Electricity supply in Europe power system with high penetration of wind power and solar PV under the North Atlantic Oscillation

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Abstract

The North Atlantic Oscillation (NAO) is an atmospheric circulation that dominates the climate variation over west-north Europe. It alters the pressure difference between the north and south air mass over the Atlantic Ocean, by either reinforcing or relieving the gap, so that the westwards storm track which drifts to Europe may shift north or south in winter. As a result, wind and surface solar irradiation over west Europe are redistributed. For intensively mitigating CO2 emission, vast integration of wind power and solar PV in the power system for electricity supply has been set on agenda. These weather-dependent and undispatchable generators are sensitive to climate variations. An in-depth understanding of the impact of the large-scale climate variation, i.e. the NAO, on the power system with high penetration of wind power and solar PV is pivotal for the low-carbon transition of the power system. This paper studied the impact of NAO on west Europe power system with the vast capacity installation of wind turbines and solar panels. By using the climate model data simulated from NAO scenario, the production profile of wind power and solar PV were estimated, which is then input into a model of the power system to simulate the system performances by the PLEXOS, the integrated energy modeling platform. Results show that the climate shift from negative NAO to positive NAO mainly enhances the system electricity production of wind power with 89.2 TWh in winter. Thermal generators are then replaced by the wind turbine. With more electricity supplied by wind power, the carbon emission, the generation cost and the electricity price in wintertime decline as much as 24.7 million tons, 5.6 €/MWh and 9.1 €/MWh respectively. Regions within the power system become more local sustained and the transmission load burden is relieved. The consequence of NAO shift on the power system is more profound with higher penetration of wind power. In addition, regions in the north have their wind production increased while south regions experience shrink of their wind power outputs.

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Abbreviations
DJF – December, January and February
ECF – European Climate Foundation
EEZ – economic exclusive zone
EWEA – European Wind Energy Association
GWE – global warming effect
iRES – intermittent renewable energy source
KNMI – Royal Netherlands Meteorlogical Institute
LHV – lower heating value
NAO – North Atlantic Oscillation
PV – photo voltaic
RES – renewable energy source
sNAO – summer North Atlantic Oscillation
SSRD – shortwave surface radiation downward
UCED – unit commitment and economic dispatch

1. Introduction
1.1 Rationale
Renewable energy sources have a pivotal role in the power generation sector to realize the ambitious climate action target proposed by the European Commission. The aim is to reduce 80-95% of the pan-European 1990-level CO_2 emissions by 2050 (Roadmap 2011). However, generating electricity by intermittent renewable energy sources (iRES[1]) is weather sensitive and is undispatchable in a power system. The high variability in weather conditions and climate variability on timescales ranging from weeks and months to inter-annual variability, can therefore bring uncertainty to the electricity supply of power system where iRES technologies are installed. Since wind power and solar PV will contribute more than 80% to the capacity growth of global renewables (IEA 2017), they will become more predominant in future power systems. Power generation will be more sensitive to climate variation. Therefore, cost-effectiveness and reliability of electricity supply can only be guaranteed

[1]The renewable energy sources (RES) consists of the intermittent (iRES) and the non-intermittent. The intermittent (iRES) includes offshore/onshore wind power and solar PV; the others refer to hydro power, biomass, geothermal and solar CSP, though insufficiently.

once we are prepared to the impacts. Understanding the performance of power system in the context of climate variation would be prerequisite and valuable to take measure.

