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Communication

Implications of the North Atlantic Oscillation for a UK–Norway Renewable power system

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HIGHLIGHTS

- Increasing use of weather-sensitive renewables in European power system.
- Multi-decadal data used to examine weather-sensitivity of idealised UK–Norway system.
- Each system component (wind, hydro, demand) affected by long-term weather patterns.
- Weather-sensitivity of combined system enhanced compared to isolated components.
- Sensitivity increases rapidly under plausible future wind generation scenarios.

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ABSTRACT

UK wind-power capacity is increasing and new transmission links are proposed with Norway, where hydropower dominates the electricity mix. Weather affects both these renewable resources and the demand for electricity. The dominant large-scale pattern of Euro-Atlantic atmospheric variability is the North Atlantic Oscillation (NAO), associated with positive correlations in wind, temperature and precipitation over northern Europe. The NAO's effect on wind-power and demand in the UK and Norway is examined, focussing on March when Norwegian hydropower reserves are low and the combined power system might be most susceptible to atmospheric variations. The NCEP/NCAR meteorological reanalysis dataset (1948–2010) is used to drive simple models for demand and wind-power, and 'demand-net-wind' (DNW) is estimated for positive, neutral and negative NAO states. Cold, calm conditions in NAO− cause increased demand and decreased wind-power compared to other NAO states. Under a 2020 wind-power capacity scenario, the increase in DNW in NAO− relative to NAO neutral is equivalent to nearly 25% of the present-day average rate of March Norwegian hydropower usage. As the NAO varies on long timescales (months to decades), and there is potentially some skill in monthly predictions, we argue that it is important to understand its impact on European power systems.

1. Introduction

Renewable energy generation is rising throughout the EU, partially driven by targets in the 2009 Renewable Energy Directive (European Parliament, 2009) that 20% of all energy consumed be produced from renewable energy sources by 2020. Since the target refers to all forms of energy, this corresponds to approximately 30% of electricity generation from renewables (ENTSO-E, 2011).

Renewable energy sources such as solar and wind power are sensitive to weather. One strategy to deal with this is to increase power system interconnectivity at international scales. A link between the UK and Norway is proposed, of 1.6 GW by 2020 (ENTSO-E, 2011) and potentially 6 GW by 2030 (Keane and Pearce, 2011). The national power systems involved are, however, very different. Norwegian electricity generation is dominated by reservoir storage hydropower (ENTSO-E, 2011), which can respond rapidly to changes in demand, although over long (annual) timescales production may be constrained by water availability and therefore temperature and precipitation. In contrast, UK renewable energy generation is principally from wind (ENTSO-E, 2011), a source which is variable on a range of timescales (Sinden, 2007) and associated with price variability (Cox, 2009; Pöyry, 2010). A possible benefit of a transmission link would be to use hydropower to meet the short-term (hours to days) shortfalls in total generation during low wind events (e.g., Pöyry, 2011). However, it is also important to consider the behaviour of the linked resource

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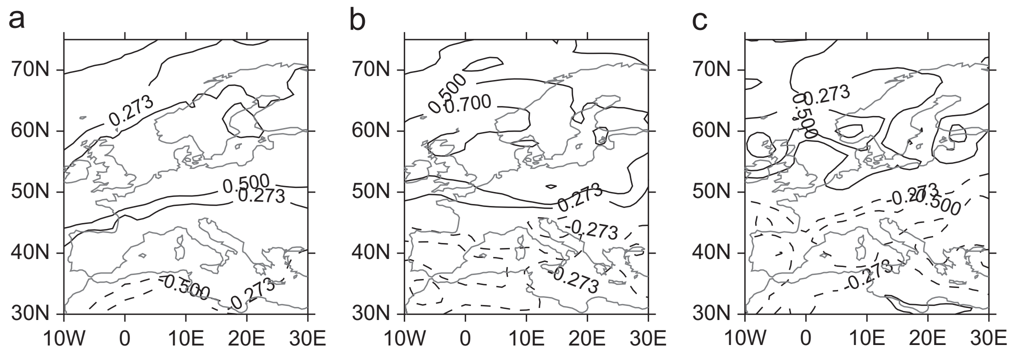

Fig. 1. Climatic impacts of the NAO in winter, given as the 1950-2010 temporal correlation between the DJFM NAO index and the DJFM average of a) 2m temperature T (°C); b) 10m wind speed u (ms^{-1}); c) precipitation rate Q (mm day^{-1}). Seasonal averages of T, u and Q are computed from the NCEP reanalysis data introduced in Section 2. The 0.273 contour would indicate the boundary of statistical significance at the 95% confidence level under the assumption of Gaussian variables. Here and throughout the study Pearson linear correlations are used.

on longer timescales (weeks, months and years) including situations where sustained periods of below-average wind combine with other stressors on hydro-availability such as sustained high demand or delayed/reduced recharge rates.

