into a single wind time series.*

294

295 Pearson correlation values (defined as the ratio of the co-variance of the two variables to the product
 296 of their standard deviations [51]) between the annual (financial year) energy values shown in Figure 3
 297 are presented in Table 3. Wind energy exhibits a weak negative correlation with demand, the only
 298 notable correlation which demonstrates any reasonable significance, with a p value of 0.05. The weak
 299 significance values highlight the challenges in making such inter-annual comparisons with long-term
 300 datasets reduced to 36 data points. The alternate year framings were examined, though omitted here
 301 for brevity, revealing a further weakening of p values.

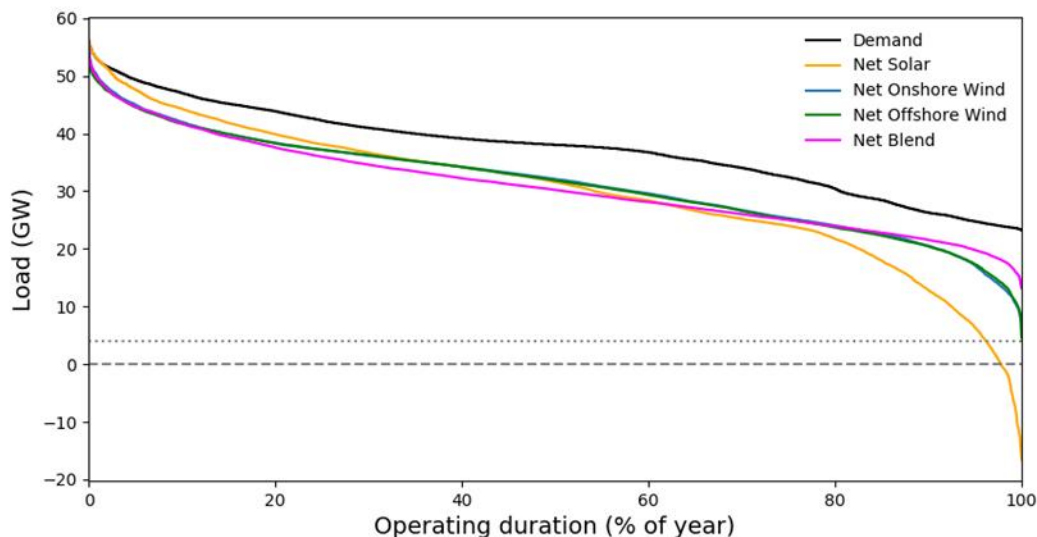
302 *Table 3. Comparison between inter-annual system influence for financial year basis. Stated values show Pearson's*
 303 *Correlation coefficient, with significance test p value outcomes in (...)*

	Demand	Onshore wind	Offshore wind	Solar	Blend
Demand					
Onshore wind	-0.33 (0.05)				
Offshore wind	-0.25 (0.15)	0.86 (<0.01)			
Solar	0.14 (0.43)	0.18 (0.30)	-0.06 (0.74)		
Blend	-0.27 (0.11)	0.97 (<0.01)	0.92 (<0.01)	0.24 (0.15)	

304

305 *3.1.1. Full range LDC curves*

306 LDC analysis for a single example year is presented in Figure 4. Given the equal energy contributions
 307 assumed, the area between demand and each net-generation curve must be the same, long-term,
 308 though not necessarily within an individual year. Widely recognised concerns with the solar resource
 309 are immediately evident. The net solar curve shows no contribution to peak load at the left hand
 310 extreme, together with significant disruption to operating opportunity for long-run residual plant (seen
 311 at higher operating durations). There is also a need for curtailment, indicated by negative net load.
 312 The net wind curves display a more promising profile, with no clear difference seen between onshore
 313 and offshore wind. In this particular year, some contribution is made to reducing system peak load
 314 and despite a notable drop towards the right-hand end of the curve, no significant curtailment
 315 concerns arise. The net blend curve shows an initially surprising contribution to system peak,
 316 alongside a minor reduction to baseload disruption, implying an improvement in terms of system
 317 contribution to the single wind cases.