1.2 Background

The North Atlantic Oscillation (NAO) is the most dominant mode of variability in the atmospheric circulation over the North Atlantic and Europe (Hurrell et al. 2003; Hurrell & Van Loon 1997; Hurrell 1995; Hurrell 1996; Kushnir 1999; Wallace & Gutzler 1981; van Loon & Rogers 1978). This mode of atmospheric variability, which is the most noticeable in wintertime (Hurrell et al. 2001; Hurrell et al. 2003; Greatbatch 2000), i.e. December, January and February, is caused by the variation of atmospheric pressure difference between the northern North Atlantic (Icelandic low pressure area) and the southern North Atlantic (Azores high pressure area). The difference of atmospheric pressure controls the position of the storm tracks and the strength of westerly winds towards Europe, on which much of the weather conditions as well as the climate of Europe depends. There are two phases of NAO, the positive phase and the negative phase (Figure 1). During the positive phase, the gradient of atmospheric pressure between Azores and Icelandic is enhanced, strengthening the westerly winds and shifting the storm tracks northwards. South Europe tend to have more sunny days in winter while an anomalously rainy, cloudy, humid and mild winter occurs from Scandinavia to Central Europe. During the negative phase, the gradient of atmospheric pressure diminishes, resulting in weaker westerly winds compared to the normal situation. This results in the situation where the storm tracks drift southwards towards the Mediterranean. As a consequence, rainy, cloudy, humid and mild winter occurs from Central Europe to the Mediterranean while anomalously sunny but cold winter occurs from Scandinavia to Central Europe (Trigo et al. 2002; Hurrell 1995). Several researches verified the significant effect and the contribution, to the variation of wind, precipitation, solar radiation and surface temperature in Europe, of the NAO (Chiacchio & Wild 2010; Pozo-Vázquez & Tovar-Pescador 2004; Folland et al. 2009; Hurrell 1995; Hurrell 1996; Pozo-Vazquez et al. 2011; Curtis et al. 2016a), which is suggested to explain more than 20% of the variation.

The summer North Atlantic Oscillation (sNAO) is a counterpart of NAO in summer time, which is induced by the same mechanism, i.e. the variation of atmospheric pressure over the North Atlantic Ocean. The sNAO also changes the position of storm track and thus can exert a strong influence on northern European rainfall, temperature, and cloudiness. It is the principal determinant for summer extreme weather events, including flooding, drought, and heat stress in northwestern Europe (Folland et al. 2009), but the amount of variability in the summer circulation which is explained by the sNAO is less profound than the NAO in wintertime (Barnston & Livezey 1987). While a strong relation has been verified between NAO and the occurrence of winter extreme weather events like windstorms or sustained periods with calm and cold conditions (Thompson & Wallace 2001; Trigo et al. 2002; López-Moreno & Vicente-Serrano 2008), the impact of sNAO is more northerly located and with a smaller spatial scale than the impact of NAO in winter. For the reasons above, this study will leave out the sNAO and investigate only the impact of NAO in wintertime.

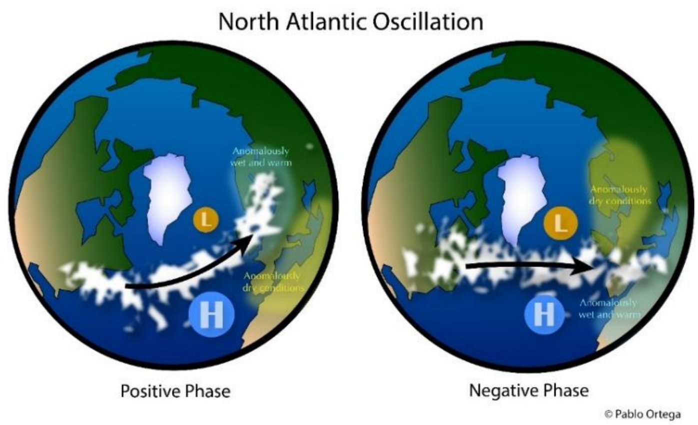

Figure 1. North Atlantic Oscillation. The black arrow represents the storm track of westly winds. The circle with 'L' represents the Icelandic low and the 'H' denotes the Azores high. The left image illustrates the positive phase of NAO and the right one illustrates the negative phase.

The dependence of electricity generation from iRES on local weather conditions renders the power system vulnerable to the anomalies of climate and the climate extremes associated with the NAO. Extreme weather events such as storms and icing alter the efficiency of wind turbines by physical impacts (Pryor & Barthelmie 2010; Pryor & Barthelmie 2013). Wind turbines can only efficiently extract wind power between cut-in wind speed and cut-out wind speed (Twidell & Weir 2015). Wind speed in either extreme or calm weather conditions that is out of the range between the cut-out and the cut-in speed of wind turbine prevents the turbine from electricity generation, cutting down its capacity factor. The efficiency of solar panel increases with decreasing panel temperature and increasing solar irradiance (Wilbanks et al. 2008; Crook et al. 2011; Mavromatakis et al. 2010; Davy & Troccoli 2012), which, along with the intensity and duration of solar irradiation, determines the production of solar power.

