Spatiotemporal disaggregation of GB scenarios depicting increased wind capacity and electrified heat demand in dwellings

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Abstract

National Grid's future energy scenarios present a range of futures where wind capacity and domestic heat pumps increase to varying degrees. Both of these changes will introduce increased variability into the GB electricity system. In order to understand the implications of this variability it is important to understand the impact that wind speeds and temperature will have on supply and demand. This study therefore presents a method that disaggregates and models these scenarios at an hourly resolution in a 0.5°grid covering GB and offshore waters. The gridded modelling approach facilitates the use of climate reanalysis data which provides spatiotemporally homogeneous and accurate hindcasted weather data over the 25 year period of the scenarios. Methods for redistributing non gridded spatial data and disaggregating non spatial data to the grid are discussed.

The results demonstrate that high offshore capacity factors have a significant impact on the projected generation of different wind capacity scenarios. Analysis of extreme events under each scenario, facilitated by the disaggregated approach, demonstrate that there will be periods of up to 50 hours where supply exceeds demand for the most ambitious wind scenarios and all but one scenario will require solutions to store or transfer excess wind generation. High demand events are shown to occur at similar levels in all scenarios.

Keywords: Wind, Electrified heat, Disaggregated, Spatiotemporal

1. Introduction

The UK Future Energy Scenarios, developed by National Grid [21], the network operator in Great Britain, describe four future pathways for the energy system, where wind capacity increases up to 20 GW onshore and 35 GW offshore. Changes also occur to electricity demand, where the number of domestic heat pumps increases up to 10 million by 2035. Like most other analyses of future energy systems, modelling and analysis is carried out at a highly aggregated spatial (national) and temporal (annual) resolution.

In reality, wind speeds that drive generation vary across space and time at fine resolutions. This means that generation will vary temporally, and this variability will be influenced by the spatial configuration of the wind fleet. Concurrently increasing the number of heat pumps will mean that temperature, which also varies over space and time, will drive electricity demand to a greater extent than experienced in the past. This has the potential to change the shape of the electricity demand curve and after wind supply has been taken into consideration alter residual demand. In order to begin to understand the implications of increased variability on the energy system it is therefore necessary to analyse both demand for electricity and wind supply at a disaggregated resolution in both space and time for each of the scenarios.

This study presents a method for disaggregating National Grid scenarios to a 0.5° spatial and hourly temporal resolution, linking the subsequent simulation of both demand and supply to accurate homogeneous weather data. Results are presented both at an aggregated resolution, to show model outputs in comparison to the National Grid outputs, and at a disaggregated resolution, describing extreme events in wind supply, electricity demand and the resultant residual demand. The latter results demonstrate the benefits of the disaggregated approach and the potential implications of National Grid's scenarios.

2. Methods

2.1. A gridded approach

In order to model electricity demand and wind supply at a disaggregated resolution, it was necessary to choose a spatial referencing system to disaggregate to and a level of aggregation which increased the level of detail of the scenario analysis and captured enough variation in wind speed and temperature to create accurate model outputs, whilst managing the level of detail to ensure that modeling was not too computationally intensive. A gridded approach was chosen as data representing two of the primary drivers of demand and supply over space and time, weather and population, are available in this format. Weather data were obtained from The National Centre for Environmental Prediction's Climate Forecast System Reanalysis (NCEP CFSR) Saha et al. [29], these data are provided hourly, gridded at 0.5° at their finest resolution. This resolution fits the criteria described above, provided that the variability in wind speed at lower spatial resolutions is well represented by these grid squares. This issue is comprehensively investigated in Sharp et al. [32], which demonstrates that overall wind speed is very well represented by the dataset, therefore this resolution was adopted as the spatial and temporal framework for modeling. Modelled scenarios are restricted to the GB land mass and associated offshore areas, the framework disaggregates this to 207 grid squares containing land and 2720 total grid squares (Figure 1). The large number of offshore grid squares are a result of the inclusion of all sovereign British waters where it may be possible to place wind turbines in future model iterations. Not all of the grid squares are used to simulate offshore capacity in this study.

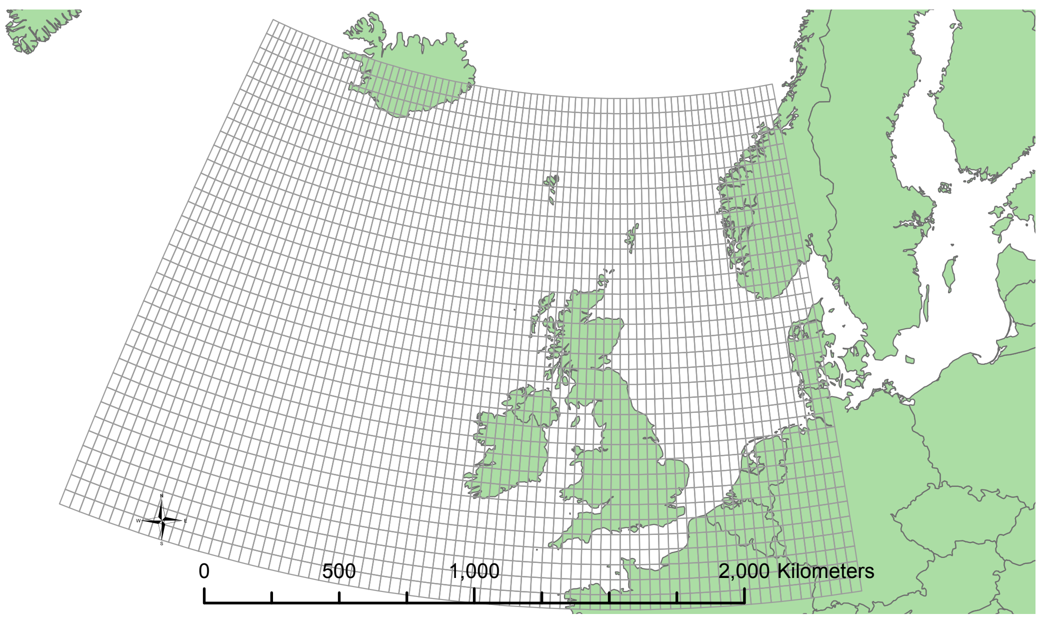

Figure 1: Map showing extent of modelling area.

As well as meeting the desired criteria for a modelling framework, the gridded approach has the advantage of spatial consistency and scalability. A disadvantage is that many spatial datasets are provided referenced to non gridded systems, particularly census or political geographies. There are also a number of datasets used in the modelling and provided as part of the scenarios which are non spatial. It was therefore necessary to identify methods to redistribute spatial data. There are a number of methods available for spatial redistribution. Each of these methods is a variation on area weighting, where a grid is overlaid on the census polygons. Each cell of the grid is then assigned a value based on the proportion of the polygon that is beneath it [11, 12]. The advantage of this method is that it is easy to implement, the disadvantage is that it presumes that people are distributed evenly within the polygon. However, since the polygons that lie along the boundaries of the grid will generally be small relative to the area of a grid squares, the error is likely to be low in percentage terms; therefore, this method was utilised for all non gridded data. Methods for disaggregating national data to the model grid in model development are described in Section 2.3, while those used in scenario modelling are described in Section 2.4.

A supply model, described in Section 2.2, and a demand model, described in Section 2.3, were developed so that wind supply and electricity demand, as depicted by National Grid, could be simulated on this model grid.

2.2. *Supply Modelling*

Previous studies examining the variability of wind speed and potential generation in GB have used manufacturer wind turbine curves, which describe the relationship between wind speed and power from a turbine (e.g. Figure 2). Studies simulating generation in the UK using this method and in situ measured wind speed data can be broadly categorised as those assuming weather stations represent wind conditions across GB [e.g. 33, 27], or those assuming weather station data represents a region [34, 13, 14, 3, 25]. There are also studies using climate reanalysis data to drive these simulations [35, 23, 15, 18] .