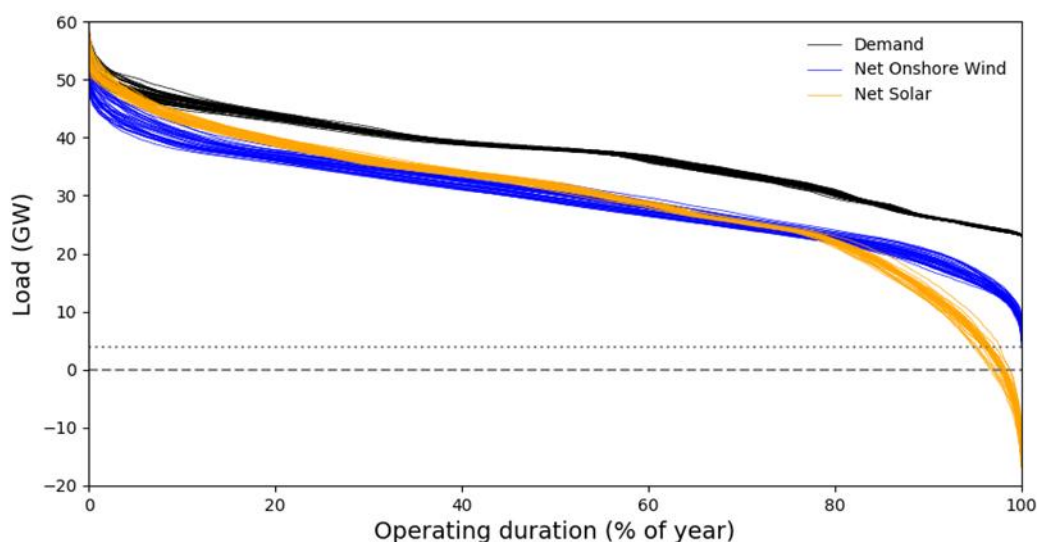


318

319 *Figure 4. LDCs for a single financial year (2011/12) – Energy Equal case. Dotted line indicates 4.2GW baseload*
 320 *contribution from anticipated new build nuclear generation.*

321 3.1.2. Batch LDCs – Interannual variability

322 In order to explore inter-annual variability, Figure 5 presents sets of 35 annual LDCs for each year in
323 the reanalysis datasets. Only solar and onshore wind resources are shown, for clarity. Although much
324 of the detail is still obscured by the amount of information on a single plot, some general trends can
325 be seen. Both the onshore wind and solar result sets indicate greater year-to-year variability than the
326 demand data set on its own. Caution is needed as the wind and solar curves here represent demand net
327 resource, so reflect temperature and resource variability.



328
329 *Figure 5. Annual LDCs for all years in reanalysis data set – Energy Equal case. Dotted line shows indicative new nuclear*
330 *baseload.*

331 A range of extreme years are identified in Table 4, given particular (a) annual energy and (b) power
332 characteristics. With growing recognition of inter-annual variability’s implications, it can be tempting
333 to seek specific extreme years for ‘stress testing’ within energy system studies. For example, in a
334 previous study we reported 1990 and 2010 were extreme weather years for UK demand influence, but
335 1986 and 2010 should be considered when wind supply is also a factor [4]. Similarly, [23] indicated
336 that the weather years 2012 and 1989 were the most representative for considering power system
337 operation at a European level. Both these studies adopted calendar year approaches. Table 4 reveals a
338 need for caution here. Peak load events occur in different years to extreme annual energy values. VRE
339 introduction further influences the extreme year, subject to capacity assumed. The choice of year
340 framing also has a significant effect. By adopting a financial year and considering overall energy
341 extremes, we find a different maximum demand year and further differences, including a change of
342 year for every lowest energy case examined.

343

344 *Table 4 Comparison of extreme years (Energy Equal case)*

345 (a) Total annual energy. Asterisk (*) denotes years where this LDC serves as the extreme case across full operating duration
 346 range.

	Year with highest total annual energy			Year with lowest total annual energy		
	Calendar year	Financial year	Astronomical year	Calendar year	Financial year	Astronomical year
Demand	2010	1985/86	1986/87*	2007	2011/12	2011/12
Net solar	2010*	2012/13	1986/87*	2014*	1989/90	2011/12
Net onshore wind	2010*	2010/11*	2010/11*	1990*	1988/89	1992/93
Net offshore wind	2010*	2010/11*	2010/11*	1990*	1994/95	1998/99
Net blend	2010*	2010/11*	2010/11*	1990*	1988/89	1992/93