Climate variability and variations in the occurrence of extreme weather events in winter relate to divergent power generation as well as intermittent outage or surplus of power supply. The atypical patterns of ambient temperature, wind speed and surface solar irradiation (both intensity and duration) alter the economic dispatch of power system. In addition to merely involving large volume of iRES technology, our future energy system should, at the meantime, be able to cope with adverse weather and climate situations so that the adequacy, reliability and affordability of electricity supply are guaranteed. This challenge requires extensive synergy among the entire power system, including other types of generator, storage and transmission grids. In this sense, quantitative estimate of the impact of weather and climate variability on the entire power system is essential. The NAO is taken to be a first estimate to quantify the variations in the atmospheric circulation over the North Atlantic and Europe.

1.3 Problem definition and research question

Several studies have verified the significant impact of NAO on the wind and solar energy resources for power generation among European countries in terms of energy output and its spatial and temporal variability (Brayshaw et al. 2011; Ravestein 2016; Ely et al. 2013; Pozo-Vazquez et al. 2011; Jerez et al. 2013). These researches focused on the solitary power generation phase of either wind turbine or solar PV whereas the consequence of entire power system was lacking. The study of climate effects on iRES technology for the whole European power system usually investigates the impact of global climate change, e.g. (ECF 2010). New results suggest that the influence of climate change on the power output of PV and wind sectors is relatively limited, especially when compared with the influence of climate variability dominated by NAO (Ravestein 2016; Jerez, Tobin, et al. 2015;

Tobin et al. 2016; Tobin et al. 2015). A few studies examined the influence of NAO on iRES in the context of an integral power system. Curtis (2016a; 2016b) confirmed that the NAO had a significant impact on wind patterns, by which the switch of NAO from negative phase to positive phase could reduce the electricity price of Irish power system with 1.5 €/MWh and the variation of NAO phase could explain 10% variation of the CO_2 emission intensity within the Irish electricity system. Since the NAO affects the climate of Europe, where an ambitious target to install iRES technology into the power system is established, it is of value to assess the performance of European power system with high iRES share influenced by NAO in the future. However, complete information pertaining to this dimension is still lacking. This study intends to fill this knowledge gap and it can add experience to the modelling of power system with climate impacts.

Research question:

What is the consequence of the NAO effect on the iRES electricity production in the European power system in 2050 with different RES scenarios where 40%, 60% and 80% of its electricity are supplied by RES, as well as on the techno-economic performance of the system?

- Where and how much capacity will wind turbines and solar panels be installed?
- What is the electricity generation profile of wind power and solar PV under the 2050 climatic conditions of different NAO phases?
- How effective does the iRES technology replace the capacity installation of (conventional) thermal generators in 2050?
- What is the techno-economic performance of the European power system in 2050 integrated with the estimated wind power and solar PV?
    - Capacity installation of other generators
    - Power generation profiles of full generation mix
    - Storage capacity
    - The variation of generation profile, electricity price and generation costs
    - Load burden of transmission lines
    - CO_2 emissions
    - What is the role of each region in the power grids, importer or exporter?

1.4 Research scope

This research following the system setting of Brouwer et al. (2016). The geographical domain to be studied involves the western part of Europe which is divided into 6 regions (figure 2). Transmission networks between regions are involved whereas those within the region are overlooked. Techno-economic parameters in 2035, of which the technological learning effect has been included, are used to represent the average level in 2050 so that no legacy power plant is necessary. Although we use annual data to simulate the power system, only winter months (December, January and February) are selected. The choice is in favor of highlighting the impact of the NAO, of which the effect is the most profound in wintertime, on the energy system because the high energy demand in winter implements stricter constraints on power generation. Climate factors are assumed to influence the electricity production of iRES exclusively. Although the other sectors in the power system, such as power demand, may also be influenced by climate change and variation, they are exempt from weather conditions for illustrating sharp insight about iRES.