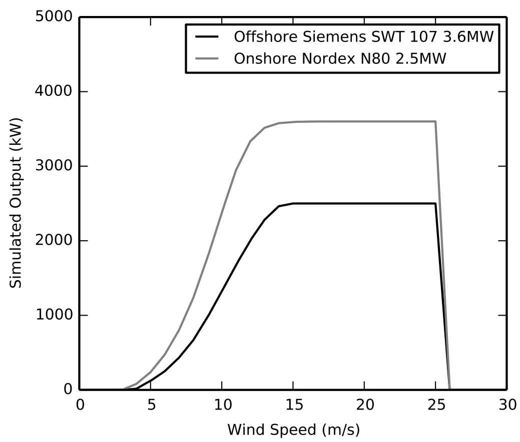

Figure 2: Turbine curves used for estimating electricity generation from wind speed.

These studies have different foci but each look at the impacts of variability of wind speed and wind power; also the hourly resolution is most widely used owing to the availability of weather data. Although all of the studies model onshore output, very few have extended methods to cover offshore capacity; also none of the studies explore multiple scenarios weighting the wind speeds experienced to expected fleets, but rather assume even diversity or that turbines will be near measurement stations and weight this to capacity or only explore the variability rather than the absolute output.

Manufacturer turbine curves are produced as a result of testing, and are therefore a realistic representation of turbine output in isolation and when new. Turbines do not, however, operate in isolation and are therefore subject to the influence of their surroundings. A key influence is other turbines, because when a turbine is operating it reduces the wind speed downwind. Therefore, closely sited turbines can produce up to 60% less energy, owing to losses in the power of the wind [30]. Wind speed is dependent on local conditions such as topography and weather characteristics such as vertical wind profiles and layer mixing, which drive the rate at which energy is replaced within the wind. Faults and maintenance will affect the output of turbines and curtailment may stop output at times. As turbines age they become less efficient at harnessing wind, an issue explored in detail by Staffell and Green [35].

Modelling of these drivers is difficult, as there is often not sufficient data, therefore methods have been created to allow for these effects. Methods include numerical models and heuristic models e.g. artificial neural networks and genetic algorithms [30]. There are methods which attempt to take these effects into account through the use of an adapted turbine power curve, which are a variation of the approach developed by Norgaard and Holttinen [22]. Alternatively these drivers can be counteracted through the use a correction factor. A commonly used method is to correct wind speed data to match a desired annual capacity factor which represents nationally averaged historical output; for example Sinden [33] uses a value of 30%. The problem with this method is that recent data and research, described above, has indicated that this may be an overestimation of the capacity factor, and it is likely that the capacity factor will be different in the future when capacity increases in both absolute terms and geographical diversity. It is also possible to apply a correction factor which breaks down factors affecting output; for example Boehme et al. [3] account for down time through using the statistic that European wind turbines are available 98% of the time, and Boehme and Wallace [4] use wake reduction (linear in proportion to turbine density), 2% downtime and 2% electrical loss. An alternative approach is to correlate simulated generation against measured data to develop a correction factor that incorporates all of the factors not included in the method.

In this study, the method applied was to simulate installed capacity in a grid square using unaltered manufacturer turbine curve. Single archetypal turbine curves were selected based on operational turbine curves (Figure 2). Wind speed data were interpolated to the hub height of these turbines, as this is wind speed represented by manufacturer turbine curves, using the power Law (Hellman equation) equation and an exponent of 1/7 (~ 0.142) onshore, and 1/9 (0.1') offshore, values which have been established as appropriate in other studies [26, 16].

This method assumes that the wind speeds provided by CFSR for a grid square represent the range of conditions within it, but does not attempt to include losses and generalises surface and atmospheric conditions in the wind speed height correction; therefore it was necessary to evaluate the model outputs against measured data so that a correction factor could be applied that accounts for these sources of error.

Measured generation data is available for GB in the form of hourly generation by fuel type from Elexon [10] and monthly aggregated generation from wind farms that are part of the Renewables Obligation Certificate (ROC) scheme [24]. Wind farms that are included in each of the datasets were identified and grouped by grid square. Generation was then simulated using the turbine curves and CFSR wind speed data. Correlation of simulated output to the monthly ROC data between 2002 and 2010 demonstrated an R^2 of 0.89; which compares favourably to similar published models (Hawkins et al. [15] R^2= 0.94 Staffell and Green [35] R^2= 0.59). Correlation with Elexon data between 2008 and 2010 was lower (R^2 = 0.66), however, greater variability at finer temporal resolutions is harder to represent with these methods. Root means square error (RMSE) to ROC data was 0.16 GW and 0.28 GW to Elexon. A linear scaling factor of 1.55 reduced the RMSE of both ROC (0.08 GW) data and Elexon (0.22 GW) data to the lowest level and was therefore adopted for subsequent modelling. The need for a scaling factor above one demonstrates that there is a significant source of error which results in under estimation of generation, whereas it would be expected that unaccounted for losses would result in over estimation. It is likely, therefore, that the method used for wind height correction could be improved; this will be investigated in future work.

2.3. Demand Modelling

Previous studies looking at wind variability have used historic demand to compare against predicted future turbine output. Sometimes in raw form, sometimes with statistical adjustments made to represent growth in demand. This has several important disadvantages; firstly this method relies on accurate weather data for turbine simulation, secondly is it is very difficult to introduce changes to electricity demand such as electrification of heat demand or transport or demand shifting. It is also difficult to apply measured data to long periods, such as that used in National Grid's scenarios. The demand model developed for this study counteracts these disadvantages by using the same weather data as the supply model and incorporating bottom up methods so that the electrified domestic heating described in National Grid's scenarios can be included.

National Grid's scenarios depict *all* demand for electricity for the whole of GB over 25 years. This is very difficult to model using only bottom up methods, particularly at the resolution described above. Therefore a hybrid demand modelling approach was adopted. The model is based on the existing Dynamic Energy Agents-based Model (DEAM).

2.3.1. DEAM

DEAM was developed by Barrett and Spataru [1] to represent energy demand and supply from both consumers (in the domestic, non domestic and transport sectors) and suppliers, as agents, both in the present energy system and under future scenarios. DEAM is designed to depict energy demand and supply at a half hourly temporal resolution and can operate at a range of spatial scales within the GB energy system. The model has been used previously to calculate the energy flows for agents connected to a local electricity substation, by investigating the possible future loads using a representative set of data from the Distribution Network Operator (DNO), Western Power Distribution (WPD) [2].

DEAM uses two distinct methods for calculating end use demands, the first method is calculated top down and encompasses those demands which *are not* influenced by building fabric, defined here as non space heat demands. With the exception of lighting, these demands are independent of weather. This method requires an annual energy demand value for each end use (for each fuel if possible), at the desired scale of the model, e.g. 2 x 10^6 Wh of electricity for lighting in a household. This value is temporally disaggregated using normalised activity profiles which represent what proportion of this demand is used at different times of year, week and hour (e.g. Figure 3). This method represents regular variation in demand, but does not include physical drivers such as weather.

