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Adapting overhead lines to climate change: Are dynamic ratings the answer?

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HIGHLIGHTS

- A model is created demonstrating the impacts of climate change on overhead line ratings.
- The model accounts for temperature, solar radiation and wind effects on line rating.
- The increased risk to network capacity due to climate change is low.
- Real-time dynamic ratings systems present a cost-effective mitigation strategy.

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ABSTRACT

Thermal ratings of overhead lines (OHL) are determined by the current being carried and ambient climatic conditions. Higher temperatures as a result of climate change will give rise to lower ratings, and thus a reduction in current-carrying capacity across the electricity network. Coupled with demand growth and installation of renewable generation on weaker sections of the network, this could necessitate costly reinforcements and upgrades. Previous UK-based work applying a subset of data from the UK Climate Projections model (UKCP09) has indeed indicated likely reductions in the steady-state OHL ratings under worst-case temperature increases. In the present work, time series data from the full UKCP09 probabilistic climate change modelling framework, including an additional algorithm to incorporate hourly wind conditions, is applied to OHL ratings. Rather than focus purely on worst-case conditions, the potential for an increased risk of exceeding nominal ratings values on thermally constrained OHL is analysed. It is shown that whilst there is a small increase in risk under future climate change scenarios, the overall risk remains low. The model further demonstrates that widespread use of real-time dynamic rating systems are likely to represent the most cost-efficient adaptation method for lines which are frequently thermally constrained.

1. Introduction

The balance of evidence from climate modelling experiments suggests that average temperatures will rise over the coming decades as greenhouse gas concentrations increase (IPCC, 2007). A changing climate has potential to affect electricity systems in many ways, not least the need for low carbon generation. The direct and indirect effects of climate change on electricity distribution and transmission networks may be disruptive and requires analysis.

Many network components such as transformers and overhead lines (OHL) are directly vulnerable to weather conditions. The reliability and safety of these devices are limited by their ability to withstand certain operational temperatures, which are in turn influenced by local ambient environment and loading conditions. In OHL, power flows exceeding defined limits referred to as 'line rating' will cause excess heat gain and damage from sag or a reduction in strength (CIGRE Working Group B2.12, 2006). With the anticipated rise in ambient temperatures in the coming decades, the threshold temperatures for OHL are likely to be reached sooner, leading to reductions in power transmission capacity. Indirectly, networks are required to cope with increasing installations of renewable generators well as demand growth. A combination of reduced capacity with increased loading could necessitate costly network reinforcement.

The issue of changing OHL ratings has featured in the literature on climate change impacts. Consideration has been mainly qualitative or used simple quantitative analysis; this is true of the original impact assessments by the Intergovernmental Panel on Climate

Abbreviations: ER, Engineering recommendation; OHL, Overhead line; PET, Potential evapo-transpiration; UKCP09, UK climate projections; UKMO, UK Met Office; WG, Weather generator; WRF, The weather research and forecasting model

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Change (IPCC), for the US (Smith and Tirpak, 1989) and UK (Climate Change Impacts Review Group, 1991) and more recent European assessments (Rademaekers et al., 2011). These used projected mean temperature changes and applied them to standard OHL rating methods. More sophisticated work by the UK Met Office (UKMO) and utilities (Buontempo, 2008; Harrison, 2008) used a subset of the data generated as part of the UK Climate Projections project (UKCP09) to explore impacts on the UK energy industry. The data subset consisted of a version of the UKMO Unified Model driven by an atmospheric climate model, HadAM3P (Buontempo, 2008). Single simulations of hourly weather data for current climate and for a future period indicate reductions in steady state OHL ratings under future climate with 'worst-case' ratings more significantly affected than the mean (Harrison, 2008). The results have been used by UK network operators in their climate adaptation statements (Electricity Networks Association, 2011) and feature in the 2012 UK Climate Change Risk Assessment (McColl et al., 2012). The worst case reductions in OHL ratings are estimated to be 8%–14% for distribution and 2%–4% at transmission by 2099. These arise from sensitivity factors of ~1.6%/°C for distribution and ~0.8%/°C for transmission, with the difference due to higher allowed transmission operating temperatures. The cost of rebuilds of affected circuits is estimated to be £1.3 billion by 2080 and although smart grids are stated to also be part of the solution, this is not elaborated on (Electricity Networks Association, 2011).

An important feature of the UKMO analysis is that due to low confidence in the wind speed output from climate models, potential changes in wind speeds were omitted from the methodology (Buontempo, 2008; Electricity Networks Association, 2011). Instead the focus was on identifying the change in extreme temperatures and lowest steady state rating within the range of possibilities. This is valuable and fits well with prevailing practice in defining OHL ratings. However, it misses an opportunity to gain a much richer picture of the distribution of ratings that occur as weather patterns vary throughout the year and into the future. This is particularly important as emerging experience with dynamic ratings of OHL (Michiorri et al., 2009; Yip et al., 2009) shows much variation in ratings throughout the year and that wind speed plays a major role in determining ratings. With dynamic ratings seen as a key smart grid technology and mooted as a climate adaptation measure (Rademaekers et al., 2011), there is a need for a method that allows the evaluation of dynamic OHL ratings within the framework of future climate change scenarios.

In addressing this challenge, the work described here makes use of the time-varying output from the UKCP09 probabilistic projections (which includes results from the model used in Buontempo (2008), among others), supplemented by additional wind modelling, to explore scenarios of future climate and the implications for the thermal rating of overhead lines. It is set out as follows: Section II provides an overview of the state-of-the-art climate change modelling for the UK, while Section III describes the methodology used for estimating ratings under future climate change and presents a simple temperature-based estimation of changes in static rating assumptions. Section IV presents the changes in climate as depicted by a model based on the UKCP09 weather generator. Section V explores the impact of these changes on OHL ratings and the risk of exceeding current assumed capacities. Section VI concludes the work by discussing the impacts and the scope for climate adaptation in the face of these changes.

2. UK climate change scenarios

Comprehensive, high resolution modelling of potential climate change effects in the UK and surrounding seas is provided by the UK Climate Projections (UKCP09, 2011). These are probabilistic projections of change for a range of atmospheric climate variables over the coming century under several "equally likely" emissions scenarios defined by the IPCC Special Report on Emissions Scenarios (IPCC, 2000). This valuable addition to the available models of future climate data moves beyond established practice in climate impacts analysis that makes use of single values for changes in temperature or other variables by a particular future time period under a given emissions scenario. By combining multiple models, UKCP09 better captures the inherent uncertainty associated with the climate projections for "high", "medium" and "low" emissions scenarios and fits with the trend of applying risk methods to infrastructure challenges.