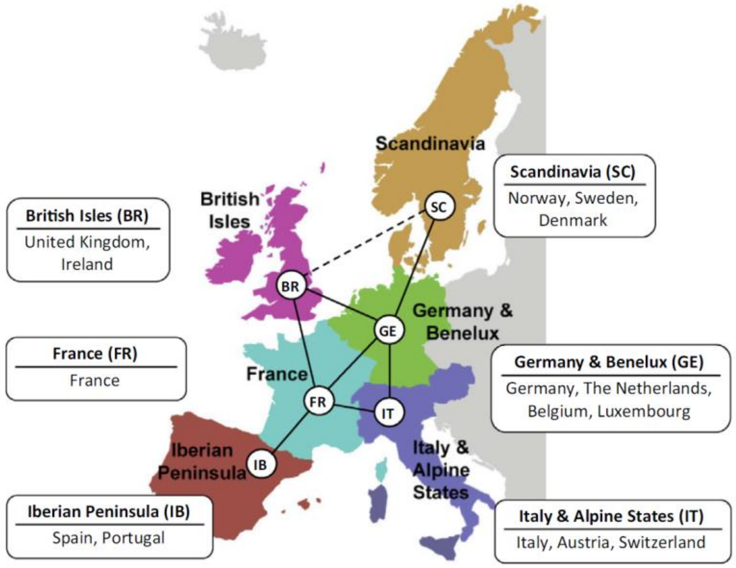

Figure 2. Overview of the geographical scope.

2. Methods

2.1 Overview

Long-term system adequacy of the power system with high iRES penetration is assessed in this research. Capacity installation of iRES is determined according to the energy scenarios proposed by ECF (2010), land availability restrictions as well as meteorological records in former periods about resource abundance of solar radiation and wind energy potential. Hourly electricity generation of the installed iRES per region in 2050 is calculated based on the climate model data simulated with the KNMI'14 scenarios (van den Hurk et al. 2014), in which variability in large-scale weather patterns and global climate change are considered. The PLEXOS tool is applied to emulate the performance of the constructed power system. It is a bottom-up integrated power system simulation modelling tool developed by Energy Exemplar (2017). Power production characters, demand load and transmission capacity are required to run the model for this research.

At first, a geographical distribution of iRES capacity in different energy scenarios is identified. Secondly, the hourly electricity generation patterns of the implemented iRES under the simulative 2050 weather conditions are calculated. Thirdly, other categories of power plants, together with demand loads and ancillary facilities, are introduced from pioneer researches. Furthermore, the integral profile of the assembled power system is run by the PLEXOS tool. Finally, the generation pattern of iRES technology and the techno-economic performance of the power system are assessed. Figure 3 gives an overview of the steps that are invoked in this research. Following passages in this chapter will particularize the procedures.