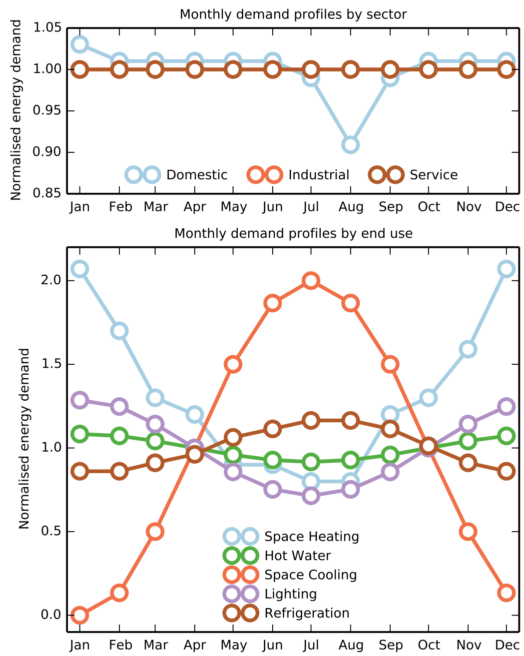

Figure 3: Example activity profiles used in the top down section of the demand model, showing what proportion of different domestic demand occurs during the months of a year.

The second method encompasses space heating and cooling demand which *are* influenced by building characteristics and are weather dependent, these demands are calculated bottom up. This method is based on the physical relationship between the required change in temperature between external temperature and a heating set point, the heat loss characteristics of a building stock and the temperature gain from excess heat from people and appliances within a building (Equation 1, Space heat demand, W is the heat loss coefficient, T_{out} the external temperature and T_{in} the internal, Ap the activity profile and ef the efficiency of the heating technology). Gains are calculated by assuming a number of watts per person and an amount of excess heat from the end uses calculated using the top down method. Like the top down method this method relies on activity profiles to ensure that heat is only demanded when required by those occupying a dwelling.

$$Spaceheatdemand = (T_{out} - T_{in}) * W - gains * Ap * ef \tag{1}$$

DEAM methods for calculating demand from transport and energy producers and methods for calculating supply from renewables are not used and are therefore not described here.

2.3.2. SpDEAM

Spatiotemporal DEAM (SpDEAM), an adapted version of DEAM, has been developed for this study so that DEAM's method can be applied at the same spatial and temporal resolution and scope as the previously described wind model. In order to manage detail, only domestic heat demand is calculated bottom up. All other domestic demand and all non domestic demand is calculated top down. This has the added advantage of tying in modelling to National Grid scenario modelling as much as possible, only adding detail on the weather driven demand and therefore hopefully the same weather systems as experienced by wind modelling. The DEAM methods described above were adjusted to represent hourly demand.

Therefore two key datasets were used to spatially disaggregate DEAM modelling. Data on population by grid square were obtained from the Gridded Population of the World (GPW) (see Sharp [31] for a detailed analysis of the accuracy of gridded population datasets in the UK). Data on the distribution of domestic building types, and heating technology types were obtained from the 2011 census and redistributed to the grid using the areal weighting method described above. Building floor area by grid square was calculated using archetype specific floor areas obtained from DCLG. [7, 8]. Population data were used to allocate the demand calculated using the top down method to grid squares by assuming that energy consumption is evenly distributed per person. Gains from these end uses and people were then assigned to different domestic building types, assuming an even distribution of people amongst building types. Heat demand was calculated based on building archetype specific heat loss coefficients obtained from DECC [9]. Heat demand was assigned to technologies using data from the census on central heating technology type and a conversion efficiency was applied so that demand for gas, electricity and other fuels is simulated.

In order to calibrate the model, SpDEAM was run for the period 2000-2010 using data on historical population, building stock and energy demand and compared against hourly electricity demand data from National Grid [19] and modelled daily gas demand data from National Grid [20]. The results showed that there was a significant underestimation of non - domestic demand when using data from Energy Consumption in the UK (ECUK) [17] representing commercial, industrial and service demand. Correction was made to the activity profiles for the non domestic sector. This correction factor takes into account factors including losses and potentially demand that is not represented by the data used as an input for the top down part of the model, e.g. theft of electricity or sub sectors not included in the ECUK data.

Following these corrections hourly electricity demand from SpDEAM closely matches published statistics (R^2 = 0.87. RMSE = 0.42 GW)(Figure 4). It is very difficult to assess the error of individual elements of the model more accurately owing to the complex nature of the electricity system, lack of published data and the fact that what little data there is is used as input into the model. Figure 5 shows that gas demand from SpDEAM also followed published data well (R^2 = 0.81. RMSE = 39.82 GW). Accurate gas demand depiction is a good indicator that heat demand from the model works well, this is important, as significant amounts of this demand is electrified in National Grid's scenarios. This has a consequence on the amount of demand that will be met by wind, especially as it is likely that this electricity will be demanded at different times of the day. It should be noted that the gas demand from National Grid is based on Seasonal Normal Demand which represents a "normal" demand which may vary when it is either warm or cold; this is the reason that SpDEAM demand varies more than National Grid's at high levels.

2.4. Scenario Modelling

Following the development, calibration and evaluation of the models they were both adapted to enable the spatiotemporally disaggregated modelling of the four National Grid scenarios. The scenarios occupy different positions on a matrix of affordability and sustainability, described in Figure 6. National Grid provide data that covers the scenario period for many variables; in other cases it was necessary to interpolate from the data used in the SpDEAM and wind model evaluations. Future modelling assumes that weather experienced in the past 25 years represents that which will be experienced in the next 25 years, this is sometimes referred to as hindcasting. The weather period chosen to represent 2010 - 2035 is 1985 - 2010. Hindcasting is an established method, which provides a pragmatic solution to the lack of measured data on some variables and need to model the effect of various changes to the system. Assuming that future weather is the same as the past means that factors such as climate change and inevitable variation are not taken into account. The models were set up using the data described in the following sub sections and run using the methods described above.

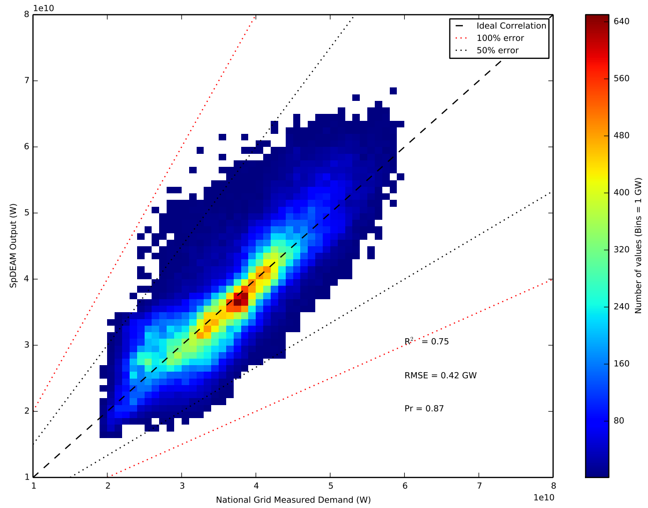

Figure 4: Correlation between SpDEAM and National Grid hourly electricity demand.

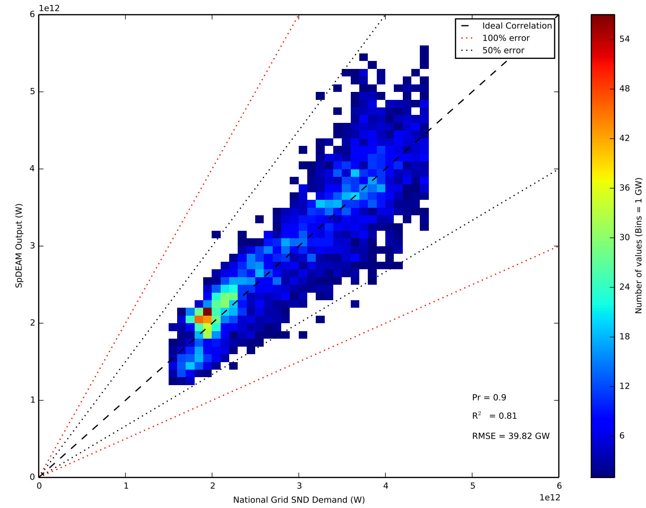

Figure 5: Correlation between SpDEAM and National Grid daily gas demand.