For specific locations and most climate variables, UKCP09 provides continuous probabilistic estimates of the magnitude of change. For example, Fig. 1 shows the probability function for annual temperature change in the 2050s under a medium emissions scenario, derived for the region of eastern Scotland. The probabilities shown are cumulative, such that if the 10% value is X, it is 10% likely that the change will be less than X (and 90% likely to be greater). If the 90% value is Y, it is 90% likely that the change will be less than Y (and 10% likely to be greater). The 10% and 90% levels can be interpreted as the likely range of changes (i.e. minimum to maximum) expected for a given scenario. For the case shown in Fig. 1 the 10% level corresponds to a rise of around 1.2 °C, the 50% level to 2 °C and the 90% level to 3 °C.

The information can also be presented as a UK-wide map showing changes at a given probability level on a 25 km grid. Considering the 2050s with medium emissions again, the temperature changes at a 50% probability level shown in Fig. 2 indicate that over the whole year, the increase is more-or-less likely to be between 2 and 3 °C, and will be worse in the south than the north. Critically, although UKCP09 does now provide some probabilistic data for future wind speeds, it is accompanied by a 'health warning' concerning the high degree of uncertainty associated with the wind projections (Sexton and Murphy, 2010). Wind speed appears to be one of the most difficult climate variables to understand under conditions of climate change, and any data used must be accompanied by suitable information about the potential errors.

For applications that require coincident changes in multiple weather variables, UKCP09 provides a 'weather generator' (WG) (Jones et al., 2009), which produces synthetic time-series of several weather variables over a small area. Each 'pseudo' time-series are statistically representative of 30 years of weather under a specific set of large-scale scenarios of current or future climate conditions, with the variables being temporally consistent with each other within each simulation. An ensemble of at least 100 weather generator 'runs' of each 30 year period are needed for statistically robust results. The weather generator produces consistent time-series that include temperature and precipitation values, but crucially, the wind speed values are not explicitly provided due to the high degree of uncertainty associated with the future projections.

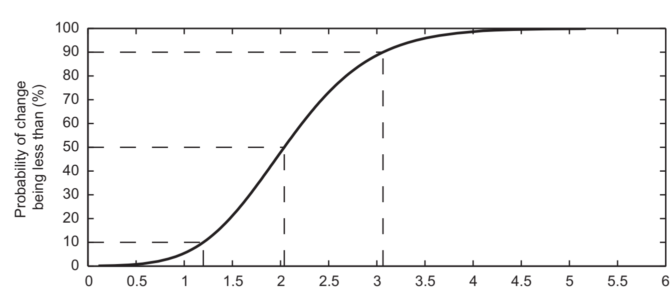

Fig. 1. Cumulative probability distribution for annual temperature change in Eastern Scotland in the 2050s under the 'medium' emissions scenario.

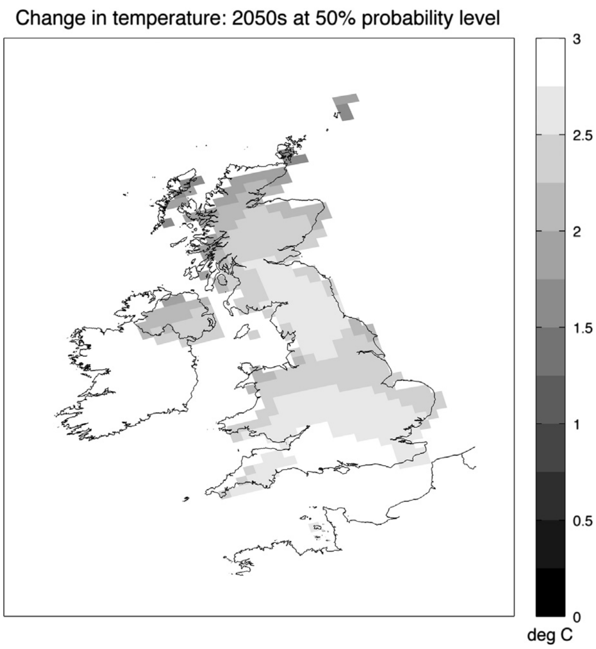

Fig. 2. Map of changes in temperature at the 50% probability level for the 2050s under a ‘medium’ emissions scenario.

3. Determination of OHL ratings

The amount of current, I, that can be carried by a given OHL conductor – the ‘rating’ – is determined by the energy balance of the conductor. The energy balance comprises the Joule (or ohmic) heating effect of the losses in the conductor q_J due to current flow, the heating effect of incident solar radiation q_S and the cooling effects provided respectively by convection q_c and radiation q_r from the material surface

$$q_j + q_s = q_c + q_r \tag{1}$$

The Joule heating effect is a function of the square of the current and the resistance R which itself varies with temperature T_c

$$q_J = I^2 R(T_c) \tag{2}$$

Beyond this, the factors affecting the heat balance arise from environmental parameters, such as ambient temperature, wind speed and solar radiation. Convection q_c has two components: natural and forced convection. Natural convection is governed by the temperature difference between the surface of the conductor and the surrounding air and forced convection is strongly affected by wind speed and direction. IEEE Standard 738-2006 (IEEE, 2007) defines the heat balance calculation for assumed material properties and local conditions to allow the maximum rated current, I, to be determined for a given conductor design temperature, T_c and assumed ambient conditions

$$I = \sqrt{\frac{q_c + q_r - q_s}{R\,(T_c)}} \tag{3}$$

UK network operators allocate seasonal ‘static’ ratings to OHLs based on ambient conditions that are defined in the standard Engineering Recommendation (ER) P27 (Electricity Networks Association, 1986). These seasonal assumptions are for mean temperatures of 20 °C in summer, 2 °C in winter and 9 °C in autumn and spring; solar radiation effects ignored and wind speeds assumed to be low at 0.5 m/s (i.e. low forced convective cooling). The conditions were determined following experiments and statistical analysis conducted in the early 1980s. The static ratings assumptions were intended to be reasonably conservative in order to minimise – but not fully eliminate – the risk of having a capacity lower than the assumed value at any given time. A study by Price, Gibbon (1983) formed part of the basis for the development of ER P27; the values presented by the authors indicate that ER P27 is based on an acceptable ‘excursion time’ of 3%, i.e. the line is allowed to exceed its maximum rating for 3% of the time. However, changes in ambient conditions since the early 1980s and the projected changes in the coming decades means that the climatic assumptions on which the figures were based need updating.