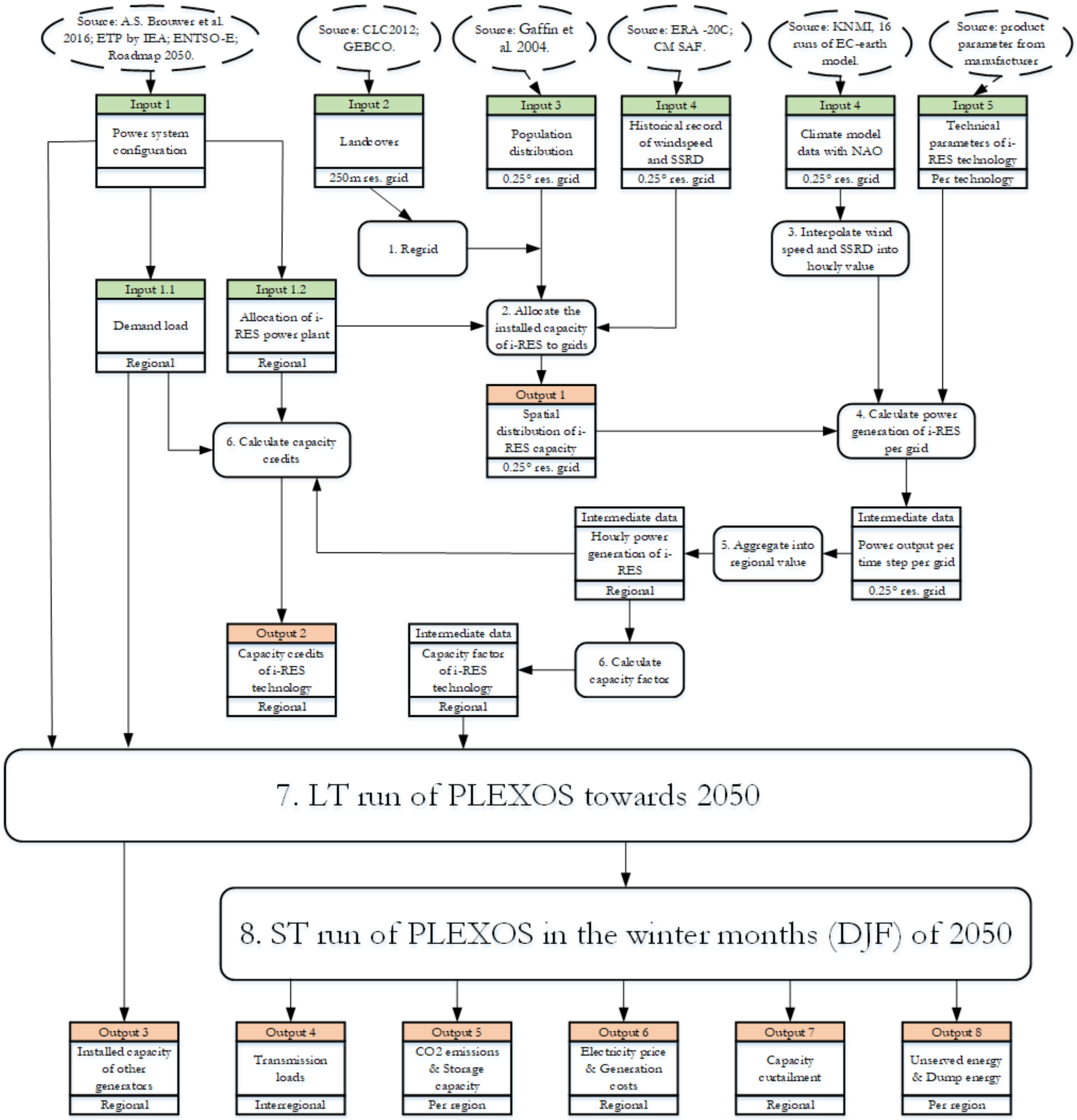

Figure 3. Overview of the input data, operation procedure and the outputs.

2.2 Allocate capacity installation of wind turbine and solar panel

Regional prognosis about the capacity installation of iRES had been made by Brouwer et al. (2016) based on Roadmap 2050 (ECF 2010) but gridded capacity installation was needed so that gridded weather data could be applied for more accurate estimation on electricity generation. Results of the gridded capacity distribution of onshore/offshore wind turbine and rooftop/utility solar panel can be found in section 4.1.

2.2.1 Define energy scenarios of 2050

Following the pathways in the research of ECF (2010), Brouwer et al. (2016) adopted three scenarios of power generation in 2050, of which the power production with RES are 80%, 60% and 40%, corresponding to 59%, 41% and 22% iRES on an energy basis respectively, from which the regional allocation of the iRES capacity (input 1.2) were derived. In this study, solar panels are classified into utility panel for large scale solar power plant and residential rooftop panel, following the assumption in the research of ECF (2010) that either type occupies half of total solar PV installation. As a result, iRES refers to onshore/offshore wind power and utility/rooftop solar PV in this research. For each type of iRES, we selected one advanced commercial product to represent their average trends in 2050. They are Vestas V117-3.3 MW turbine for onshore wind power, Vestas V164-8.0 MW for offshore wind power, Sunpower X21-345 (monocrystalline silicon) for rooftop solar panel and TrinaSolar TSM-PD14 (polycrystalline silicon) for utility solar panel. Relevant characteristics of the four technologies and their capacity installed per region can be found in appendix A.