2.4.1. *Wind capacities*

The onshore annual wind capacities described by National Grid's four scenarios (Figure 7) were redistributed to the model grid following a multi criteria analysis of suitable land for development. The analysis took into account absolute environmental restriction on development including areas protected by, for example, being sites of special scientific interest. Criteria based restriction were also applied, including proximity to airports. Finally, all unsuitable land use was eliminated including, for example, urban areas. This analysis resulted in an amount of each grid square that could be used for wind development onshore. This analysis described a free onshore area of 122,740 km^2 in total or 53% of GB, equivalent to 191,781 turbines or 481 GW. This is very large, which reflects the fact that there are some restrictions that have not been taken into account, such as socially acceptable distance from towns, and the fact that planning permission rates are falling as a result of both political and local opposition to development, meaning much development is unlikely to happen. However the analysis does permit a more realistic location of wind farms by removing a large portion of GB that definitely cannot be used for development and means that subsequent simulations of wind generation will represent a realistic harnessing of the wind conditions across GB. The annual national scenario capacities were allocated to the remaining area, prioritising high mean annual wind speeds (although all sites are suitable based on a threshold of > 5 m/s) and geographical diversity. Onshore capacity was placed to ensure that there was the equivalent of 10 blade diameters between each turbine. It was not necessary to carry out a capacity assessment offshore as development zones have already been allocated by the Crown Estate. These were filled ensuring that the closest to shore sites were used first and an equivalent of 15 blade diameters (larger than onshore as wind must replace more energy due to the differing roughness of sea and land). Figure 8 shows the resultant spatial capacities in 2035 for each of the scenarios in comparison to 2010 (a spatial dataset was created for each year of the scenarios to describe the capacity generating in that year).

2.4.2. *Demand scenarios*

National annual values of energy demand to feed into the top down section of the demand model are provided as part of the scenario modelling and take into account many changes to the energy system. The domestic values closely matched those used in the model calibration. The non domestic values varied, which may be a result of representing the sub sectors not included in the previously used data. The non domestic data were therefore altered to match the evaluation data so that the corrected profiles still worked.

The spatial data used to distribute demand described above were assumed to remain static in terms of spatial configuration. Change and growth was introduced by altering absolute population using annual values from the

Figure 6: National Grid's scenario matrix, source: National Grid [21, p. 5].

office for national statistics. Required dwelling numbers were calculated based on expected falling house size values from DCLG [6]. Assuming that the proportion of each archetype remained the same as in 2011 and a demolition rate of 20,00 dwellings per year, evenly distributed amongst archetypes, the required new number of dwellings per year was calculated. It was assumed that these were built in locations proportional to existing capacity. This resulted in separate stock models of existing and new stock. This allowed divergent modelling of building size and heat loss characteristics. While existing stock floor area remains static, new dwellings steadily reduce in size and all dwelling archetypes revert to 2000 levels by 2035. Heat loss characteristics change at different rates depending on the scenario.

National Grid provide data on whether heat pumps are placed in new dwellings or which technology they should replace in existing buildings. This was used as a guide to allocate the new technology and therefore allocate heat demand to this and other technologies. Heat pump coefficients of performance were based on a field trial of the technology in Finland and therefore represent a step forward from those currently installed. The main difference between the scenarios is the large uptake of heat pumps in the Gone Green scenario, which is not seen in the other scenarios (Figure 9).

3. Results and discussion

The following analysis begins by comparing aggregated model outputs against National Grid's published data. This is necessary in order to verify the accuracy of the demand model as model outputs should closely match the data, despite bottom up modelling being added. Wind supply is modelled completely separately so differences between time series can be attributed to modelling methods. The aggregated analysis is followed by an analysis of extreme events over the entire length of the scenarios. This analysis is used to demonstrate the effects of increased wind capacity and changing demand on the energy system and results point towards issues that may be caused by each of the scenarios.

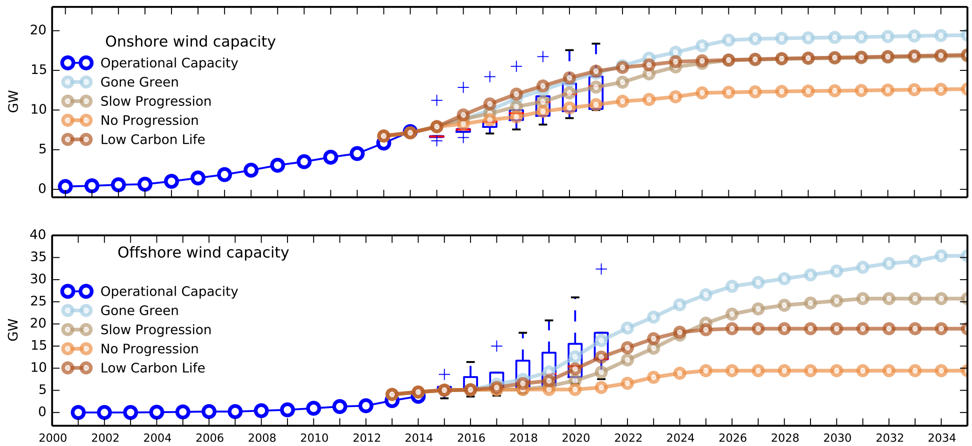

Figure 7: GB wind capacities 2000 - 2035, the line plots represent the scenarios used in this study, boxplots are other scenarios of annual wind capacity, data sources: National Grid [21].

3.1. Aggregated outputs

Figure 10 shows the difference between the wind generation simulated using the described wind model and that shown in National Grid's scenarios at a spatial and temporally aggregated resolution. The plot shows that modelled output is larger than that predicted by National Grid for all years. There is also greater variability due to the linking of generation to wind speed data, whereas National Grid predict output by assuming a mean percentage of capacity that will operate over the year. The difference between modelled and National Grid output is approximately proportional to the capacity described in Figure 7.

Figure 11 shows the difference between the total electricity demand as simulated by SpDEAM and that described by National Grid. The plot shows very little divergence, although SpDEAM consistently underestimates demand in comparison with National Grid. As with wind supply there is greater variability, which is also driven by weather; however, the difference is caused by the fact that National Grid's outputs are weather corrected as their intention is to show annual changes in demand.

Figure 12 indicates a possible reason for the the greater simulated wind generation when using a disaggregated approach. The plot shows that offshore capacity factors are high in comparison to onshore ones over the same time period, and also those used in other studies, which as described above are approximately 30% (capacity factors represent the proportion of rated capacity at which turbine have been operating at on average over the year). The higher offshore capacity factors reflect the generally higher wind speeds that are consistently experienced over the sea in the locations described in Figure 8. It is possible that National Grid used lower capacity factors, in line with previously published literature, to estimate annual output, therefore potentially underestimating generation in comparison to the model results presented here.

The larger, more spatially diverse capacities in the Gone Green and Slow Progression scenarios result in larger capacity factors. However there are also changes driven by wind speed, for example the difference between capacity factors over the period 2027 - 2029. There is a dip in capacity factor in 2028 that is due to wind speed rather than capacity, which will continue to increase.