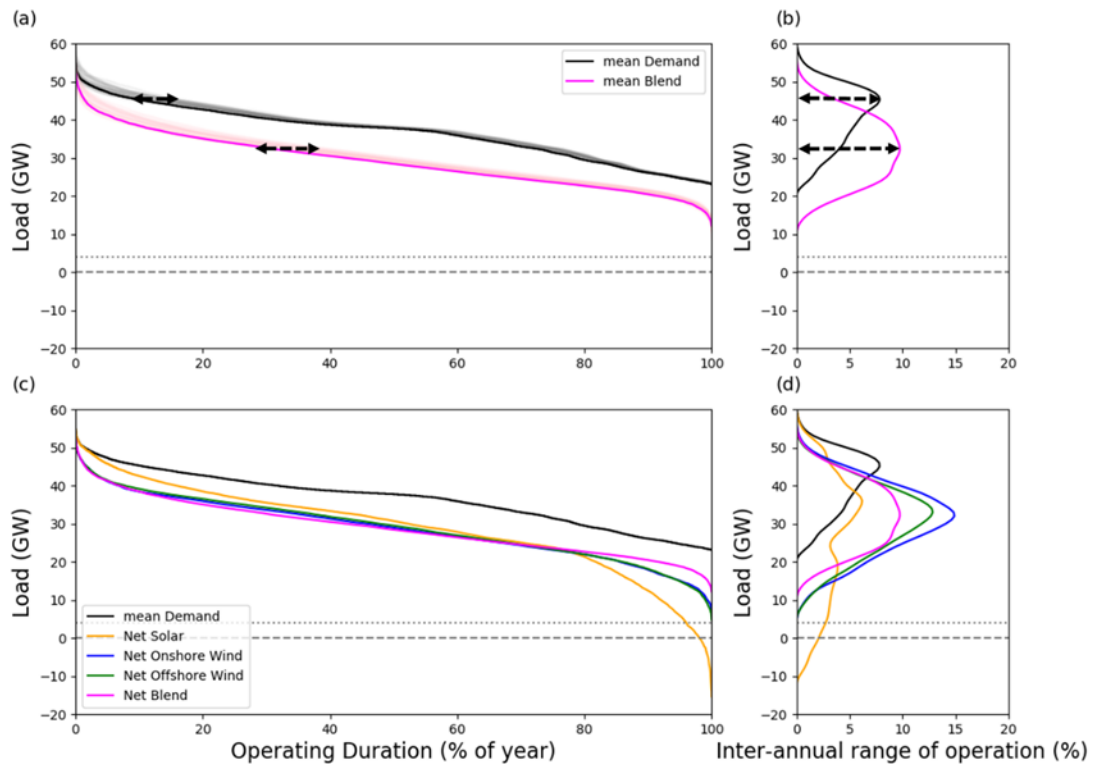
347 (b) Long term load extremes

	Max load (GW)	Calendar year	Financial year	Astronomical year	Min load	Calendar year	Financial year	Astronomical year
Demand	60.9	1987	1986/87	1986/87	23.0	Multiple	Multiple	Multiple
Net solar	60.9	1987	1986/87	1986/87	-17.0	2009	2009/10	2009/10
Net onshore wind	57.8	1982	1981/82	1981/82	4.0	1988	1988/89	1988/89
Net offshore wind	56.3	1985	1984/85	1984/85	4.4	1983	1983/84	1983/84
Net blend	56.5	1982	1981/82	1981/82	9.1	1996	1996/97	1996/97

348

349 Further analysis of the LDC batches has been carried out to investigate the spread between years, with
 350 conventional annual LDCs presented in Figure 6 panels (a) and (c). Panels (b) and (d) keep the same y
 351 axis as (a) and (c), respectively, but show the horizontal separation for each capacity level between
 352 the years with the shortest and longest operating opportunity. Black dashed arrows have been added
 353 for two example load levels to translate the spread in LDC curves from panel (a) to the separation
 354 shown at the same level in panel (b).

355 Onshore wind shows the highest spread between years, a little above that from offshore wind. By
 356 contrast, the net-solar line indicates the lowest inter-annual variability, reducing the spread at any
 357 given capacity level below that seen for demand alone. This comes at the expense of a greater
 358 disruption to the opportunity for longer running residual plant. At this installed capacity, solar leads to
 359 hours where negative load is seen with a high, relative inter-annual variability. Blending resources
 360 offers multiple benefits, by reducing inter-annual variability further below offshore wind, while
 361 simultaneously smoothing the disruption to residual plant.