2.2.2 Appoint land availability of each type of landcover

Land availability for iRES is dependent on the category of landcover (see Section 3.2.1). A survey on literature (Ordóñez et al. 2010; Mainzer et al. 2014; Deng et al. 2015; Hoogwijk et al. 2004; Bruninx et al. 2014; Hoefnagels & Junginger 2011) had been conducted by ir. William Zappa from the Copernicus Institute. It gives clues to determine the ratio of available land for the installation of wind turbine and solar panel under a certain landcover, from which we made the assumptions of land availability factor for each iRES and each landcover category. The survey and land availability assumptions can be found in appendix B.

2.2.3 Construct the spatial grids for the area of interest

Gridded geographical information, including population and landcover per grid (input 2 and 3), was processed by ArcGIS[2]. The area of interest encompasses both land and available ocean area of the regions. Based on the investigation done by EWEA (2013), we assume that offshore wind turbines in 2050 would be installed within the EEZ of the region where water depth is less than 50 m and distance to shore is less than 100 km. A regular longitude-latitude grid with resolution of 0.25°×0.25° working grid, aligned with the resolution of climate model data in 2050, that covers the area was thus constructed to contain the geographical information as shown in figure 4. For each grid, the type and the scale of landcover and population (see Section 3.2.2) were counted.

[2] A program developed by ESRI to manage, display and analyse data of geographical information systems (Environmental Systems Research Institute (ESRI) 2016).

Figure 4. Geographical grids of the research area (0.25°×0.25° res.).

2.2.4 Evaluate installation priority of geo-grids for wind turbine and solar panel

Installing the iRES facilities in each grid was determined by the population scale and the resource abundance. Offshore wind turbine can only be installed in the sea where population has little influence. Onshore wind turbine and utility solar plant are more likely to be constructed in the place with small population, whereas rooftop solar panel has a larger installation in the place where there are more people. Resource abundance consists of available land area for the iRES in each grid as well as the capacity factor of wind power and solar irradiation derived from historical weather records (see Section 3.2.3). Based on the proposed criteria, a score system, where a higher score indicates higher possibility of the grid to install the corresponding iRES facility, is established for each type of iRES technology in all grids of the area. Table 1 introduces the criteria.

Table 1. Formulas to evaluate the priority of iRES installation.

iRES technology		Score	Nominal score
Wind	Onshore	$S_i = \frac{Capacity\ factor \times Available\ land\ area}{(1/_{Grid\ area} + population\ density)}$	$\text{nomi } S_{i,j} = \frac{\ln(SC_{i,j}+1)}{\ln(\max(i)\, SC_{i,j}+1)}$
	Offshore		
Solar	Rooftop	S_i = SSRD × Available land area × Population	
	Utility	$S_i = \frac{SSRD \times Available\ land\ area}{(1/_{Grid\ area} + population\ density)}$	

*A grid is denoted by i, and j denotes each of the four types of technology. The denominator for wind turbine and utility PV is designed to avoid grids without inhabitants. The nominal score is a ratio between the score of one technology in a grid and the maximum score among all grids of the same technology. It allows the cross-technology comparison of priority in each grid.

2.2.5 Allocate the regional iRES capacity to grids

Capacity of each type iRES technology is committed to fulfill the available land of the technology, using its capacity density, grid by grid in terms of the score ranking of the technology among all grids, until the capacity of the region is used up.

2.3 Calculate hourly power generation per region for each climate scenario

Hourly capacity factor is required for simulating the power system. However, climate model data is in either daily resolution (SSRD and temperature) or 6-hourly (wind speeds at hub height) resolution. Downscaling interpolation on the climate model data for hourly estimated values was therefore exercised as presented in appendix C.

Hourly power generations per grid was estimated at first according to the capacity distribution and the gridded weather data in 2050 and then were aggregated in terms of the region to which they belonged. The generation was converted into capacity factor per region per hour for the PLEXOS model as the potential of iRES electricity production. Results can be found in section 4.2 of this potential generation pattern, built upon gridded geoinformation and weather data considering NAO in winter months, in comparison with that of Brouwer (2016) which is initially in regional scale.