Previous studies have examined the effect of meteorological variability on individual aspects of the power system. Sinden (2007) and Oswald et al. (2008) found that spatial aggregation of UK wind power produced limited smoothing of high frequency variability in wind power output, while Giebel (2000) concluded likewise for northern Europe. Harman and Morgan (2005) and Pöyry (2011) found large-scale interannual variability of wind speeds and wind power across northern Europe. However, relatively little attention has been given to the covariability of multiple renewable energy sources and demand. Some exceptions include Taylor and Buizza (2003), Sinden (2007), Pöyry (2011), and Brayshaw et al. (2012) who investigated high demand, low wind power events, and Vogstad (2000) who suggested that wind power and hydropower in Scandinavia have complementary annual cycles.

In this paper, we therefore investigate the effects of longer timescale meteorological variability that may introduce new stresses on an interconnected power system. For simplicity, we characterise meteorological variability using an index of the North Atlantic Oscillation (NAO), the dominant regional pattern of atmospheric pressure variability (Hurrell et al., 2003). NAO variability is strongest in the winter (December to March, 'DJFM' hereafter) and is associated with shifts in the path of weather systems travelling across the North Atlantic. The positive phase is generally associated with anomalously warm, wet and windy conditions in northern Europe (the reverse applies for negative phase; Hurrell et al., 2003), and significant[1] positive correlations between the NAO and temperature, precipitation and wind speed span the UK–Norway region (Fig. 1).

Previous studies have examined the impact of the NAO on individual power system properties. Uvo and Berndtsson (2002) highlighted enhanced Norwegian orographic rainfall related to positive wintertime NAO as a possible predictor of reservoir levels, and Cherry et al. (2005) found positive correlations between Norwegian summer reservoir inflow and the NAO in the previous winter. Harman and Morgan (2005) and Atkinson et al. (2005) related NAO variability to Northern European wind power production and Brayshaw et al. (2011) showed that the probability distribution of wind power output over the UK is dependent on the phase of the NAO.

This study demonstrates the atmospherically driven covariability of three power-system components on monthly time scales: Norwegian hydropower availability, UK wind generation, and demand in the combined region (UK and Scandinavia). These three components are considered in isolation and combination under various future scenarios of UK wind capacity (Table 1). In this setup the coupling between these components is not directly modelled; no attempt is made to simulate transmission or plant-scheduling constraints. While this is a dramatic simplification compared to a real network, it enables a first exploration of the potential meteorological impacts on interconnected components (a more complete study would also need to consider interactions with other European weather-sensitive power system components and the possibility of technological, economic and climatic change). The values produced here are therefore intended to be indicators of the magnitude of the effects arising from a policy of interconnectivity, rather than definitive estimates.

Table 1
Total installed wind capacity of the UK grid in 2010, 2020 and 2035 scenarios following projections of Pöyry (2011). The spatial distribution of the installed capacity also changes fractionally between these scenarios.

Year	Offshore capacity (GW)	Onshore capacity (GW)	Total capacity (GW)
2010	1.4	4.0	5.4
2020	13.0	14.9	27.9
2035	38.5	20.1	58.6

Section 2 describes the meteorological and power-system data, outlines simple models of demand and wind power output, and discusses key properties of Norwegian hydropower reservoirs. Section 3 investigates how the NAO affects each individual component (hydropower availability, wind power, demand) and regional 'demand-net-wind' under various idealised wind capacity and interconnectivity scenarios. Section 4 draws together the findings to explore the implications of NAO variability given: (a) increasing power-system interconnections between the three components (UK wind, UK/Scandinavian demand, and Norwegian hydro), and (b) the anticipated growth of UK wind capacity over the next 25 years (Table 1).

2. Atmospheric data, derived wind power and demand estimates, and Norwegian reservoir data

Meteorological data is taken from the NCEP/NCAR reanalysis[2] (Kalnay et al., 1996), covering 1948–2010 on a 2.5° grid. (Table 2

[1] 'Anomalously' is taken to mean 'relative to the long term mean' throughout the paper.

[2] Correlations are stated as significant where $p < 0.05$, given a two-tailed test against the null hypothesis that data pairs are taken from an uncorrelated bivariate normal distribution.

Table 2
List of abbreviations used in the text.

Abbreviation	
CPC	Climate Prediction Centre (USA)
DJFM	December January February March
DNW	Demand-Net-Wind
ENTSO-E	European Network of Transmission System Operators for Electricity
NAO	North Atlantic Oscillation
NCAR	National Center for Atmospheric Research (USA)
NCEP	National Centers for Environmental Prediction (USA)
NOAA	National Oceanic and Atmospheric Administration (USA)