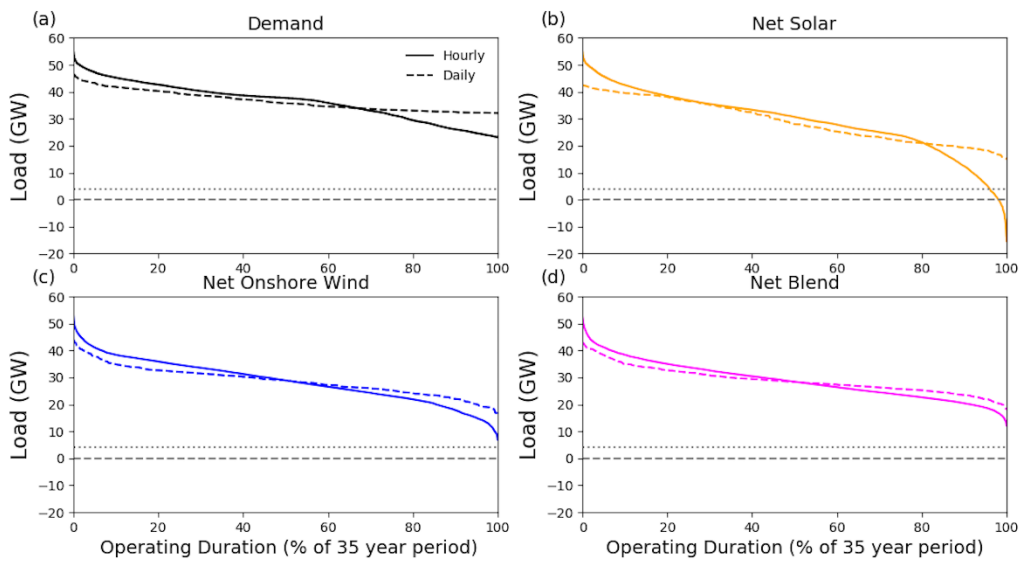


362

363 *Figure 6. 35 year LDCs and analysis of inter-annual spread – Energy Equal case. In panels (a) and (c) solid lines represent*
 364 *the LDC for 2011, the most typical single year. Panel (a) also includes shading to show the range exhibited by all annual*
 365 *LDCs. Black, dashed arrows on panels (a) and (b) show how the horizontal spread translates to the inter-annual range seen*
 366 *in panels (b) and (d). Dotted line shows indicative new nuclear baseload.*

367 3.1.3. Daily smoothing, full range LDCs

368 Widespread attention is being given across the energy industry to the development and
 369 implementation of energy storage and other flexibility approaches. (Flexibility is used as a collective
 370 term below to include storage.) Much of this is explicitly linked to the challenges of integrating
 371 variable renewable generation. This brings a potential contradiction for the analysis here, which seeks
 372 to identify the fundamental constraints brought by meteorological factors, without introducing the
 373 other uncertainties inherent in much techno-economic modelling. Accordingly, we have tested daily
 374 aggregation to scope a limiting case for flexibility introduction, without needing to make assumptions
 375 about economic potential. This is consistent with the great majority of currently proposed solutions,
 376 which are best suited to daily, or more frequent, operation. Figure 7 presents long-term LDCs (1980 –
 377 2015) for the Energy Equal capacity set, using data aggregated to daily values. The daily match
 378 between each resource and demand represents the limiting case that a perfectly operated store could
 379 deliver if sized for maximum daily imbalance.



380

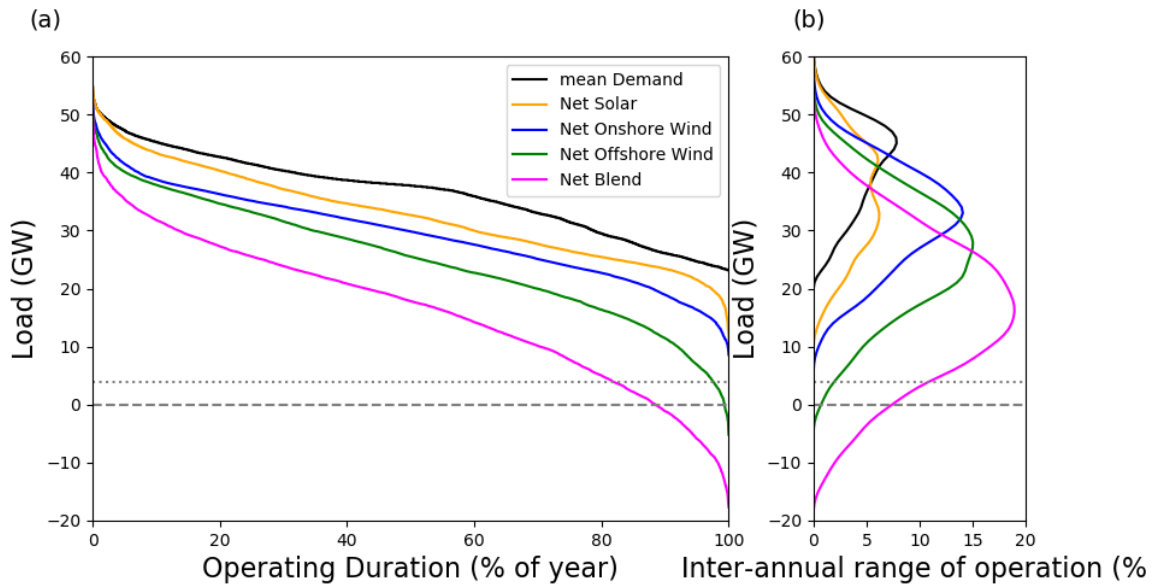
381 *Figure 7. Hourly and daily smoothed 35 year LDC for Energy Equal case. Dotted line shows indicative new nuclear*
 382 *baseload.*

383 It can be seen from Figure 7 (a) that adding flexibility to demand alone, provides a significant
 384 advantage, both reducing peak load and expanding the residual operating opportunity at high load
 385 factors. The greatest benefit is seen with the solar resource (b), showing a slight additional reduction
 386 in system peak and a dramatic increase in operating opportunity for baseload plant. However, the
 387 vertical gap between hourly and daily lines informs the power capacity of store that would be needed.
 388 The improvement seen for solar requires close to 30GW of storage capacity. By contrast the blended
 389 case (d) shows a more subtle, but more promising improvement. A gap is seen between the daily and
 390 hourly curves across a wide spread of operating durations, indicating potential for high storage
 391 utilisation. Further, the capacity contribution is similar for both peak reduction and baseload
 392 improvement, requiring a more modest power capacity of storage, no greater than 10GW.