2.3.1 Wind power generation

Formula 1 was used to calculate the hourly power generation of wind turbine.

$$P_{wind} = P_{in} \times W_{pot} \times \delta(T) \times \eta_{opt} \quad (1)$$

Where,

P_{wind} = hourly power generation [MWh];

P_{in} = installed capacity [MW];

W_{pot} = wind potential factor [unitless];

$\delta(T)$ = de-rated temperature factor [unitless];

η_{opt} = 88% represents the operational efficiency which accounts for losses in turbine wake effects (7%), electrical conversion (2%) and other factors (3%), in accordance with other relevant research (Rivas et al. 2009; Myhr et al. 2014; McKenna et al. 2014; Tamura 2012).

Wind potential factor was determined by the power curve method illustrated in formula 2. It is a simple but effective way to estimate potential power output under certain wind velocity suggested by Twidell and Weir (2015).

$$W_{pot} = \begin{cases} 0, & 0 \leq u < u_{ci} \text{ or } u \geq u_{co} \\ \frac{u^3 - u_{ci}^3}{u_r^3 - u_{co}^3}, & u_{ci} \leq u < u_r \\ 1, & u_r \leq u < u_{co} \end{cases} \quad (2)$$

Where,

u = instant wind speed at hub height at the hour [m/s], wind speed at 120m for onshore wind turbine and that at 100m for offshore wind turbine;

u_{ci} = cut-in wind speed of the turbine [m/s];

u_r = rated wind speed of the turbine [m/s];

u_{co} = cut-out wind speed of the turbine [m/s].

The latter three speeds (u_{ci}, u_r, u_{co}) can be obtained from the wind curve offered by the manufacture of turbine. The values used in this research can be found in appendix D.

Operational temperature range at hub height is provided by the manufacture. Wind turbine is to decelerate to avoid damage when the temperature is out of the range (de-rated temperature). Although the decrease of power generation is gradual, in this research we assume a sharp brake of the turbine when it comes to de-rated temperature for simplification. Formula 3 was used to calculate the de-rated factor.

$$\delta(T) = \begin{cases} 1, & T_{min} \leq T \leq T_{max} \\ 0, & T < T_{min} \ or \ T > T_{max} \end{cases} \qquad (3)$$

Where,
T = operational temperature at the hub height;
T_{min} = lower bound of the operational temperature range;
T_{max} = higher bound of the operational temperature range.
More detailed information about the calculation regarding specific assumption in this research can be found in appendix.

2.3.2 Solar PV power generation

Power generation by solar PV is usually calculated by adjusting the value under STC[3] according to actual temperature and actual solar irradiation, as shown in formula 4.

$$P_{solar} = P_{STC} \times \frac{G}{G_{STC}} \times PR_{STC} \times \eta_T \qquad (4)$$

With PR_{STC} = 90% represents performance ratio at STC, suggested by Freeman et al. (2013) and Philipps & Warmuth (2015);
P_{STC} = nominal capacity at STC [W];
G = actual solar irradiation [W m^{-2}];

$$\eta_T = 1 + \gamma \cdot (T_c - T_{STC}) \qquad (5)$$

Where,
T_c = cell temperature;
$T_{STC} = 25℃$, temperature at STC;
$\gamma =$ power temperature coefficient which represents the efficiency change when T_c deviates from T_{STC}, of which the value are offered by the manufacture (see appendix).

Cell temperature was estimated by a linear model (formula 6) proposed by Chenni (2007), as suggested in Jerez, Thais, et al. (2015), according to ambient temperature of the cell T_a [℃] during the day light, actual solar irradiation G [W m^{-2}] and wind speed at 10 m height u_{10} [m s^{-1}].

$$T_c = 0.943 \cdot T_a + 0.028\,[℃ \cdot m^2 \cdot W^{-1}] \cdot G + (-1.528\,[℃ \cdot s \cdot m^{-1}]) \cdot u_{10} + 4.3℃ \qquad (6)$$

To estimate T_a, we only have daily average, maximum and minimum temperatures in the outputs of EC-Earth model. The minimum temperature is usually attained at night and the maximum temperature is attained during daytime. Average temperature during daytime should be higher than the average of the whole day, between daily average and daily maximum. Hence, we estimate the value as $T_a = \frac{T_{avg}+T_{max}}{2}$, the average of maximum and average temperatures of the day.