To illustrate the influence of weather variables on OHL ratings, a simple analysis of temperature and wind speed has been carried out for a typical conductor used extensively in UK (sub)transmission and distribution networks. ‘Lynx’ is an Aluminium Cored Steel Reinforced conductor with the operating temperature limit set here at a maximum of 75 °C (see Kopsidas, Rowland (2009) for specification). Fig. 3 shows the variation of the Lynx rating with temperature assuming the ER P27 conditions of no solar radiation

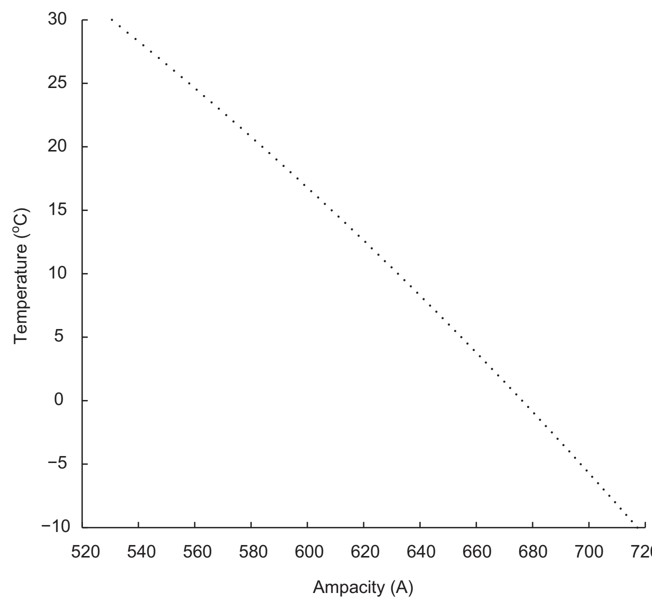

Fig. 3. Sensitivity of rating to ambient temperature at low wind speeds.

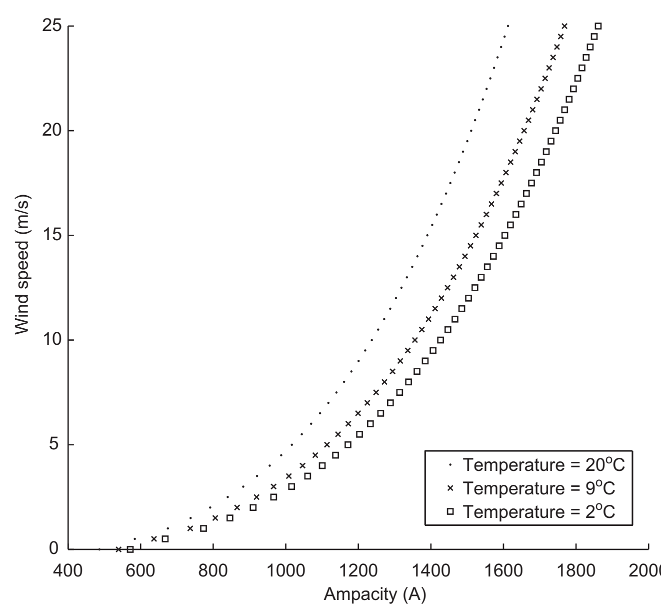

Fig. 4. Sensitivity of rating to wind speed at seasonal temperatures.

and 0.5 m/s wind speeds; it shows a slightly non-linear inverse relationship with rating falling by 0.8%/°C temperature rise. This relationship largely explains why the ER P27 OHL ratings are lower for summer than winter months. Fig. 4 presents the conductor rating across a wide range of wind speeds at the ER P27 assumed seasonal temperatures of 2, 9 and 20 °C. The wind is assumed to be blowing at a 45° angle to the conductor, mid-way between the optimum perpendicular and worst-case parallel directions. The cooling effects of wind speed are considerable and particularly evident between 0 and 5 m/s where the rating at the lowest temperature doubles from around 600 A to 1200 A.

4. Simple application of UKCP09 temperature changes

To illustrate how changes in the static rating of the conductor can be inferred from the UKCP09 probabilistic temperature change scenarios, calculations with present-day ER P27 summer and winter standard temperatures (20 °C and 2 °C), and changes in temperatures implied by the UKCP09 temperature changes were carried out for the whole of the UK. Changing only the temperature, conservative assumptions about site elevation, time of day and wind speed (0.5 m/s), and solar radiation were applied to represent plausible summer and winter conditions. The inclusion of solar radiation heat gain will give more conservative outcomes than ER P27 (Electricity Networks Association, 1986) which omits it.

The changes in ratings are much greater in summer than winter and changes in ratings for summer maximum temperatures are greater than those from mean summer changes. Changes by 2020 are relatively small but progressive warming means that the highest changes are to be expected by 2080. The most severe 90% probability case for summer maximum temperatures in the 2080s suggests static ratings will reduce by up to 11% across the UK. The existing UK north-south temperature gradient is enhanced in future scenarios with proportionately smaller changes in the north (Fig. 5). The approach and results are broadly similar to those presented by the UKMO and utilities (Buontempo, 2008; Harrison, 2008), who for the 2080s medium emissions scenario suggest OHL de-rating of between 7 and 11% (the higher values quoted earlier apply to the high emissions scenario). However, concentrating purely on a single

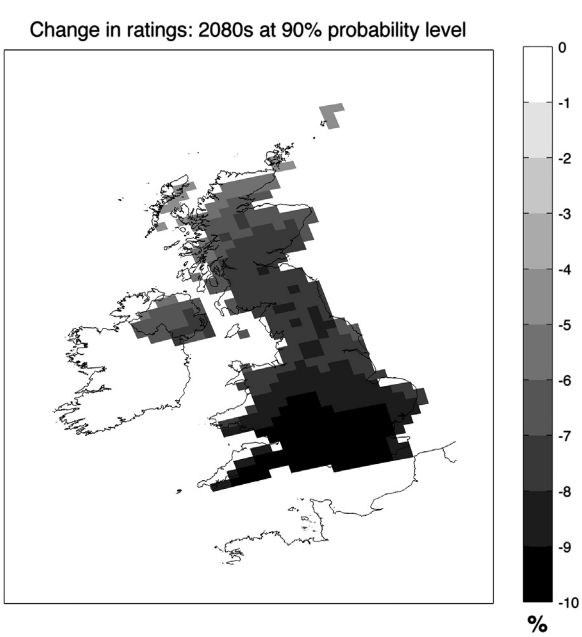

Fig. 5. Change in 'worst case' static rating of Lynx OHL at summer maximum temperatures alone for 2080s at 90% probability.

ratings value for a whole season and looking at temperature change alone misses the potentially much more significant impact of the full range of weather conditions including wind speed (Fig. 4). Without explicit consideration of the frequency of occurrence, it is difficult to discern enough detail from this analysis to assign appropriate future seasonal ratings.

5. Probabilistic assessment of OHL ratings

To better understand how the determination of line rating may have to change under future climate conditions, a probabilistic framework has been devised that makes use of the UKCP09 weather generator (WG). The WG has been used to create 100 thirty-year time series datasets of hourly temperature and solar radiation data for each of the present and future periods (Jones et al., 2009). Three representative locations have been chosen for analysis: 1Ed is a semi-urban area in the east of Scotland; 2Gy is a region in south-east England in the vicinity of distribution-connected offshore wind farms; and 3Wa is a rural area in Wales with many small onshore wind farms.