3.2. Extreme events

3.2.1. Wind Generation

The following analysis uses a method established by Cannon et al. [5] who look at extreme events in wind generation using NASA's MERRA reanalysis [28]. They describe the most extreme events of wind generation by simulating output using a turbine curve and the MERRA data, they then define the events using percentile of supply

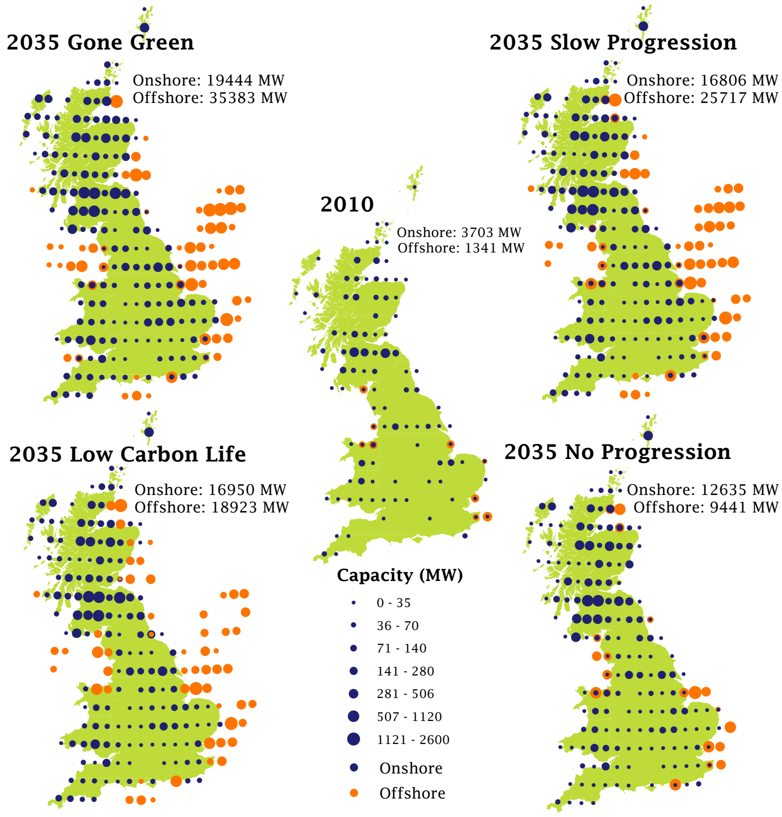

Figure 8: Maps of wind capacity spatial scenarios, 2010 and 2035.

in the 1st, 10th, 20th, 80th, 90th and 99th bracket over a 33 year period. The persistence of these high and low events is then plotted against number of occurrences to display the characteristics of GB's wind resource. Here this method is used to show how this variable wind resource is harnessed by each scenario, which will be exposed to different wind conditions. The method is then built upon by repeating for demand under each of the scenarios and then residual demand so that the effect of the two components of the energy system on the end balancing can be seen. Finally the temporal patterns of the 99th and 1st percentile events are explored to analyse whether events occur at the beginning or end of the scenarios and to find out what season of the year they occur.

The percentiles were separately calculated for each scenario. These differed due to different levels of wind capacity and electricity demand. In order to allow direct comparison of the results a mean value was calculated for each percentile for supply, demand and residual demand (Table 1); these mean values were then used in the ensuing plots. Supply percentiles are calculated as capacity factors so that the scenarios can be compared, otherwise there would be a divergence between onshore and offshore. Consequently, care must be taken when comparing the supply plots to the demand and residual demand plots.

	High			Low		
Percentile	99	90	80	20	10	1
Mean Wind (%)	100	79.6	64.65	15.6	9.7	2.35
Mean Demand (GW)	59.9	50.7	45.7	31.2	28.3	22.6
Mean Residual demand (GW)	54.5	42.6	37.5	17.0	10.5	-3.8

Table 1: Mean percentiles for each scenario (GW).

Figure 13 shows the extreme supply events as described by the wind model, the 1st, 10th and 20th percentiles represent very low wind events and the 80th, 90th and 99th very high events. The plot shows that under all of the

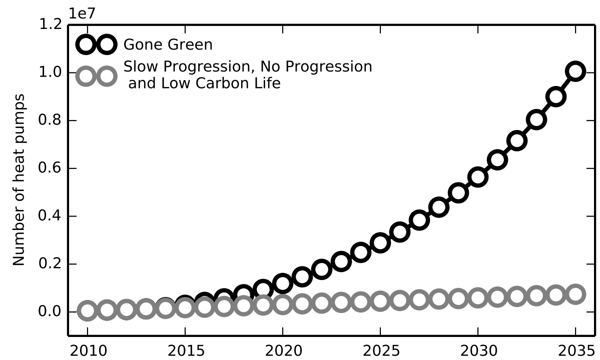

Figure 9: Heat pump take up.

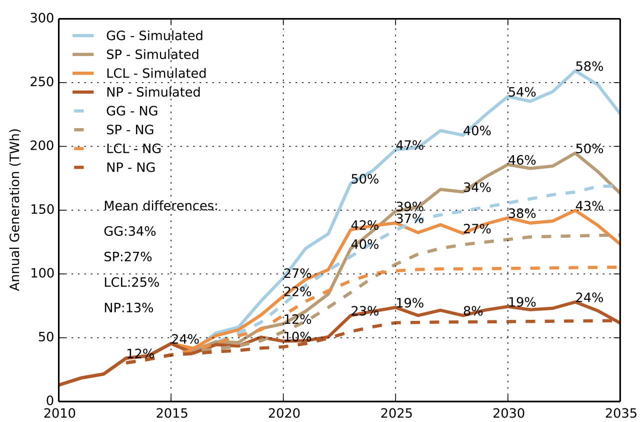

Figure 10: Annual wind generation, simulated output vs. National Grid.

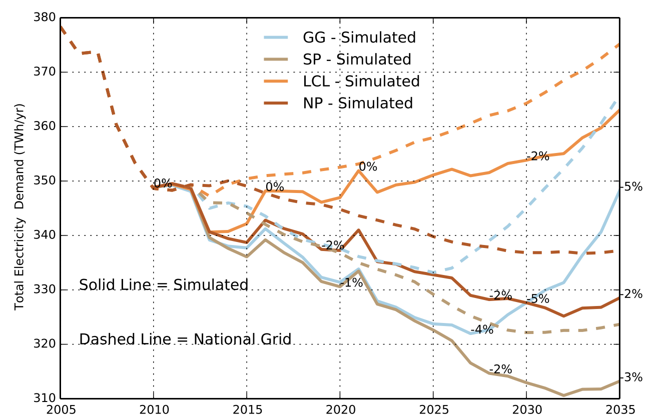

Figure 11: Annual total electricity demand, simulated output vs. National Grid.

scenarios there should only be one day every 25 years where capacity drops below 2.4% for more than 15 hours; however, the occurrences increase as their persistence decreases, so that there are between 180 and 350 single hour events for different scenarios (this is equivalent to 0.08% and 0.15% of the time). The electricity system under each of these scenarios will have to satisfy demand that cannot be met at these times, resulting in the need for significant amounts of alternative generation. It should be noted that the plots are not cumulative so the events above 1 hour are not included in the 1 hour events and the events above 2 hours are not included in the 2 hour events, etc.

Despite the large difference between onshore and offshore capacity factors (Figure 12), the scenarios with larger offshore capacity still experience these extreme low events, suggesting that they are result of still conditions, onshore and offshore, that cover the extent of the furthest development zones. As the minimum capacity factor increases in the 10th and 20th percentile brackets, the persistence increases to the point where there are events which last over 80 hours. In terms of the highest capacity factor events, the plot shows that the Gone Green scenario experiences longer lasting events than the other scenarios. Figure 8 illustrates how that scenario has a higher magnitude of capacity in the easternmost areas and a small amount of capacity in the south west that is not included in other scenarios, which may ensure the longer lasting high capacity factor events.

Otherwise, as with low events, there is little difference between the scenarios. This demonstrates the limits on geographical diversity possible under the constraints of the offshore development zones. This is partly because they do not add a significant extra distance between the two furthers apart wind farms compared to onshore sites, an important factor in ensuring variation in wind supply as the correlation between wind speed reduces as distance increases, this is a point established in analysis by Sinden [33].