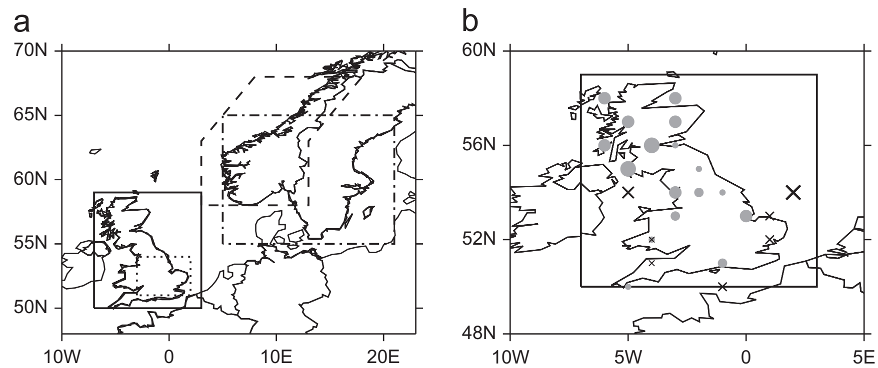

Fig. 2. (a) The power regions used in the study; UK-S (solid); UK-D (dotted); Nor-S (dashed); Sca-D (dot-dashed) and (b) the location of wind power generation capacity within UK-S, on a 1° grid, onshore (grey circles) and offshore (black crosses). Symbol size is determined by the 2010 capacity, in ranges < 0.1 GW, 0.1–0.2 GW, 0.2–0.5 GW and 0.5–1.0 GW.

lists abbreviations used in this study.) Three daily-mean variables are interpolated onto a 1° grid:

- Temperature T at 2 m above the surface (°C).
- Precipitation Q (mm day^{-1}).
- Vector-magnitude wind-speed u at 10 m above the surface (m s^{-1}).

NAO indices, standardised by the 1981–2010 climatology, are obtained from the NCEP Climate Prediction Centre (CPC; NOAA, 2011). Fig. 1 demonstrates the correlation pattern between seasonal averages of each of the variables above and the DJFM NAO index (calculated as the average of the monthly indices) over the period 1950–2010. These relationships are well documented, and those for Q and T have been verified against plots available at the CPC.

Given the simplicity of our representation of the power 'system', the use of a different reanalysis product or NAO index is extremely unlikely to qualitatively affect the meteorological impacts described either in sign or magnitude (e.g., the station-based NAO index of Hurrell, 1995, is very strongly correlated with the CPC index used here). Moreover, variables such as u and T are A type reanalysis variables, meaning that they are least sensitive to the details of the model used in reanalysis (Kalnay et al., 1996).

The four regions used in this study (Fig. 2) represent UK wind power generation (UK-S), electricity demand in the population centers of southern UK (UK-D) and Scandinavia (Sca-D), and Norwegian hydropower generation (Nor-S). The supply and demand for each region is modelled separately before being combined to examine the co-variability of these components in an interconnected system.

Fig. 3 plots the DJFM NAO timeseries against those of u, T and Q. To obtain the latter three timeseries the relevant variable is averaged over DJFM and over the relevant region, in each year. A 30-year climatological average is obtained from this timeseries of DJFM values, and the figure displays each year's anomaly from this climatology. Each variable displays a significant positive correlation with the NAO index and strong interannual variability.

2.1. Wind power model (UK-S)

Daily wind power output in UK-S is estimated from 10 m wind-speed as follows:

1. In each 1° grid-box, a logarithmic vertical wind-shear profile (Holton, 1992, Section 5.3.5) is assumed. This is used to extrapolate the 10 m wind speed data to typical hub-height (80 m onshore, 85 m offshore). Roughness lengths of 0.0002 m offshore and 0.1 m onshore are used (corresponding to "open sea" and "agricultural land with some buildings and vegetation" respectively; Danish Wind Industry Association, 2012).
2. A representative power curve converts the hub-height wind speed in each grid-box to a capacity factor (the fraction of theoretical maximum output attained at the current wind speed). The power curve of the Vestas V90 3.0 MW turbine (Vestas, 2011) is used.
3. This capacity factor is multiplied by the total installed capacity of all wind-turbines in the grid-box (Fig. 2b) and aggregated over the UK-S region to find the total output. Finally, this is divided by total installed capacity to obtain a total capacity factor.

While more advanced models could be constructed (e.g., Nørgaard and Holttinen, 2004), comparison between the simple model and annual reported production values for 2004–2008 (BERR, 2008) and 2009–2010 (Young, 2011) confirms that the simple model captures the gross features of low-frequency variability (not shown) and produces a time-mean total capacity factor of 26.8% between 2004 and 2010 using the installed wind capacity of 2010. This compares favourably with 26.1% (offshore) or 26.6% (onshore)