As mentioned earlier, there are no wind speed data provided from the UKCP09 WG. To fully analyse real-time ratings under current and future scenarios, hourly wind conditions must be included in the calculation along with temperature and solar radiation to obtain the best approximation to real situations. Here, wind speeds have been derived from the WG data using a method originally applied for building services applications (Eames et al., 2011; Watkins et al., 2011). The WG produces daily values for potential evapo-transpiration (PET) which is a function of wind speed and other variables. Knowledge of the other contributing factors allows a daily wind speed to be reconstructed from the PET values. The WG calculates PET using the well-known Penman–Monteith method

$$PET = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{\overline{T}+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad (4)$$

where R_n is the net radiation at ground level (MJ/m^2/day), G is the soil heat flux density (MJ/m^2/day), $\overline{T}$ is the mean 2 m air temperature (°C), u_2 is 2 m wind speed (m/s), e_s and e_a are the saturated and actual vapour pressures respectively (kPa), Δ is the gradient of the vapour pressure–temperature curve at the mean air temperature (kPa/K), and γ is the psychrometric constant (kPa/K). The calculation of the various components is given in some detail in Nandagiri and Kovoor (2005). The parameter G is computed on a daily basis using the mean temperature difference between successive days multiplied by 0.38 MJ/m^2/day/K (Watkins et al., 2011). Eq. (4) is rearranged to find daily 2 m mean wind speed which is transferred to typical OHL height (10 m) using the log-law profile

$$u_{10} = u_2 \ln(10/z_0)/\ln(2/z_0) \quad (5)$$

This assumes a local surface roughness equivalent to short grass ($z_0 = 0.008$ m). Corrections are required to the resulting wind time series to account for specific computational issues (Eames et al., 2011; Watkins et al., 2011). Eames et al. (2011) identifies points where the differential of PET with respect to wind speed is very high, with insensible wind speeds. Similarly, 'negative' PET is not possible with values truncated at 0 mm/day which, in the reverse calculation, leads to erroneous wind speeds. In these cases, the data is linearly interpolated.

In order to obtain an hourly time step, a further model is required. There is little or no explicit relationship between wind speed and other WG variables, such as temperature (Buontempo, 2008; Eames et al., 2011) that could be used to generate hourly wind profiles from daily mean values. Season does appear to affect the profile, however. Here, a modified version of the method in Eames et al. (2011) has been applied. For the locations described in the previous section, hourly weather observations have been extracted from an 11 year (2000–2010) hindcast from the numerical model, 'The Weather Research and Forecasting Model', (known as 'WRF') (Hawkins, 2012). For each daily 10 m wind speed derived from the WG PET value, all the daily mean wind speeds from the WRF model that occur in the same season and lie within 0.5 m/s are identified. A 24-hour profile for wind speed and direction is then selected at random from all the qualifying days.

Wind speeds, particularly at a local level applicable to electricity networks, are difficult to model under climate change conditions (Harrison et al., 2008; Sailor et al., 2008; Pryor and Barthelmie, 2010; Cradden et al., 2012). However, it is felt that the wind speeds derived here will indicate the extent of the typical cooling effect of wind on OHL limits. The weather forecast model used has been thoroughly validated under current conditions (Hawkins, 2012), and analysis of the statistics of the hourly wind climate generated by the PET calculation model using the control period runs of the WG shows a good match to historical statistics for the sites. Alongside providing appropriate mean and variance, the adequate preservation of the temporal autocorrelation of wind speeds was also confirmed. Future modelled wind conditions cannot, obviously, be verified. A caveat therefore is that these future wind speeds are given as an indicator of the potential for extra capacity on the network and for using wind cooling factors to mitigate the effects of higher ambient temperature. They are not necessarily fully representative of the wind climate expected under conditions of climate change as presently, it is not possible to provide confident estimates of this. A schematic diagram showing the inputs to and outputs from the final model is shown in Fig. 6.

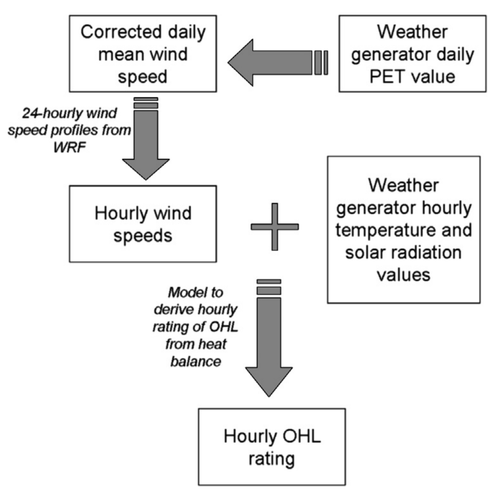

Fig. 6. Schematic of hourly OHL ratings model.

Table 1
Mean winter and summer wind speeds and temperatures for all three sites for current and 2050s climate.

		1Ed		2Gy		3Wa	
		Current	2050s med	Current	2050s med	Current	2050s med
Mean wind speed (m/s)	Summer	4.26	4.07	4.71	4.88	4.35	4.35
	Winter	5.35	5.25	6.68	6.60	6.24	6.32
Mean temperature (°C)	Summer	14.5	17.0	15.2	17.9	13.5	16.1
	Winter	3.59	5.72	4.33	6.52	3.27	5.20

6. Projected changes in temperature

In this section, the seasonal weather conditions depicted by the WG output under both current and future scenarios are analysed. These will be compared to assumptions made by network operators, in order to understand if these assumptions will require adjustment in future. The highest risk events for a thermally constrained OHL will occur when temperatures are extremely high and wind speeds simultaneously low. Table 1 presents the mean temperatures and wind speeds for winter and summer seasons at each of the three sites. '1Ed', being a more urban site, and a little way inland, has lower wind speeds than the other two sites in both summer and winter. '2Gy' has the highest wind speeds, and '3Wa' slightly lower. In terms of temperature, 2Gy is the warmest, followed by 1Ed, and 3Wa has the lowest seasonal temperatures. The future patterns for temperature are similar at all three sites – increasing by around 2–3 °C. As would be anticipated given the model used, the changes in wind are more subtle and not consistent in any one direction per season or per site.

The seasonal distributions for temperature at the 1Ed site are shown in Fig. 7, with the mean temperatures marked on the plots (as vertical lines). Typically, summer and autumn show increases of a larger magnitude than spring and winter, but all seasons demonstrate a shift of the distribution towards higher temperatures whilst retaining a similar distribution shape. The same pattern of a shifting of the distributions to the right occurs at all sites, to a fairly similar degree at each. This analysis compares well with the country-wide mean projections as described previously, confirming that the enhanced weather generator produces hourly data that is consistent with the general pattern of the whole UKCP09 model.