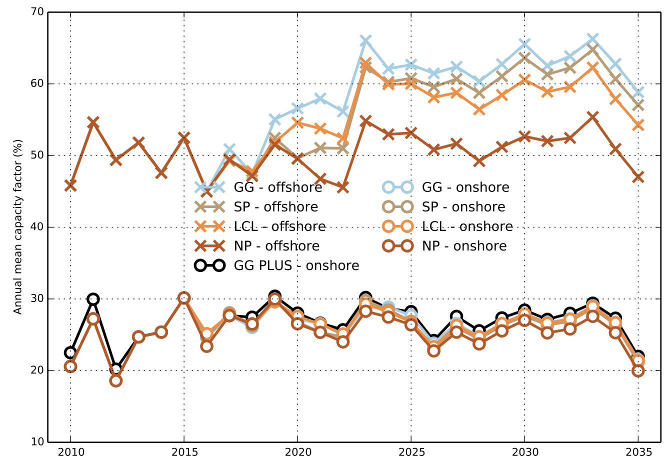

Figure 12: Annual mean simulated capacity factors 2010-2035.

3.2.2. *Electricity demand*

Figure 14 describes extreme high and low demand events; the 1st, 10th and 20th plots represent very low demand events and the 80th, 90th and 99th percentile plots very high demand events. The 1st percentile plot shows that the extreme low demand events are relatively short with no events below 22.8 GW for more than 10 hours. The magnitude of these events shows the minimum demand that can be expected over the length of the scenarios. There is a slightly higher occurrence of these events under the Slow Progression scenario. There are more events that last longer for each scenario below the 10th percentile. There is not a very clear divergence between scenarios, but Slow Progression contains slightly fewer events that last longer.

In terms of high demand events there is a clear peak between 7 and 11 hours which roughly matches the period over which demand is high during a typical day, indicating that these periods will often last across the daytime, but not the whole day. Here there are more occurrences in the Low Carbon Life scenario, roughly four times as many as the other scenarios. The changes follow each other, suggesting that whatever is driving the occurrences and persistence is relatively similar between scenario. There is at least one event for each scenario where demand will be over 59.9 GW for 11 hours

In the 90th percentile the persistence increases; the Low Carbon Life scenario has more events at this higher persistence, but the scenarios converge at lower persistence. In all scenarios except Low Carbon Life demand is over 50.7 GW for 14 hours at least once; these events increase to 16 hours for Low Carbon Life and occur more regularly (8 times).

3.2.3. *Residual electricity demand*

Figure 15 describes extreme high and low residual demand events; the 1st, 10th and 20th plots represent very low residual demand events and the 80th, 90th and 99th percentile plots very high residual demand events.

The impact of larger wind capacities can clearly be seen in the low residual demand plots on the left hand side of Figure 15. Gone Green lowest events persist longer than Slow Progression and Low Carbon Life; there are no instances where residual demand is below -3.8 GW in the No progression scenario. The plot demonstrates that under these conditions there will be periods of more than one day where Gone Green can produce more electricity than is demanded in GB. There are over 100 times where this will last more than 10 hours. This is a clear indication that capacities of this magnitude will require solutions in terms of electricity storage, transmission or demand shifting so that this potential will not be wasted. It would, of course, be possible to curtail generation at these times; however, given the high cost of wind this would not make economic sense.

The Slow Progression scenario has a similar number of low residual demand events to Gone Green; however, they do not last as long. A similar pattern is shown for the 10th and 20th percentile to the 1st percentile. These events last much longer, but are less significant as residual demand is not negative over this entire period. The

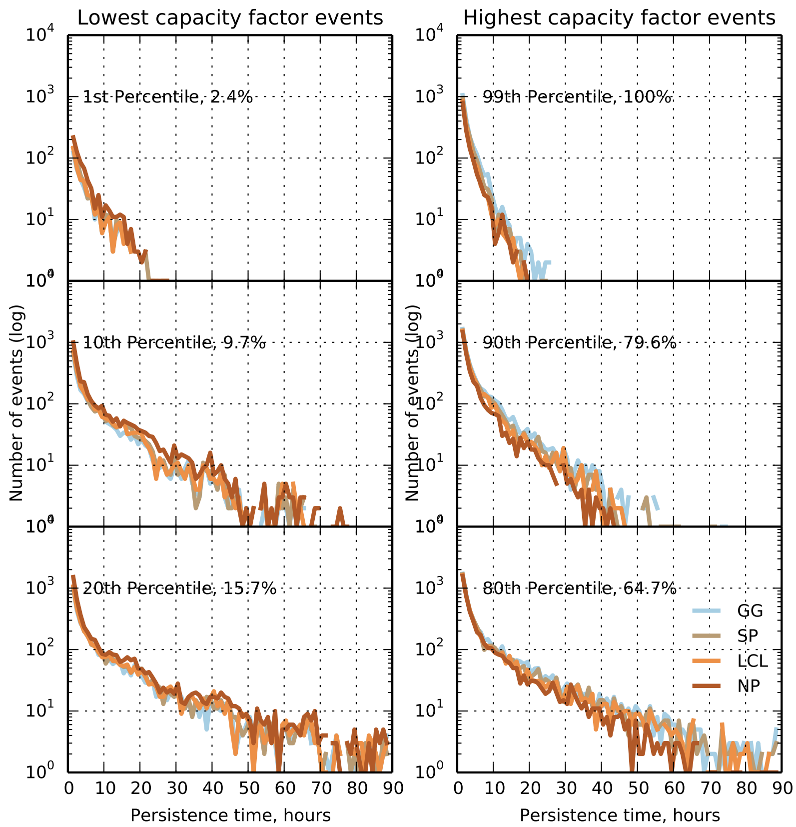

Figure 13: Extreme events, supply.

No Progression scenario has some events in these brackets indicating that they can be experienced with very little offshore capacity

The 99th percentile for residual demand (54.5 GW) is lower than the 99th percentile demand (59.9 GW), demonstrating the net effect of wind across all four scenarios. The pattern in the high demand events is very similar to that shown in Figure 14, demonstrating that demand heavily influences these events. The slightly lower threshold means that the events last slightly longer (7-14 hours in contrast to 7-11 hours). The same pattern is seen in the 90th and 80th percentile where the persistence of the events increases due to lower thresholds, but the occurrences drop in some cases. This shows that these high events are dictated by demand, but that in some cases this may be reduced by wind in the lower persistence events.

3.2.4. Residual electricity demand over time

The above plots have shown the persistence and occurrence of extreme events over the course of 25 years for each of the scenarios. By comparing the three plots it is possible to understand what might be causing these events. However these insights are not very clear and could have been caused by a number of factors. Therefore the following plots show how these events vary over time. Through analysis of these plots it is easier to show what is causing the extreme events by comparing them with the plots showing wind capacity and number of heat pumps.