393 *3.2. Renewable expansion*

394 This section examines the 2030 Plausible capacity assumptions, derived in section 2.3 (individual
 395 capacities of 33.0 GW solar, 23.4 GW onshore wind, 29.9 GW offshore wind, and a blended case
 396 comprising 24.3 GW solar, 19.5 GW onshore wind, 29.9 GW offshore wind). The individual
 397 capacities for solar and onshore wind are lower than those assessed above, whereas offshore wind is
 398 now higher. The blended capacity here is considerably higher than the individual resource cases.

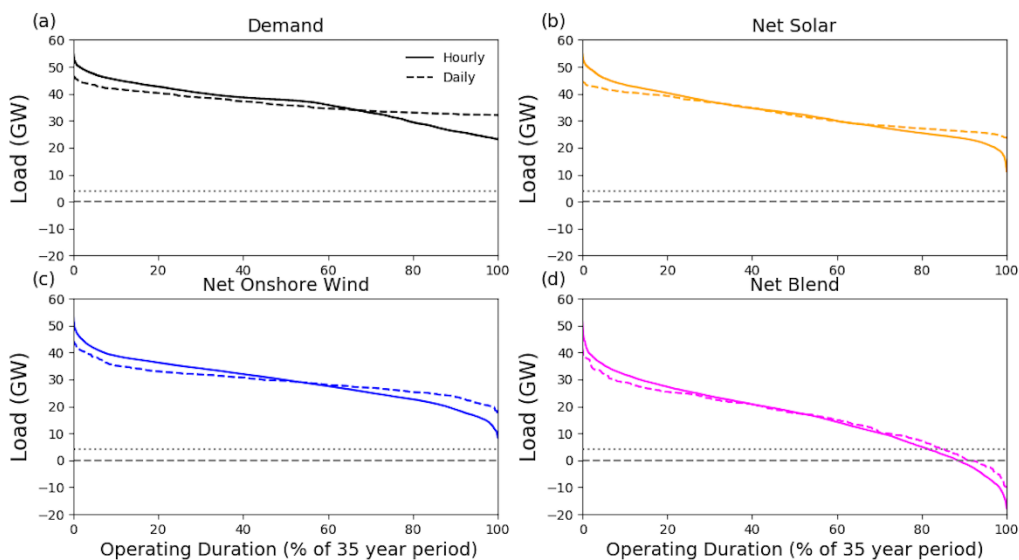
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Figure 8. LDC inter-annual spread analysis – 2030 Plausible capacities (a) Single year typical LDC (2011) and (b) spread analysis. Dotted line shows indicative new nuclear baseload.

403 The increased capacity of offshore wind and the blended case contributes to emerging challenges,
 404 with Figure 8 showing a significant reduction in the operating opportunity for residual baseload plant.
 405 The blended case indicates that substantial curtailment could be expected and from panel (b) that there
 406 would be a sizeable swing from one year to another in both curtailment level and baseload disruption.
 407 The horizontal dotted line reflects a possible 4.2GW of new nuclear plant and a 10% horizontal range
 408 in the operating opportunity is seen at this level. This represents a range to either side of the 80%
 409 value shown in panel (a). Given uncertainty in market preference between renewable generation and
 410 new nuclear this could translate either as lost operating opportunity for nuclear or increased renewable
 411 curtailment. From Figure 9 (d) it can be seen that daily smoothing provides a modest improvement but
 412 does not eliminate the need for curtailment.