The changes in the frequency of higher temperatures and low wind conditions relative to the seasonal assumptions of P27 are given in Table 2. With respect to current conditions, the 3Wa location has the lowest frequencies of high temperatures in all seasons, whilst 2Gy has the highest frequencies of high temperatures, but the fewest occurrences of low wind speeds. The 1Ed site has the highest risk of low wind speeds in both summer and winter. Under the 2050s medium emissions scenario, similar patterns persist among the locations. The 2Gy site has the highest risk of exceeding seasonal temperatures, and 3Wa the lowest – but there is still a significant increase at all sites in terms of this particular risk. The changes in wind, again as expected, are less clear, but there does appear to be an increase in the instances of summer low wind conditions at 1Ed, but a decrease at the other two sites, whilst the winter low wind occurrences decrease at all three sites.

7. Projected changes in OHL rating

In order to understand how the projected temperature changes may impact on OHL ratings, the ratings method described in IEEE (2007) has been used with the time series of hourly current and future weather scenarios. Fig. 8 shows the resulting distribution of dynamic, or "real-time", hourly ratings calculated from the WG weather data under the current scenario and the future 2050s medium emissions scenario for the 1Ed site. Unlike the temperature distributions, the drop in the mean rating is generally quite small, and qualitatively, the change in the distributions appears minimal. There is some evidence of more frequent lower ratings in all seasons, but it is a more minor change than the temperature shifts would suggest.

Table 3 indicates that, in agreement with Buontempo (2008) the biggest changes will affect the minimum summer ratings, i.e. those which occur at the highest temperature/lowest wind conditions, by up to 12% at the 1Ed site, 10% at 2Gy and 5% at 3Wa. These changes are larger than the effect on the mean ratings – for example, the drop in the summer mean rating at 1Ed is around 3%, indicating that the tail of the distribution on the left might be extended in future.

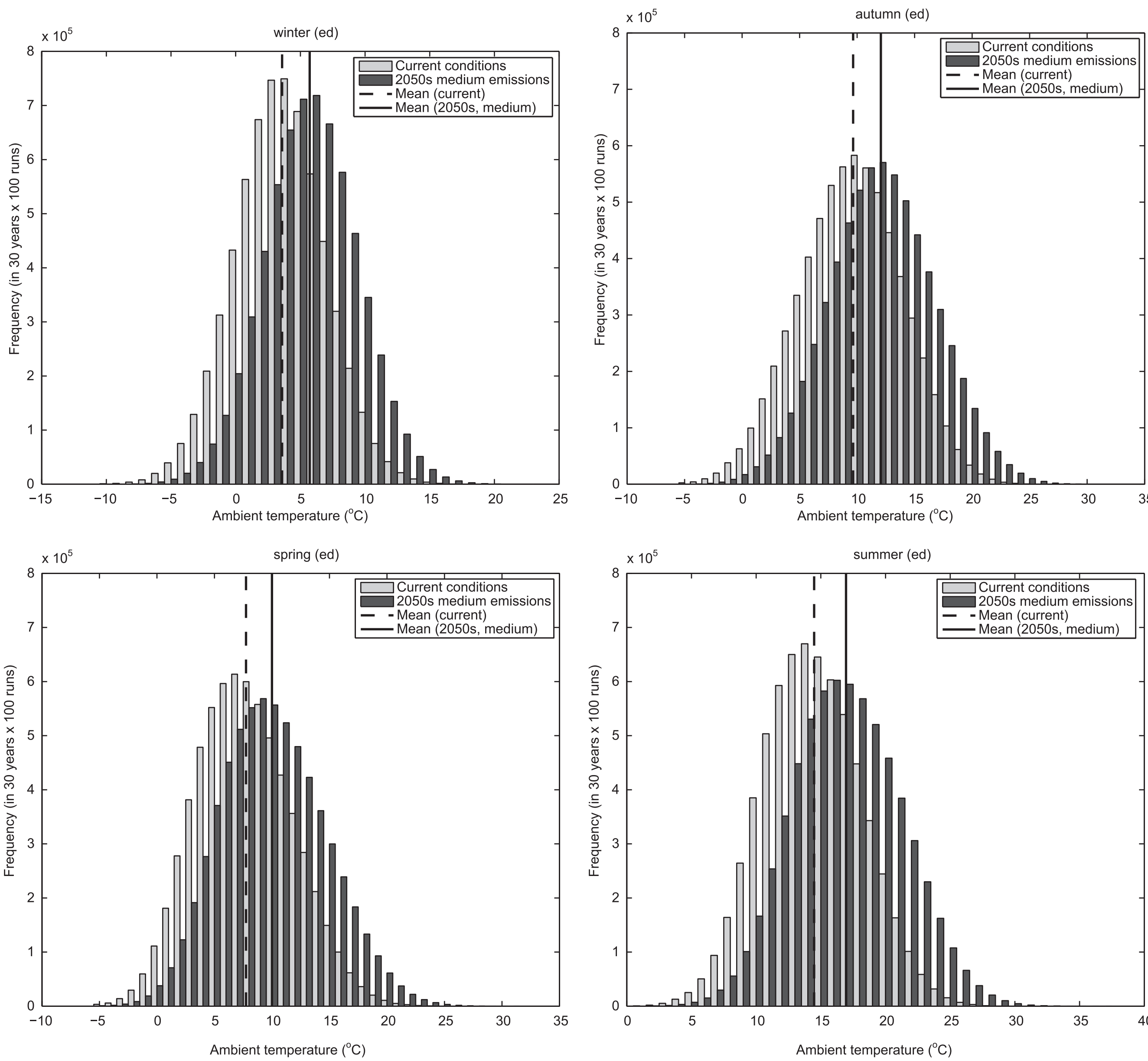

Fig. 7. Seasonal distributions of hourly temperature for the 1Ed site under current and 2050s climate.

Table 2
Percentage frequency of specific weather conditions under current 2050 medium emissions scenario.