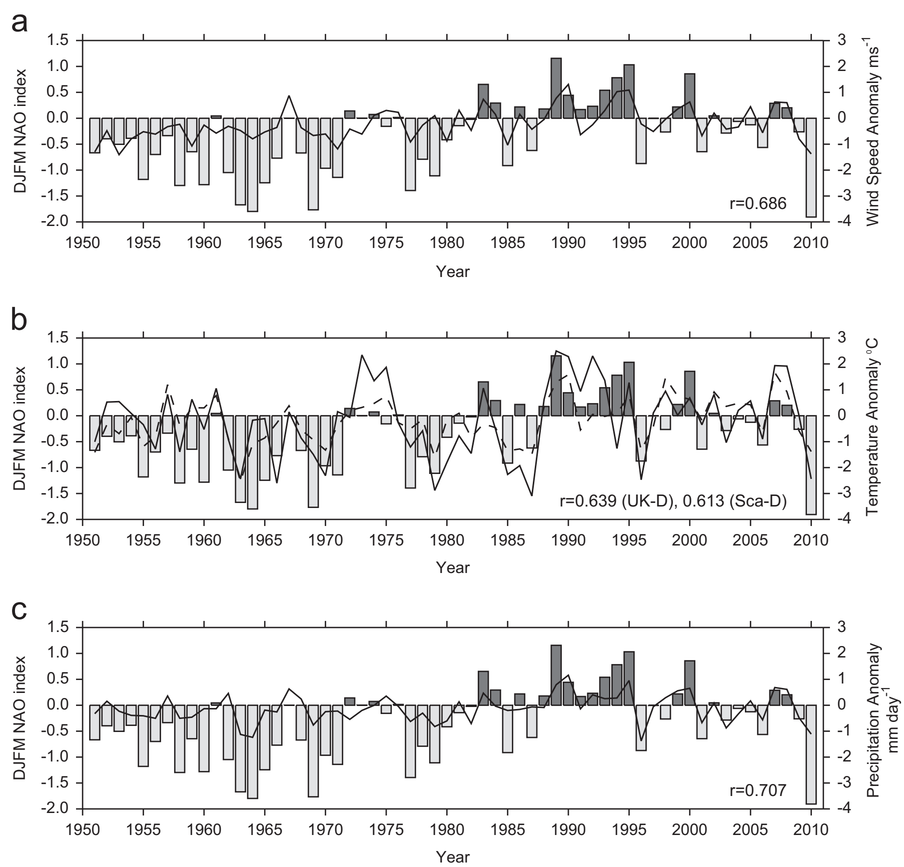

Fig. 3. Time series of the DJFM NAO index (bars) plotted against the DJFM anomalies (from the 1981 to 2010 climatology) of wind speed, temperature, and precipitation rate over the study regions. (a) Wind speed anomalies in UK-S region; (b) temperature anomalies in Sca-D (solid line) and UK-D (dashed line) regions; (c) precipitation anomalies in Nor-S region. The Pearson linear correlation coefficient, denoted by r, is also shown.

in the published production data. Sensitivity tests also confirm that the temporal variation (daily and longer timescales) of modelled wind power output is robust to moderate variations in roughness length and power curve.

2.2. Demand model (UK-D and Sca-D)

Demand forecast models typically use several meteorological variables (e.g., temperature, cloud cover, and wind speed; Taylor and Buizza, 2003). For simplicity, we model daily-mean demand as a linear function of daily-mean regional-mean temperature alone.

Metered demand data from national Trade System Operators for 2003–2009 was adjusted to largely remove the effect of economic variations but retain effects due to weather such as cold winters or warm summers. To do this, annual historical electricity demand was regressed against GDP growth in each country. National annual electricity demand was then normalised to a GDP base year of 2010 using this relationship.

The temperature-demand model is constructed using linear regression over March weekdays only. March is used for reasons related to the hydrological cycle (Section 3.1), and the restriction to weekdays limits human behavioural effects unrelated to weather (Taylor and Buizza, 2003). In northern Europe the link between demand and temperature is due to heating appliances such that decreased temperature causes increased demand, so the two are inversely related (linear correlation −0.758 for 2003–2009).

The adjusted demand data is expressed as a percentage of a mean value. Denoting this demand by D and 2 m temperature averaged over the relevant region (Sca-D or UK-D) as T (°C), we obtain the linear model $D = 1.15–0.02\,\mathrm{T}$ for both regions. Finally, the demand percentage value is converted to realistic GW values by scaling the 2008 average for each region (Table 3).

Table 3
The mean demand level assumed, the maximum daily proportional value from the 2003 to 2009 demand data, and the scaled peak demand (proportional value × average demand), to nearest GW. Scandinavian demand is defined as the sum of Danish, Norwegian and Swedish demand. The assumed mean is taken from 2008 values from the International Energy Agency energy statistics (IEA, 2008).

Region	2008 IEA average (GW)	Daily proportional peak	Daily peak (GW)
Sca	32	1.42	45
UK	39	1.31	51
Combined	71	1.34	95

Subsampling estimates suggest that the linear model is reasonably robust (intercept range [1.148, 1.162]; slope range [−0.016, −0.024]). The relationship is assumed constant in time.

2.3. Norwegian reservoir inflow data (Nor-S)

Weekly Norwegian reservoir inflow data for 2002–2010 and reservoir content data for 1998–2010 is obtained from the Norwegian Water Resources and Energy Directorate (NVE, 2011a). In this study, data is amalgamated from three regions (NVE, 2011b).