The plots are 2d histograms of the extreme events. Four examples are given. Figure 16 shows the 99th percentile of residual demand for the Gone Green scenario. Figure 17 contrasts this with the same percentile events for the No Progression scenario. These plots therefore represent two of the scenarios in the top right corner of Figure 15 with different paths in terms of electricity demand. To compare, Figure 18 shows the 1st percentile for the Gone Green

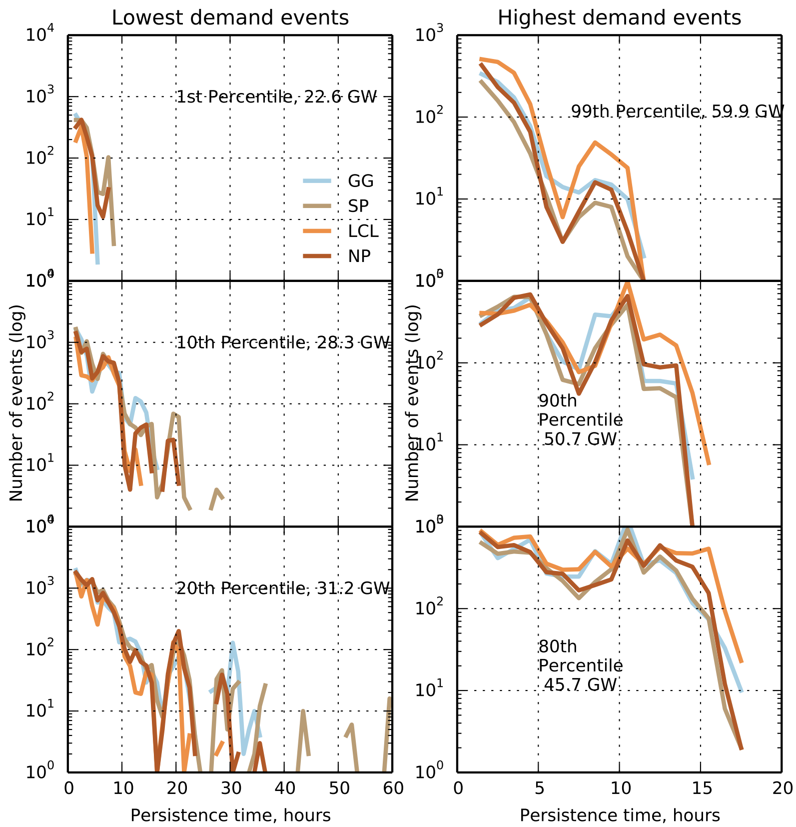

Figure 14: Extreme events, demand.

scenario and Figure 19 the 1st percentile for the Low Carbon Life scenario. The latter plots represent two scenarios from the top left box in Figure 15. The No Progression scenario could not be shown as it does not present any events where demand is below -3.8 GW. Each plot contains a 2d histogram of the persistence of the percentile events for each year. Above this plot these events are attributed to a season so that it can be shown when these events occur during the year over time.

In both Figure 16 and Figure 17 it is clear that the events of the highest persistence occur at the beginning of the scenarios; this demonstrates that as wind capacity increases long lasting high demand events are reduced. The number of shorter lasting events also reduces significantly, particularly in the Gone Green scenario which sees significant amounts of wind introduced. The majority of the events shown in Figure 15 occur at the beginning of the scenarios, demonstrating that analysing the whole length of the scenarios at once can be misleading. Spring and summer events exist in both scenarios, but only at the beginning of the time period. Autumn events significantly reduce in the Gone Green scenario over time but remain in the No Progression scenario.

In contrast to the 99th percentile plots the 1st percentile plots, Figure 18 and Figure 19 show an increase in extreme events at the end of the scenario period. The plots show that under the Gone Green scenario, solutions will be needed for wind storage from 2019 (it may in fact be earlier as this is -3.8 GW rather than all negative residual demand). This change occurs slightly later in the Low Carbon Life scenario (2022). The number and persistence of events increases over time. From 2026 the Gone Green scenario experiences 1 event a year where residual demand is lower than -3.8 GW for 19-20 hours. During the same periods Low Carbon Life only experiences 9-10 hour events. Short term events become more prevalent over time. Low residual demand events persist up to 58 hours, or over 2 days. A greater number of the events occur in the winter for both scenarios; however up to 50% of the events can

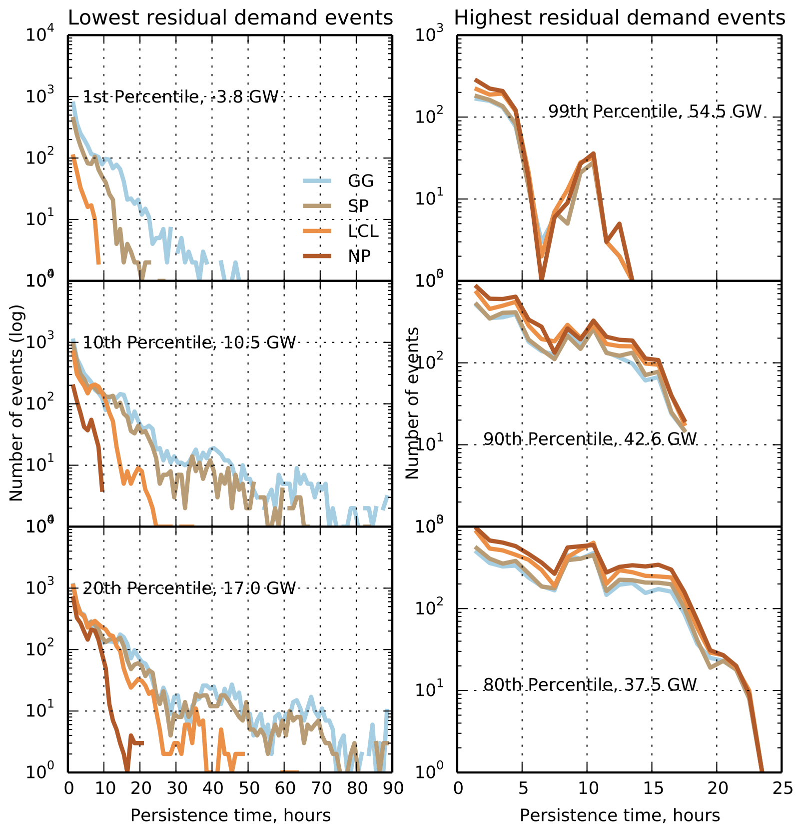

Figure 15: Extreme events, residual demand.

occur in either summer or spring in certain years.

4. Conclusions

The approach for developing disaggregated models that allow National Grid's aggregated scenarios to be linked to spatially comprehensive and homogeneous weather data for GB has facilitated an analysis of the impacts of variability on the GB energy system. The summary of the evaluation of the disaggregated models has demonstrated that they are reasonably accurate, given the complexity that must be incorporated, and should provide useful tools.

The benefit of the disaggregated approach is shown in the ability to separate onshore and offshore capacity factors, demonstrating that they are much higher offshore. This should be taken into account in estimates of future wind generation. The rate of occurrence of extreme events has been examined. This analysis has demonstrated that there will be significant excess production under all but the lowest wind capacity scenarios and indicated that this excess production will start from approximately 2020, before which solutions for the storage or transmission of this excess should be developed. Despite the addition of significant numbers of heat pumps the Gone Green scenario exhibits fewer high demand events towards the end of the scenarios than other scenarios which include very few heat pumps. Further analysis will examine whether these events occur at different times of the day or week, or as a result of electrification of heat demand.

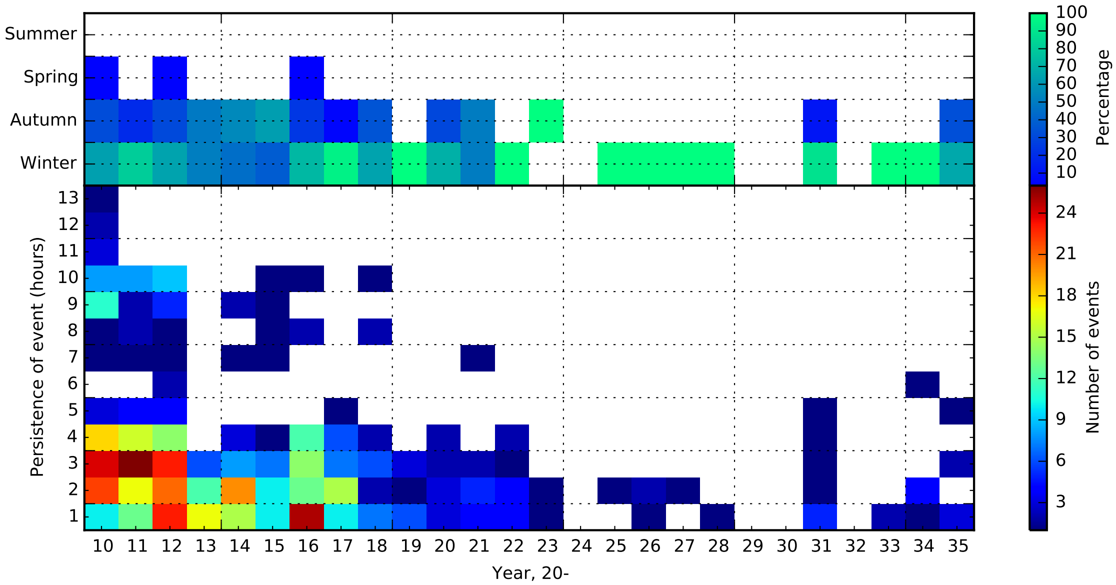

Figure 16: Extreme events in the 99th percentile over time for the Gone Green scenario.