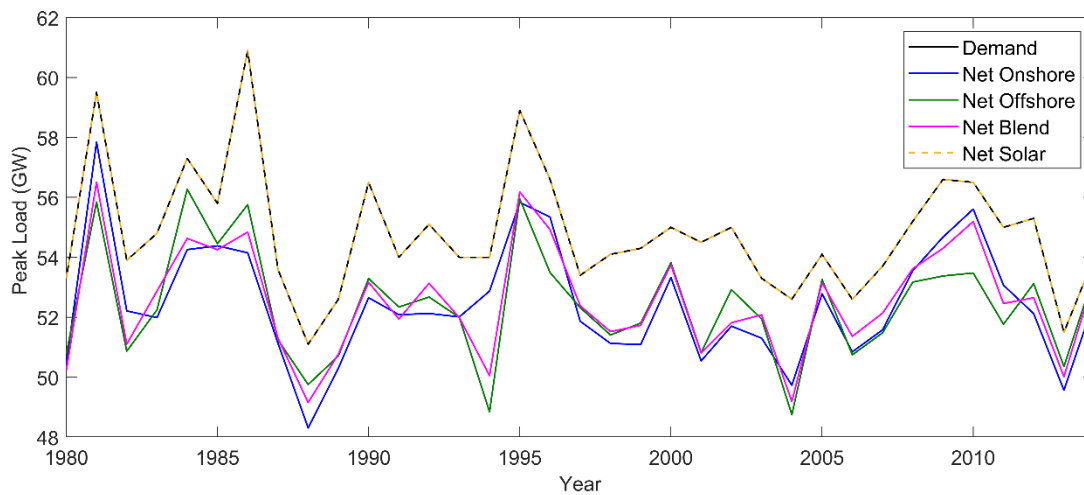


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Figure 9. Hourly and daily smoothed 35 year LDC for 2030 plausible capacities. Dotted line shows indicative new nuclear baseload.

417 3.3. Variability of peak demand: Energy Equal

418 Annual peaks for demand only and Energy Equal net-renewables cases are shown in Figure 10. There
 419 is a large inter-annual variability in peak demand, with a range of 51.1 GW to 60.9 GW. All these
 420 events occur during the darkness peak in winter when there is no contribution from solar. As a result,
 421 lines for demand and solar are coincident throughout the entire range. Wind generation leads to a
 422 reduction in the peak residual demand in all years, though this varies widely. For example, for the
 423 1985-86 winter the peak is reduced by 6.1 GW, in comparison to only 0.7 GW for the 2013-14 winter,
 424 albeit a lower reduction from a lower peak. Peak reduction is broadly similar for the onshore, offshore
 425 and blended resources. However, certain anomalous years invite further investigation to understand
 426 the large-scale meteorological drivers of peak residual demand as the capacity and ratio of offshore
 427 and onshore wind changes.



428
 429 *Figure 10, Long term variation in annual peak demand / residual demand (Energy Equal case, financial year basis)*

430 This section explores the occurrence of demand exceeding supply if a consistent long-term generating
 431 capacity is set based on an average Loss of Load Expectation (LOLE) of three hours per year (as
 432 outlined in Section 1). With 35 years in the data set, this translates to 105 hours in total. Table 5
 433 presents the capacity level that would be exceeded for 105 hours given Energy Equal capacity
 434 assumptions. Figure 11 presents the number of hours in each year that these capacity levels would be
 435 exceeded. Consistent with the approach used throughout, this describes what would be seen if historic
 436 weather conditions aligned with the assumed capacity assumptions. This should not be directly
 437 compared with the UK System Operator’s Average Cold Spell method, which applies a statistical
 438 sampling approach in combination with a demand model to establish a winter peak demand with a 50
 439 per cent chance of being exceeded as a result of weather variation alone [52].

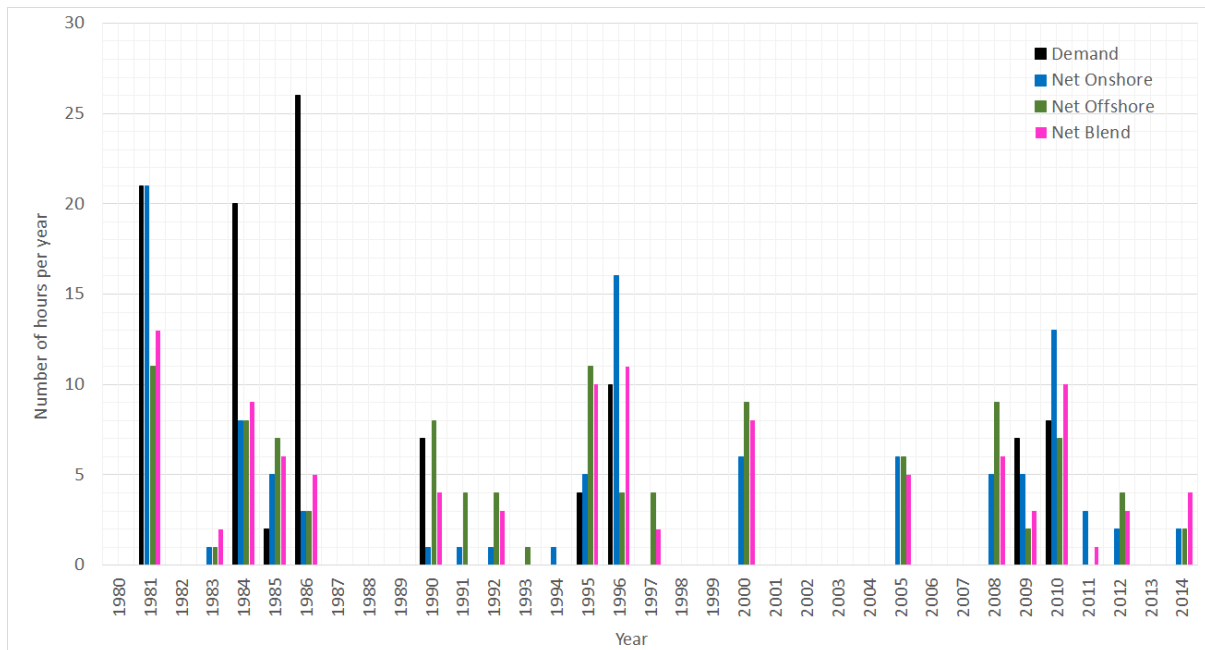
440 *Table 5 Capacities required to maintain long-term LOLE of 3 hours per year*