Data are ordered by calendar weeks (Monday to Sunday) so two of the nine years contain 53 weeks. The ‘week 53’ data-points are discarded to facilitate interannual comparisons; this is sufficient for the qualitative purposes of this part of our analysis. Since the dates in the nth week of the year vary each year, the date of an event in week n (any n) is taken to be the date at the end of that week.

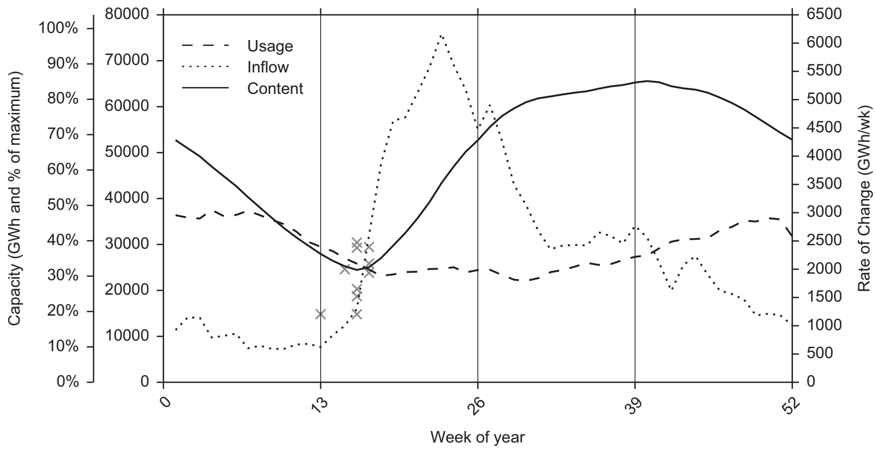

Fig. 4. The annual cycle of Norwegian hydropower, constructed from weekly inflow and content data for the period 2002–2010. Reservoir content valid for the end of the corresponding week is plotted according to the left hand axis, whilst inflow and usage totals valid for the corresponding week are plotted according to right hand axis. The usage in week i is derived using the expression $\text{usage}_i = \text{inflow}_i - \text{content}_i + \text{content}_{i-1}$. Grey crosses indicate the reservoir minima between 2002 and 2011.

2.3.1. *The annual cycle of Norwegian hydropower availability*

Fig. 4 shows the 2002–2010 composite annual cycles of inflow, reservoir level, and power usage (calculated as a residual from inflow and change in content). Three key features are evident: winter rundown (weeks~40–16), a late spring minimum (week~16), and rapid increases in content over spring into summer (weeks~17–39). This is discussed below.

The Norwegian mainland lies between 58°N and 72°N and is mountainous. Winter and early spring average temperatures are mostly below freezing. Precipitation builds up snowpack rather than contributing immediately to inflow, while the cold temperatures cause high demand; usage therefore exceeds inflow and reservoir content decreases. Given negligible winter inflow then, if hydroelectric generation is assumed to meet a roughly constant fraction of total demand, the winter rundown rate of the reservoir can be expected to be directly related to winter demand.

Reservoirs reach a minimum in April (weeks 13–16) and their recovery thereafter is principally due to an increase in inflow rather than reduced usage (Fig. 4). The date of the minimum is therefore strongly related to the timing of the snowpack melt.

The melt season for snowfall accumulated over the winter is April to September (Cherry et al., 2005; Uvo and Berndtsson, 2002), consistent with the reservoir inflow data (Fig. 4). Rainfall is heaviest in autumn and, consequently, inflow remains high until late in the year. During this period (weeks~17–39) inflow greatly exceeds usage and levels rise. Management decisions taken in this period are therefore unlikely to immediately affect hydropower availability although, on aggregate, they may impact the water levels at the start of the subsequent winter.

3. The impact of the NAO

3.1. *Timescales of interest*

We are interested in periods likely to cause stress on systems containing the three components being studied (demand, wind, and hydro). Our analysis therefore focuses on the period where reservoir content approaches its minimum, such that the ability of hydro-reserves to mitigate unexpected multi-day departures from ‘normal’ in the other components is least. We take March as a particular period of interest. The relationships between surface climate and the NAO for March are similar to those for DJFM (Fig. 1). Moreover, while there is little skill in predicting the NAO more than 1–2 months ahead (Johansson, 2007; Muller et al., 2005), there is evidence for some skill in one-month forecasts. This would have substantial value for energy stakeholders; for example, if hydropower is forecast to be abundant during March then it can be readily used to ameliorate low wind-power events.

Table 4
Top row: the linear correlation between reservoir properties (date of minimum and minimum content) and the NAO index. Bottom row: as top row but for average temperatures over the relevant region. All correlations significant at least 95% significance level.

DJFM Index	Correlation with minimum content	March Index	Correlation with time of minimum
DJFM NAO	0.636	March NAO	−0.572
DJFM T (Sca-D)	0.719	March T (Nor-S)	−0.483

3.2. *Norwegian hydropower availability and the NAO*

This section investigates the effect of interannual variability in the NAO on winter reservoir ‘rundown’ (defined as the net reduction in reservoir content during winter) and the spring minimum date.