	1Ed		2Gy		3Wa	
	Current	2050s med	Current	2050s med	Current	2050s med
Summer > 20 °C	7.42	23.45	8.92	28.93	7.14	21.14
Autumn > 9 °C	56.00	74.18	64.86	85.25	45.33	68.28
Winter > 2 °C	67.39	84.76	74.81	91.38	61.25	77.60
Spring > 9 °C	36.74	56.19	38.83	58.44	32.48	46.16
Summer wind < 0.5 m/s	2.16	2.39	1.18	0.87	2.04	1.70
Winter wind < 0.5 m/s	2.12	1.84	0.67	0.62	1.45	1.36
Summer > 20 °C and wind < 0.5 m/s	0.08	0.31	0.14	0.23	0.06	0.15
Winter > 2 °C and wind < 0.5 m/s	1.00	1.31	0.47	0.56	0.61	0.83

The changes – albeit small – that are apparent may be best appreciated in terms of changes in the level of risk to the network operator. Currently, using the assumptions of seasonal temperatures presented in the previous section, the Distribution Network Operators (DNO) effectively accept a level of risk on lines that are frequently thermally constrained. This is represented by the number of hours in which the maximum capacity, as calculated using local hourly weather parameters, is less than that which would be derived using the standard seasonal assumptions, including conservative wind speed. Should the load on the line exceed the actual real-time rated capacity at this time,

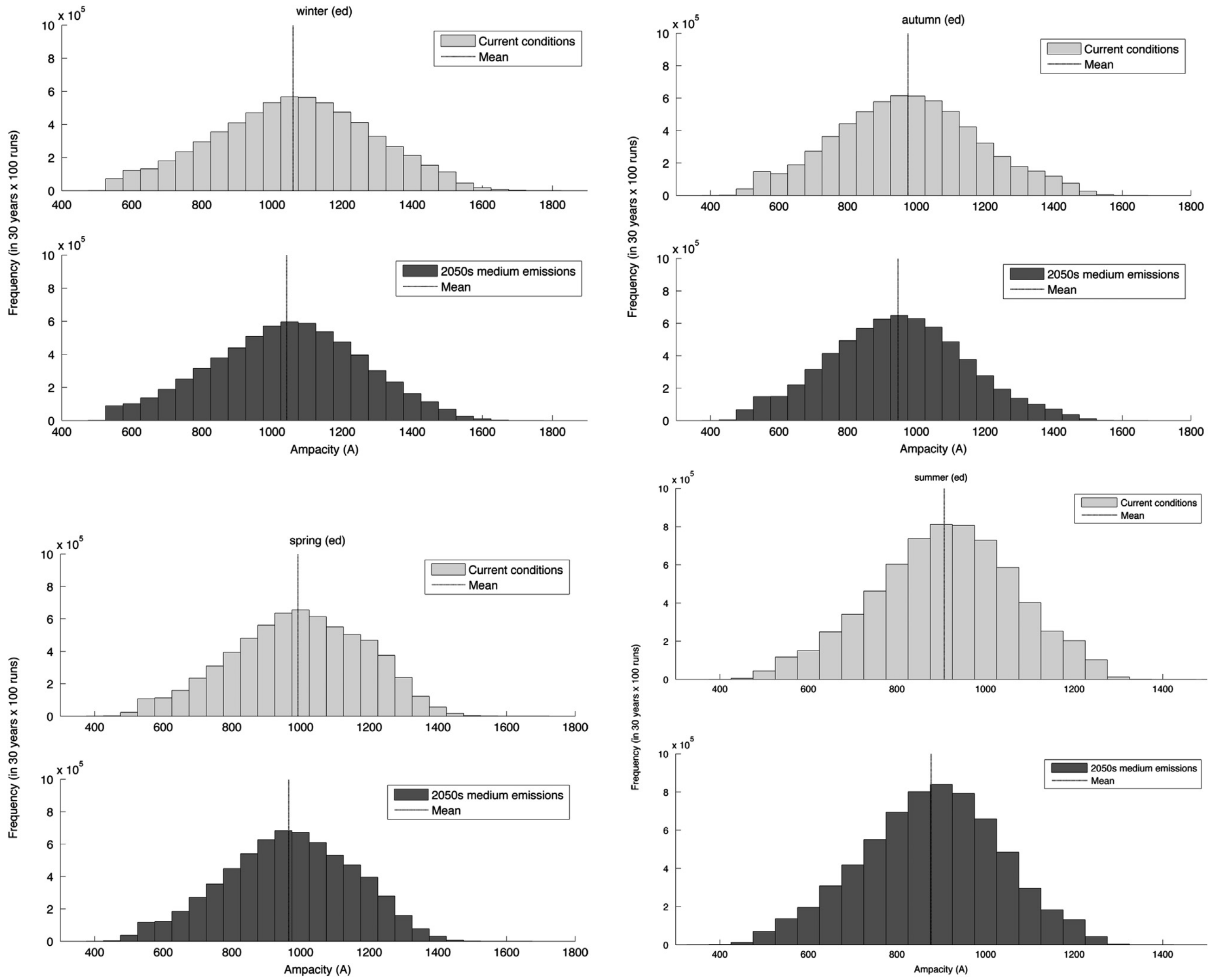

Fig. 8. Seasonal distributions of hourly ratings the 1Ed site under current and 2050s climate.

Table 3
Minimum seasonal ratings (i.e. worst-case).

	1Ed		2 Gy		3Wa	
	Current rating (A)	2050s med rating (A) (% change)	Current rating (A)	2050s med rating (A) (% change)	Current rating (A)	2050s med rating (A) (% change)
Summer	390	341 (−12.6)	413	371 (−10.2)	380	359 (−5.5)
Autumn	420	405 (−3.6)	442	402 (−9.0)	408	386 (−5.4)
Winter	486	488 (+0.4)	508	492 (−3.1)	476	466 (−2.1)
Spring	424	401 (−5.4)	434	423 (−2.5)	405	412 (+1.7)

Table 4
Percentage risk of real time rating being lower than nominal rating.

	1Ed		2Gy		3Wa	
	Current	2050s med	Current	2050s med	Current	2050s med
Summer	2.50	3.29	1.62	1.61	2.27	2.35
Autumn	4.84	5.52	1.40	1.63	2.42	2.75
Winter	3.93	3.97	1.12	1.24	1.99	2.10
Spring	3.60	4.15	1.83	2.08	2.08	2.17

load must be shed or the line may exceed its maximum allowable temperature and incur damage. Under future conditions of typically higher temperatures (but, notably, with fairly similar wind climate) it would be anticipated that the risk level would increase.