	Capacity requirement (GW)
Demand	55.9
Net onshore wind	52.7
Net offshore wind	52.4
Net blend	52.9

441
 442 Taking a long-term average LOLE threshold leads to a large range in the number of hours of capacity
 443 exceedance in any given year, as seen in Figure 11. This is particularly the case for demand only (27
 444 hours in 1986-87 whereas in many others it can be zero). Initially it appears surprising that renewable

445 based cases demonstrate a lower range. However, closer analysis of the demand only data has shown
 446 that peaks in 1981-82, 1984-85 and 1986-87 include multi day events. By contrast, introducing
 447 renewables decreases the number of multi-day events, with the presence of wind acting to reduce
 448 persistence and smooth out the combined effect of wind supply and demand.

449



450

451 *Figure 11, Annual loss of load, given total system capacity required to achieve long term average of 3 hours.*

452 **4. Discussion**

453 Variability of renewable power generation has been represented with growing sophistication in energy
 454 system modelling studies to reflect the technical and economic challenges of operation and / or
 455 investment. Widespread uncertainty is seen, though, especially when multiple studies are compared,
 456 with particular exposure to economic uncertainties. One consequence can be to obscure the influence
 457 of fundamental weather characteristics. There is a need for approaches which give policy makers
 458 greater visibility of underlying meteorological influences, in a manner which can be distinguished
 459 from other social, technical and economic assumptions. Inter-annual variability is especially
 460 significant in this context. Alongside the recognised need for sophisticated modelling, there is a role
 461 for relatively simple energy system assessment approaches which can highlight sensitivity to
 462 meteorological drivers and allow closer scrutiny of weather influence.

463 Energy applications of meteorological approaches have grown in sophistication alongside the growth
 464 of renewable generation. One notable advance has been the increasing use of meteorological,
 465 reanalysis datasets. The analysis presented above adds weight to our earlier argument [4] that energy
 466 modelling studies should seek to use the longest feasible range of weather data and that this must span
 467 multiple years, more recently supported by multiple studies including [16,23,24]. Such practice is
 468 increasing but not yet widespread, as it can be attractive to use single years for ease of computation
 469 and data representation. Stress testing with just a few extreme years can offer a compromise but must
 470 be approached with caution. We are not aware of any previous consideration of the implications of
 471 annual reference frame. Our exploration has shown that care is needed in considering the annual
 472 reference basis and the specific research question if selecting such sample years. Clarity can be
 473 improved by choosing an annual frame that reflects meteorological factors. By example, a UK
 474 financial year corresponds to approximately complete ‘meteorological seasons’ whereas a calendar
 475 year splits the meteorological winter season (DJF).

476 The analysis above suggests a higher value for solar generation in temperate climates than previously
477 recognised. It has been widely argued that solar energy brings little system value in high latitude
478 countries, such as the UK, where electricity demand is highest during cold, dark, winter evenings. By
479 contrast, a load duration perspective emphasises the likelihood that solar generation is available when
480 wind generation is not. This is shown by the difference between the wind only and blended cases in
481 Figure 6. When added to a system that already has moderate levels of wind generation, there is greater
482 operating opportunity for new solar than for continuously operating plant such as baseload nuclear.
483 Similarly, a mix of wind and solar offers greater opportunity for other plant than an equal energy
484 contribution from wind alone. Solar output also exhibits a much lower inter-annual variability than
485 wind, with little or no correlation seen with demand or wind. A sizeable solar contribution can
486 therefore go some way to mitigating the inter-annual variability of wind supply.

487 Electricity system decarbonisation is bringing new challenges for energy market design. Section 1
488 noted an ongoing debate whether energy only markets can ensure supply adequacy, or supplementary,
489 power linked, capacity assurance mechanisms are needed. Inter-annual variability will bring different
490 implications for the UK's CFD and Capacity Mechanism schemes, set to grow with further, planned
491 increases in renewable generation:

492 - Figure 8 indicates that certain mid-merit plant could face inter-annual load factor variation above
493 15%. For plausible 2030 installed capacities, the blended case shows a maximum 19% inter-annual
494 range in operating opportunity for residual plant with a typical load factor of 60%. This contrasts with
495 a 5% range for the no renewable case and would represent a significant economic uncertainty for
496 plant with high capital costs. This would also be reflected as a difference in annual CFD payments,
497 exposing such schemes to criticism for being too generous in years when output is high.