We expect demand and therefore rundown to be inversely related to temperature and the NAO (Section 2.2). Comparing rundown in the period 1998–2011 to two DJFM winter climate indices (NAO index and average temperature in the highly intra-connected Sca-D region) confirms this: rundown is significantly negatively correlated with both indices (e.g., $r = -0.586$ for the NAO). Interannual variability is large; DJFM rundown rates vary by over 1000 GW h/wk. Moreover, Table 4 shows a positive correlation between the minimum reservoir content (which itself displays strong interannual variability, Fig. 4) and both climate indices. These results are consistent; rundown rate is generally above average and the minimum content below average in a cold winter (negative NAO).

Although we found that melt date is not significantly related to the minimum level reached (not shown), it is crucial for understanding how long hydropower reserves must last in spring. Table 4 indicates that melt date (defined as the time of minimum content), which varies between weeks 13 and 17 (Fig. 4), is negatively correlated with both average March temperatures in Nor-S and with the March NAO index. This is consistent with physical arguments; a warm March (NAO+) tends to prompt an early melt, whilst NAO− implies cooler temperatures. Based on the

Table 5
The scenarios considered in the analysis of Section 3.3: the name of the scenario, the variable describing demand or demand-net-wind (DNW), and the power system properties included in each scenario. Details of UK wind capacity scenarios can be found in Table 1.

Scenario name	Demand variable name	Power system components modelled
2010a	D_{Sca}	Demand in Sca-D only
2010b	D_{Sca+UK}	Demand in Sca-D and UK-D
2010c	DNW_{10}	Demand in Sca-D and UK-D; 5.4 GW UK wind capacity
2020	DNW_{20}	Demand in Sca-D and UK-D; 27.9 GW UK wind capacity
2035	DNW_{35}	Demand in Sca-D and UK-D; 58.6 GW UK wind capacity

Table 6
Modelled power system average properties (GW, except where otherwise specified) during March in three NAO states. (NB: the term 'system' is used here to refer to the combination of the components listed in the relevant scenario in Table 5.) Demand D, wind W and demand-net-wind DNW are calculated from reanalysis data for 1950–2010 using models summarised in Section 2 and wind-power capacity scenarios described in Table 5. Demand model assumes all days as weekdays and thus demand is assumed to be an overestimate. The final row shows the difference in weekly rundown rate required to make up the difference in demand or DNW between a high and low NAO year, calculated as difference*24*7. This allows comparison with the hydropower resource shown in Fig. 4. Critical values for determination of NAO categories are ± 0.5.

NAO state	2010a	2010b	2010c		2020		2035	
	D_{Sca}	D_{Sca+UK}	DNW_{10}	W_{10}	DNW_{20}	W_{20}	DNW_{35}	W_{35}
Negative	37.8	82.7	81.2	1.5	75.6	7.1	68.3	14.4
Neutral	37.0	81.0	79.2	1.8	71.9	9.1	62.9	18.1
Positive	36.3	79.7	77.3	2.4	68.0	11.7	56.5	23.0
Difference negative-positive	1.4	3.0	4.0	−0.9	7.5	−4.5	11.9	−8.8
Weekly difference (GWh)	240	510	660	−160	1270	−760	1990	−1480

limited inflow data available, the melt date is on average a week earlier in NAO+ compared with NAO−.

3.3. 'Demand-Net-Wind' and the NAO

3.3.1. Definitions

We now investigate the NAO's impact on the combination of demand and wind during March, enabling us to explore the ramifications of using wind and hydropower together to help meet demand. Given the simplicity of our assumptions about the power system we focus on daily-average values and assume that hydropower can be used to instantaneously supplement high frequency variability in the wind. Clearly this introduces a further simplification (sub-daily meteorological variability along with power-system constraints are deliberately ignored). More complex models are an area for future research.

Following Cox (2009) we define daily demand-net-wind (DNW) as

$$\mathrm{DNW} = \text{electricity demand} - \text{generated wind} - \text{power}.$$

Daily demand and wind-power output are calculated from temperature and wind speed, as described in Sections 2.1 and 2.2, respectively. DNW is interpreted as the part of demand which must be met by generation other than wind. The daily DNW values are then composited by the monthly NAO 'state':

- negative if $\mathrm{NAO} < -0.5$ (28 months fall in this category)
- neutral if $-0.5 \leq \mathrm{NAO} \leq 0.5$ (20 months)
- positive if $\mathrm{NAO} > 0.5$ (13 months).

According to these definitions, 868 days occur in an NAO negative March, 620 in an NAO neutral March, and 403 in an NAO positive March. This provides a large dataset of DNW values based on historical weather.

Different wind-power capacity scenarios are considered (Table 5). The difference in wind-power output between the scenarios is chiefly due to a change in magnitude of the total installed capacity rather than its spatial distribution. The average demand in each region (UK-D and Sca-D) is kept constant between the scenarios; we do not consider projected future changes in demand driven by socioeconomic factors. In scenarios 2010b onwards, the demand is simply summed over the two regions.