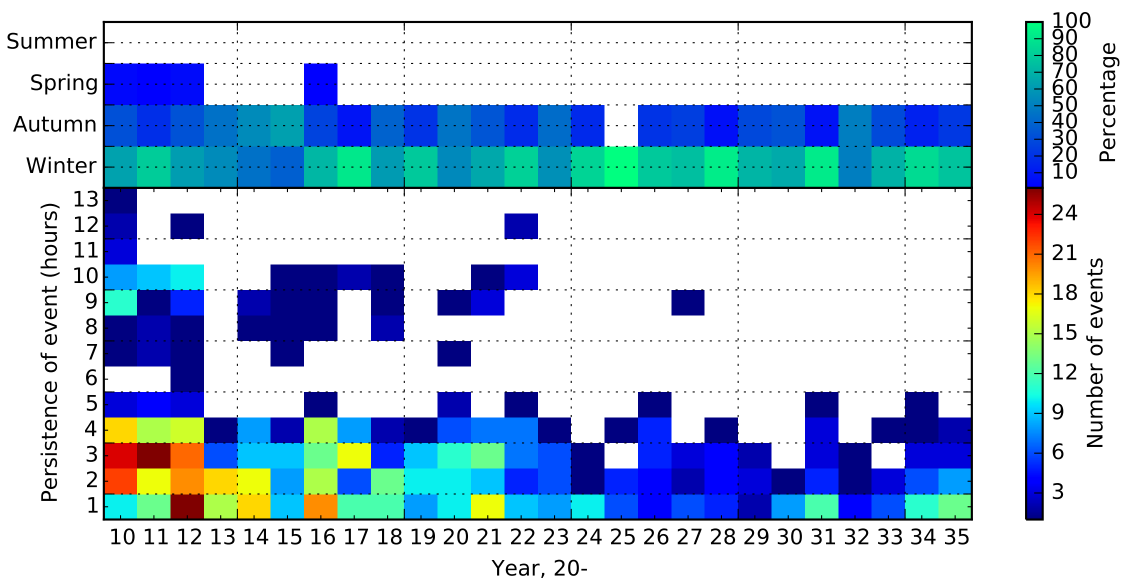

Figure 17: Extreme events in the 99th percentile over time for the No Progression scenario.

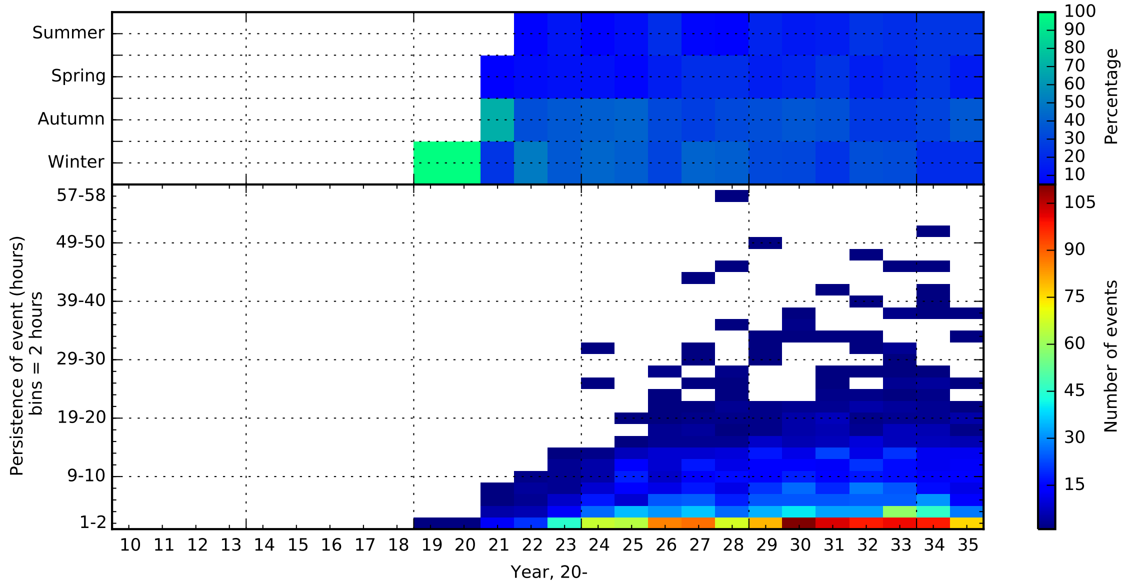

Figure 18: Extreme events in the 1st percentile over time for the Gone Green scenario.

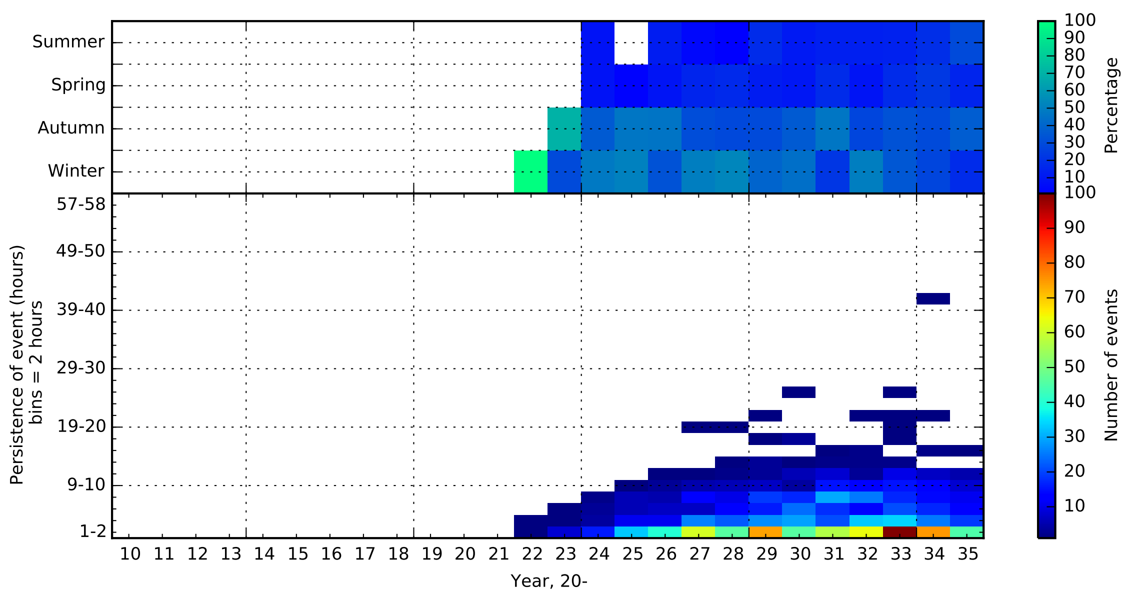

Figure 19: Extreme events in the1st percentile over time for the Gone Green scenario, there is only one event in the NP scenario so it is not used here.

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