Using the WG output for the scenario corresponding to current conditions, the seasonal risks are defined as the frequency of occurrence of the actual real-time rating falling below the stated nominal seasonal steady-state rating. It is shown in Table 4 that the risks do increase in each season, but – as might be anticipated by looking at the changes in the distributions (Fig. 8), not by

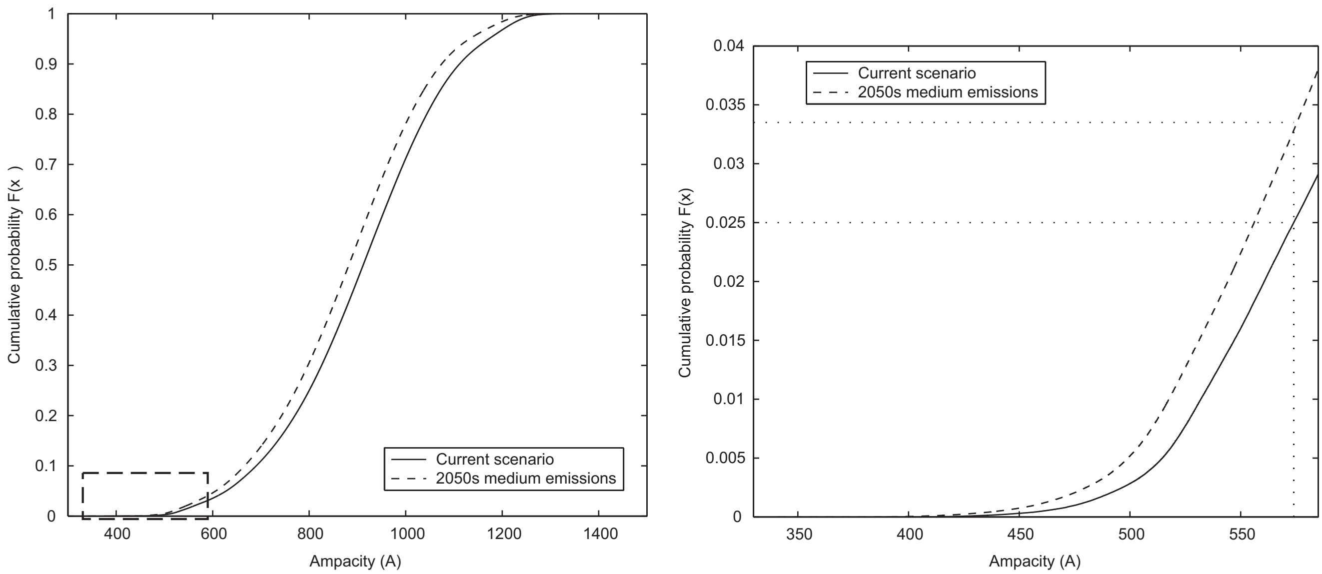

Fig. 9. Cumulative distribution plot for 1Ed ratings in the summer season – left panel shows the whole CDF, right panel zoomed in on lower left 'critical' portion.

very much. The most significant change is an increase of 0.8% in summer at the 1Ed site, whilst the summer risk actually appears to decrease by a very small amount at the 2Gy site. Overall, the 1Ed site has the highest risk of having a capacity lower than its nominal rating; this is due to its typically lower wind speeds.

The change in risk can also be visualised as the non-exceedence probability of the static value for the season, seen in Fig. 9 for 1Ed in summer, where the probability of being below the assumed summer rating of 574A increases from 2.5% to 3.3%.

Table 5
Adjustments to seasonal static ratings based on current acceptable risk.

1Ed	Current risk (%)	Current rating (A)	Future rating for equivalent risk (A)	Change in rating (%)
Summer	2.50	574	556	3.1%
Autumn	4.84	623	610	2.1%
Winter	3.93	651	650	0.1%
Spring	3.60	623	610	2.1%

8. Adaptation

The changes in ratings demonstrated by the probabilistic assessment framework for the 2050s under a medium emissions scenario, suggest that despite some significant increases in the seasonal mean temperatures, the additional risk incurred by the DNO of exceeding OHL ratings is still small. By adopting a more comprehensive approach than previous studies, using hourly values of all the important weather conditions, the apparent influence of wind speed – above the conservative assumptions of ER P27 – is shown to be important. Examining temperature changes alone whilst ignoring the effect of wind cooling, might overestimate the impact of climate change and lead to expensive interventions that are unnecessary. Also, since the sensitivity of rating to wind speed is higher, the analysis highlights that it is in those areas with lower wind speed where the risk of breaching the static assumption is greatest and these may require additional attention. It is imperative to stress that whilst the confidence in the model of wind speeds for the current conditions is high, the nature of the investigations of wind speeds under the influence of climate change is tentative. By interpreting the scenarios and sites explored in this work as potential 'case studies' with a high degree of uncertainty, some important issues are raised, including how to best adapt to any changes that might occur in order to mitigate the increased risks.

One such adaptation method would be to adjust the seasonal static ratings to maintain a similar level of future risk as is currently deemed acceptable. For the 1Ed site with the highest present-day risk level, values for ratings from the '2050s Medium' scenario that correspond to the current seasonal risk levels are shown in Table 5. The percentages correspond reasonably to the assumption of 3% of operating time above the nominal rating, as was apparent in the ER P27 values and Price, Gibbon (1983), perhaps with the autumn risk being slightly greater than expected. The magnitude of the adjustments under the climate change scenario is small, losing only a few per cent of the capacity at most. This may be trivial for many OHL that are not typically thermally constrained.

For those lines that are thermally constrained, the small decrease in nominal rating might be more problematic. The increasing penetration of renewable generation on the distribution network – mainly wind power, but it is also likely that solar PV will become more prevalent – increases the potential for the network to be operating at higher capacities, and thus a greater number of OHL may be thermally constrained. As a result of the conservative wind speed assumption in the ER P27 calculations, the true capacity often exceeds the nominal static rating, as shown for sample years under current and future scenarios in Fig. 10. There is a substantial amount of unexploited headroom available which a dynamic (or real-time) rating system could provide access to. In Ochoa et al. (2010) it was demonstrated that building dynamic rating into a 'smart grid' operating algorithm to allow the extra wind cooling available at times of high wind power generation to be fully recognised was potentially very effective. If the lines analysed in this work were to be particularly stressed by increasing wind (or solar) power connections, there is a small increase in the risk of the current exceeding the ER P27 nominal ratings under future climate change scenarios. Dynamic rating systems offer the opportunity to both eliminate the risk of this occurring when the weather conditions do not permit it, and open up additional capacity when they do. They offer the additional advantage that they can be retrofitted relatively quickly to existing circuits without upgrading the line itself. It is of particular note that a real-time ratings system has been recently fitted in the vicinity of the 2Gy site to allow extra headroom to be exploited when winds are particularly strong and a