3.3.2. Results: mean DNW

Table 6 shows the NAO's impact on March-average demand, wind-power output and DNW for each scenario.

As expected, the addition of wind-power capacity reduces the total DNW in any NAO state (compare the top three rows of scenario 2010c with 2020 and 2035). However, the focus of this paper is the effects of large-scale atmospheric *variability*. In absolute terms, the NAO state (NAO− vs NAO+) has a growing impact from left to right across the table (see row four of the demand and DNW columns).

Considering first the effect of combining demand in Scandinavia and the UK (i.e., comparing scenarios 2010a and 2010b), it can be seen that the difference between NAO− and NAO+ increases in absolute terms from 1.4 GW in the isolated Scandinavian scenario (2010a, D_{Sca}) to 3.0 GW in the linked 2010b scenario (D_{Sca+UK}). However, this NAO-driven difference in demand, expressed as a percentage of the total demand in NAO neutral,[3] is approximately constant ($\pm 2\%$).

More interestingly, the NAO's impact when UK wind-power is included is much greater (compare scenario 2010c's DNW with 2010b's demand); adding wind capacity increases the overall sensitivity to the NAO in both absolute and relative terms. The difference between NAO− and NAO+ is 4.0 GW, or approximately $\pm 2.5\%$ relative to NAO neutral. This increase is to be expected; for example, NAO negative is associated with low wind speeds and high temperature-driven demand, both of which act to increase DNW. Increasing wind capacity (scenarios 2020 and 2035) further increases this sensitivity, to 7.5 GW ($\pm 5.2\%$ relative to NAO neutral) and 11.9 GW ($\pm 9.5\%$ relative to NAO neutral) respectively.[4]

[3] Meteorological 'reanalyses' are an optimal combination of model output and observational data. They are widely used in the atmospheric science community (Kalnay et al., 1996) and provide the best available tool for examining the continental-scale spatio-temporal structure and long-term variability of the atmosphere.

[4] The average DNW value in NAO neutral is up to 2% lower than the March long term average, depending on the wind-power capacity scenario considered.

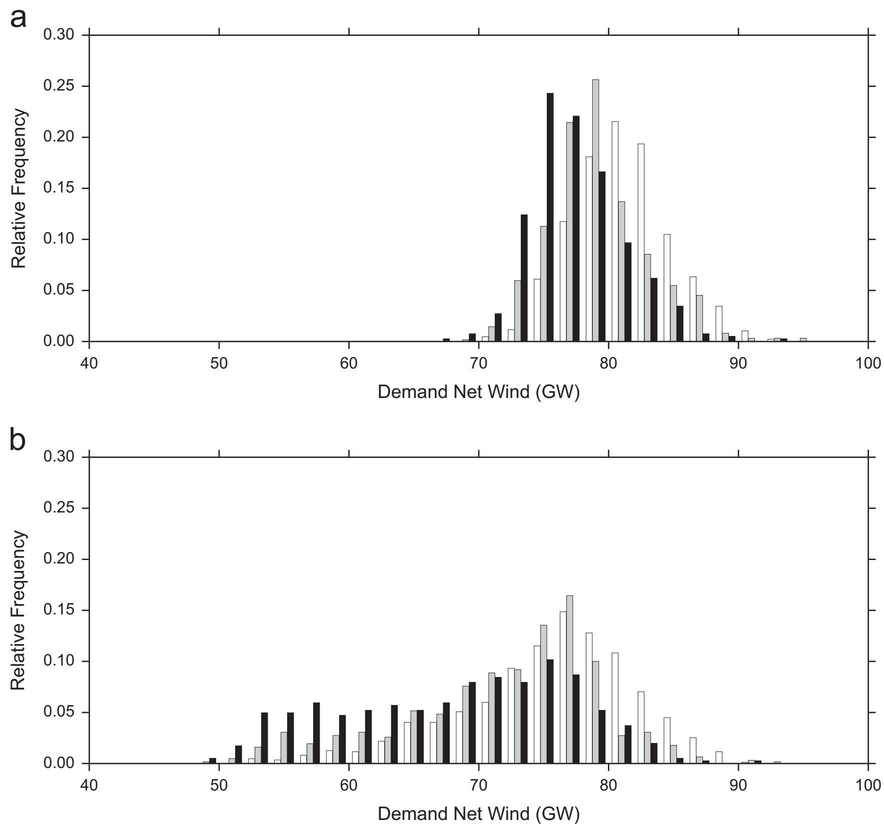

Fig. 5. Probability distribution of daily demand-net-wind (DNW) for March 1950–2010 composited by NAO state; negative (white), neutral (grey) and positive (black). Wind-power capacity levels representative of (a) 2010 and (b) 2020, assuming no change in demand behaviour (scenarios 2010c and 2020 in Table 5). Wind and demand are modelled as described in Section 2.