498 - Annual peak demand is seen to vary by up to 10GW for the demand only case in Figure 10 (using
499 Energy Equal capacity assumptions). This range represents an inherent risk with the Capacity
500 Mechanism. Any threshold that ensures robust adequacy across all years will reward plant that
501 appears unnecessary in many or most years. The demand only variation here is entirely a feature of
502 temperature variability. It is slightly surprising that introduction of renewables reduces the inter-
503 annual range in residual demand to approximately 6.5GW (blended case). This suggests renewables
504 can reduce Capacity Mechanism uncertainty. Our demand model should be treated as indicative, here;
505 the model is calibrated with system demand recorded across 2006-2015 and demand-side energy
506 using technologies are changing rapidly. Any increase in the adoption of electrical heating would be
507 expected to amplify the sensitivity to temperature.

508 As well as assuring physical generating capacity, it is common system design practice to accept some
509 level of lost load each year. Once again, inter-annual variability brings a risk for the perceived
510 effectiveness of energy policy / system planning. Figure 11 estimates the number of weather
511 influenced loss of load events that would have been experienced each year given a long term average
512 of 3 hours LOLE per year. Surprisingly, the highest number of events in any individual year comes
513 with the demand only case. The blended renewables case is seen to reduce the severity of system
514 stress events. In mature systems such as the UK, 'lost load' is very unlikely to mean uncontrolled loss
515 of supply, but instead suggests periods where the system operator can call on certain non-routine
516 measures to maintain system balance. This reflects a balance between the cost implication of such
517 actions and the cost of retaining rarely used generating plant. Detailed analysis suggests that years
518 with higher LOLE are driven by persistent weather events. Increasing wind generation leads to a
519 reduced likelihood of persistent stress events as low temperatures do not coincide exactly with low
520 wind speed periods.

521 **5. Conclusions**

522 In seeking the policy implications of inter-annual renewable energy variability, we have chosen to
523 apply a simple modelling framework. This has allowed us to concentrate specifically on the behaviour
524 and implications of the underpinning weather characteristics, which are widely recognised to have a
525 growing significance for global energy systems. We note and fully encourage the increasing adoption
526 of long-term weather data sets within studies that use more sophisticated energy system models.

527 However, we argue that significant value remains in using more parsimonious approaches in parallel.
528 Care is needed not to lose sight of weather fundamentals which can be masked by other highly
529 uncertain assumptions of technologically rich and mathematically sophisticated models, not least
530 uncertain economic factors such as plant cost assumptions and financial discount rates.

531 Although inter-annual variability has seen recent, growing recognition in energy system research, it
532 has commonly been neglected in policy discourse where long-term average approaches are widely
533 used. The significance of inter-annual variability will increase markedly in energy systems that deploy
534 greater electrification of heating alongside higher levels of variable renewable energy. This suggests a
535 need to consider which market actors are best placed to manage long term variability and view
536 revenues across multiple years rather than single annual accounting periods. This needs to be reflected
537 in the design of electricity markets and in any related incentive mechanisms.

538 - The operating opportunity for mid-merit and baseload generation will vary substantially from one
539 year to another. This could be highly problematic where sole reliance is placed on energy payments to
540 cover fixed costs.

541 - Consideration of capacity assurance approaches needs to better reflect inter-annual variability as the
542 characteristics of demand net renewables will deviate increasingly from absolute demand

543 - The operating opportunity for energy storage also presents problematic inter-annual variability. This
544 suggests that energy storage cannot be economically deployed to absorb all curtailment that could
545 otherwise occur in a high renewable system.

546 Perhaps more surprisingly, notable benefits are seen from increasing the level of solar generation
547 when long-term variability is considered. Solar energy displays significantly lower inter-annual
548 variability and little or no correlation with wind generation, as well as a gap-filling role when shorter
549 timescales are addressed. Blends of renewables which include a sizable solar contribution benefit
550 from this reduced inter-annual variability and show less disruption to the operating opportunity for
551 other generating plant requiring high load factors.

552 The need for energy policy approaches to reflect the increasing impact of weather variability can be
553 supported by growing sophistication in meteorological methods. While comprehensive weather
554 records span mere decades and climate change introduces new unknowns, studies drawing from state-
555 of-the-art, high-resolution climate models are expected to offer increasing insights. Our analysis
556 emphasises the value of a diverse resource mix when moving to a high renewable system, with solar
557 energy bringing benefits that might seem surprising for a country such as the UK, with a poor solar
558 resource and high winter energy demand. Above all, an increased recognition of inter-annual
559 variability is needed when addressing energy market design and any incentive mechanisms deployed.

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567 components of the enabling research.

568 **Data Availability**

569 The data used in this study are freely available for download from the University of Reading Research
570 Data Archive, at <https://researchdata.reading.ac.uk/191/> [37].

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