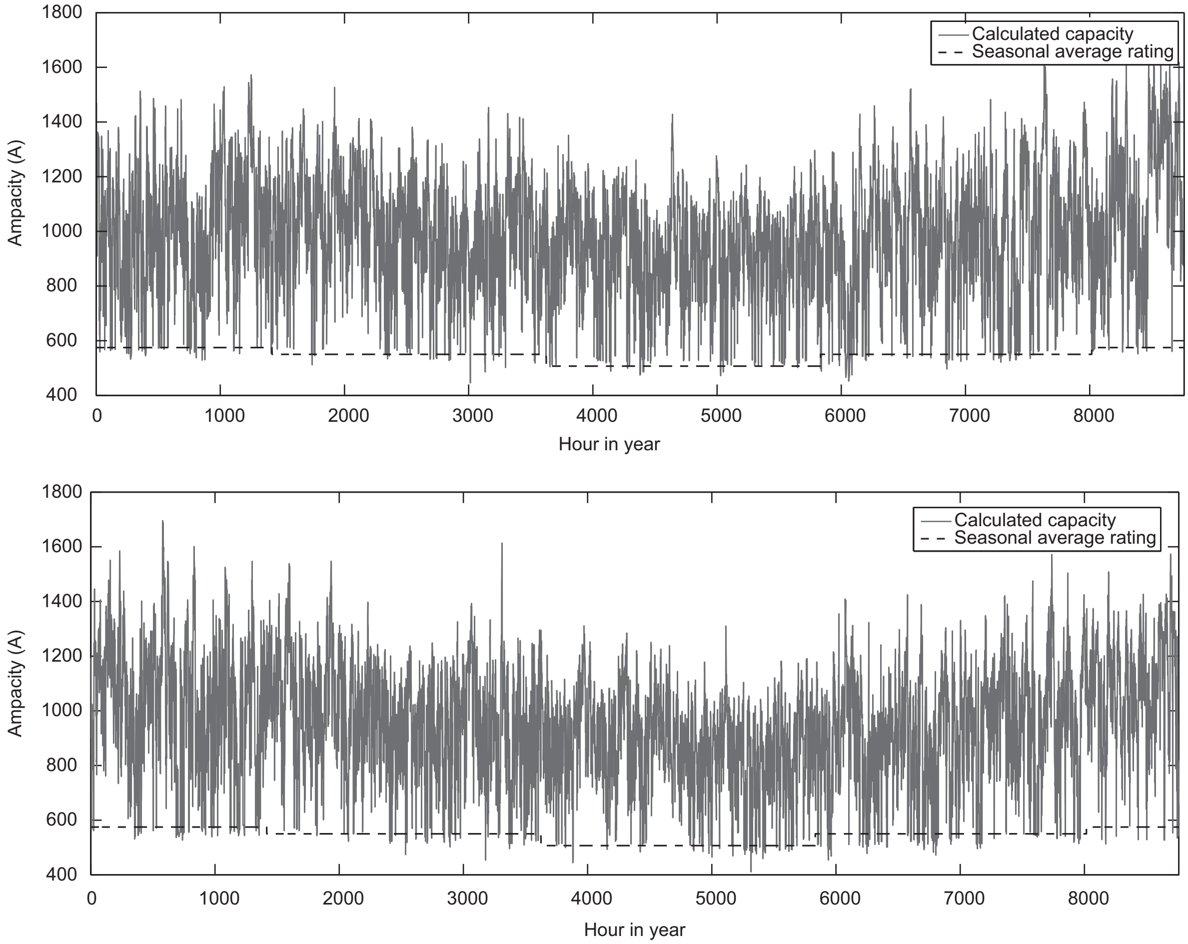

Fig. 10. Sample year of dynamic hourly ratings calculated from the weather generator runs for 1Ed showing current (upper) and future (lower) occurrences where dynamic rating < static assumptions.

local offshore wind farm requires high capacity on the distribution network (Yip et al., 2009). The cost avoided by implementing a dynamic rating system in this case rather than a network reinforcement or upgrade was stated to be 'in the region of £5 million' (Electricity Networks Association, 2008). The Electricity Networks Association (2011) suggests the typical cost of upgrading or replacing lower voltage OHLs in general to be around £30–40 k per km. The relative cost of implementing a real-time ratings system is shown in CIGRE JWG B2/C1.9 (2010) to be significantly lower than alternative options, although the amount of capacity increase available is limited compared to that which can be obtained by some of the reconstruction options.

Another issue that requires consideration is the possibility of changing patterns of consumer demand. Currently, peak demand in the UK occurs during very cold winter spells when space-heating requirements are highest. Shifting that demand peak to summer (or at least increasing the current summer demand) due to a demand for space cooling as temperatures increase, increases the risk of reaching the nominal OHL rating more often. For example, the number of days where the summer temperature reaches 20 °C rises from 7–9% under current conditions to 20–30% in the climate change scenario presented. It is highly likely that the UK would follow trends established in other western countries with higher summer temperatures and begin to utilise air-conditioning more heavily. The need for extra capacity may then become more wide-spread – further analysis would be required to ascertain the risks of this capacity being required during low-wind spells, in order to understand if dynamic ratings would offer any benefit.

9. Conclusions

Using the UKCP09 climate projections via the WG with additional wind modelling, this work has shown that the likely effects of climate change on the thermal limits of the OHL in the UK are relatively modest. The effects on OHL that do not often operate close to the thermal limits will be minor, perhaps necessitating a small reduction in the nominal ratings. The difficulties in future, however, may become more apparent if a number of additional factors coincide – namely rising temperatures, increasing renewable penetrations, and the possibility of rising demand for space cooling. In such circumstances, dynamic rating of thermally-limited conductors may present a cheaper alternative to network reinforcement. This study highlights that in the coming decades, calculations of the risk of exceeding the thermal limits on OHL may require re-evaluation more frequently, using more up-to-date weather data. The model developed presents a suitable method for doing so, and as the science progresses to produce ever more accurate projections of future climate, this can be expanded.

It is important to highlight the limitations to the study. The daily mean and maximum temperatures are given by the WG at a height of 1.5 m above ground level and conductors fitted to wood pole and lattice towers will be at higher elevations (8 m+) and experience slightly lower temperatures. However, the temperature lapse rate is generally noticeable over larger vertical distances and it is likely that projected temperature changes would be similar at higher levels, giving changes of comparable magnitude. The analysis was limited to three locations; further work would benefit from additional locations and climate change scenarios. More in-depth analysis would directly include modelling of power flows on the line resulting from variations in demand and generation to allow the frequency and extent of overloading and constraints to be assessed. This will be particularly important given the potential changes in power flows resulting from wind, marine and solar PV connections, new demand patterns and the effect of smart grid controls. More detailed models of conductor temperature and sag would also be valuable. While the Lynx conductor is largely used on distribution and sub-transmission networks, the implications are similar for transmission lines of different construction and conductor temperature limits.

The analysis presented here relates to the UK and its current and potential future climate. So far much of the climate change research suggests modest and uncertain changes in UK wind speeds but projections for other parts of the world e.g., the USA (Sailor et al., 2008) suggests more significant changes in wind speeds. As such, more significant impact on OHL ratings and consequent benefits from dynamic ratings may be more apparent elsewhere. The probabilistic assessment framework developed and applied here could be re-applied elsewhere, given similar WG-type weather data.

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