3.3.3. *Results: variability of daily DNW*

Fig. 5 shows the distribution of daily DNW in each NAO category for the interconnected scenarios 2010c (top) and 2020 (bottom). Comparison of the two scenarios shows that, while increasing wind capacity shifts all the distributions to the left (DNW is reduced), it also results in much wider distributions (a greater range in daily DNW) consistent with previous wind intermittency studies (Section 1). Moreover, for each scenario, the histograms demonstrate that NAO conditions affect the distribution of DNW, with NAO− increasing the probability of high DNW relative to the same scenario under NAO+ conditions.

4. Discussion

In this paper, meteorological data has been used to study the relationships between three components relevant to the UK and Scandinavian power systems – UK wind energy generation, Norwegian hydroelectric generation, and UK and Scandinavian temperature-driven demand – each of which is sensitive to climate variability as summarised by the North Atlantic Oscillation (NAO). This has provided a preliminary understanding of how climate variability might affect an interconnected 'North Sea Grid'-style power system.

The annual cycle of reservoir levels suggests that March is a critical period for the combined behaviour of the three components: at this time, hydropower reservoirs approach their annual minimum (inflow is limited until snowmelt begins in mid-spring) while temperature-driven demand remains high. The ability of hydropower reserves to compensate for a sustained shortfall of windpower (Norwegian hydropower is often considered as a generator possibly able to meet shortfalls in power output in an integrated renewables system (e.g., Cox, 2009)) is therefore likely to be at its most marginal around March.

4.1. *A 2020 wind capacity case study*

The potential impact of the NAO in March is illustrated by considering a 2020 scenario (by 2020, the UK–Norway connector may be operational). In an NAO− March:

1. It is anomalously cold across the UK and Scandinavia, causing anomalously high electricity demand (relative to NAO neutral or NAO+).
2. UK wind-power production is anomalously low, contributing on average 7.1 GW to meeting demand (compared with 9.1 GW in NAO neutral or 11.7 GW in NAO+).
3. High demand-net-wind (DNW) days are therefore more likely than in other NAO states (e.g., a 13% probability of DNW in NAO − exceeding 82.6 GW, compared to a 5% probability in NAO neutral).
4. DNW is on average 3.7 GW higher than in NAO neutral (7.5 GW higher than NAO+; Table 6). This corresponds to a requirement for an extra 620 GWh/wk (relative to NAO neutral) from sources other than wind-power.

As the current mean March hydropower usage in Norway is 2700 GWh/wk (Fig. 4), this $\pm$620 GWh/wk change in DNW matched entirely from hydropower reserves would correspond to a departure of approximately $\pm$25% from the current normal March usage rate. Moreover, under NAO− conditions, the inflow from snowmelt required to recharge the reservoirs is likely to be delayed by the lower-than-average temperatures (Section 3.2) so that reservoirs must also last longer on existing reserves.

The NAO-driven differences are relevant for reservoir management. Reservoir levels at the start of March are determined by a mixture of previous climate conditions and management decisions. One might therefore wish to either: (a) determine a 'safe minimum' which must be held in the reservoir at the start of March with implications for reservoir draw-down earlier in the winter, or (b) assess how 'abundant' the current reservoir level is relative to the anticipated DNW for the coming month based on a forecasted NAO state. A skilful NAO forecast for March could therefore inform better decision-making by reservoir managers in March. Improving NAO forecasting skill is an active research concern of the meteorological community (e.g., Johansson, 2007).

4.2. Concluding remarks

Our discussion has focussed on the effect of the large-scale atmospheric circulation (quantified using the NAO) on DNW in a highly-simplified UK–Norway power network. Although increasing the wind generation capacity decreases *time-mean* DNW under all NAO states (therefore 'preserving' reservoir reserves), the magnitude of the difference in DNW under positive and negative NAO states increases dramatically. Our analysis therefore highlights that an interconnected, high wind-power capacity grid may be more affected by interannual climate fluctuations (i.e., changes in the NAO) than one with fewer interconnections and lower wind capacity. This has implications for the effective management of hydropower resources and, although the addition of wind capacity reduces the total capacity and energy requirements for the balance of system generators, marginal generators will experience greater variability in use, both day-to-day (Fig. 5) and at the month-to-year timescale (Table 6). While the increase of day-to-day variability due to wind generation has been widely discussed, relatively little research has considered longer time-scale variability across multiple power system components.

This paper begins to explore the meteorological relationships likely to influence a future European power system; a full study would include demand growth, transmission capacities, generation constraints, and more advanced models for wind-power and demand. Further work could also incorporate other renewable energy sources over a broader region. The large spatial scales of the NAO's surface impact (Fig. 1) suggest that the DNW distributions shown in Fig. 5 would be qualitatively robust to incorporation of wind resources over Northern Germany and France. However, the correlation is of opposite in sign in southern Europe, such that the relationships found over a broader region would depend on the area considered. Finally, other meteorological patterns of variability could be investigated as well as shorter-term events such as blocking.

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