2.3.3 Power capacity factor and capacity credits

Hourly capacity factor is required as the input of the PLEXOS program. It was calculated by dividing the hourly electricity generation of the region with the full load generation of the region at the hour.

2.4 Simulate the power system in 2050 using the PLEXOS model

The PLEXOS is an integrated modelling software developed by Energy Exemplar (2017) that use mathematical optimization algorithm to simulate power system. It was used in this research to build the power system model of western Europe in 2050 and simulate the performance of iRES power sector under the influence of NAO.

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[3] Standard Test Conditions (G_{STC} = 1000 W m^{-2} irradiance, air mass 1.5, 25° C).

Brouwer (2016) built a power system model for the west Europe. In this research, our model was constructed upon that model by substituting the generation profiles of iRES in winter months (December, January and February). Brouwer's model consists of a full generation mix of non-fossil generators, in which the iRES generators investigated in this study are included, as well as supplementary options of thermal/non-thermal generators, demand response (DR), interconnection capacities and electricity storage. It also provides data about the predicted electricity demands pattern and the transmission capacity proposed in the ECF energy pathway. The model employed LT plan and MT schedule to determine the optimal capacity installation of all generators except for that of iRES, which is fixed. Then the ST schedule was applied to optimize hourly unit commitment and economic dispatch (UCED) of all generators.

(1) The LT plan is a mixed integer programming (MIP) tool to optimize investment decisions on yearly perspective, by minimize the sum of the net present value of build cost, Fixed Operation and Maintenance (O&M) costs and operational costs, while meeting minimum reliability and maximum emission requirements. The power system is simulated based on an energy-only market design.
(2) The MT schedule translates annual constraints, such as hydropower generation and planned outages, to weekly constraints as an input to the ST schedule.
(3) The ST schedule applies a mixed integer programming (MIP) based chronological optimization for UCED decisions via minimizing the total generation costs of power system, which is subject to five constraints (Exemplar 2014):

(1) electricity supply and demand must be equivalent;
(2) the flexibility of the generators;
(3) limitation of transmission network capacity;
(4) scheduled and random outages of power plants; and
(5) the reserve requirement of the system for balancing.

In this research, we conducted LT plan and MT schedule to determine the new optimal capacity installation of the system with updated iRES technology input in each case. The (ST) schedule on hour basis of selected weather years around 2050 was then run on the inputs of hourly capacity factors of iRES generators, their regional capacity installation, together with corresponding techno-economic parameters, and other system settings in Brouwer's model. Cost profile for iRES was assumed to be the same whereas the generation profiles were updated.

Among the outputs from the PLEXOS platform, we are going to discuss the following indicators:

(1) capacity installation per category of generators for the entire area;
(2) burden loads of interregional transmission lines;
(3) CO2 emission and storage demand for the system;
(4) power generation of non-intermittent generators;
(5) capacity curtailment of demand and generation;
(6) unserved (shortage) and dumped (surplus) energy;
(6) electricity price and generation cost either of the system;

Transmission loads are given on hourly capacity basis per connection line. Both directions are counted separately. In this research, we investigate the amount of electricity that is transmitted on certain line. This quantity is determined by formula (7).

$$ET_{i,\Delta t} = \sum_{t_0}^{t_n} \left(\left| h_{i,t_j}^{+} \right| + \left| h_{i,t_j}^{-} \right| \right) \qquad (7)$$

where $ET_{i,\Delta t}$ is the transmitted electricity on line i during period Δt; t denotes the concerned period, from t_0 to t_n, with $\Delta t = t_n - t_0$ on hourly basis; h is the hourly flow of electricity on the line [MW]; the '+' and '-' denote the direction of the flow.

In addition to the absolute value of transmitted electricity, the hourly average share to the maximum capacity of the line is also concerned. This can be calculated by formula (8).

$$share\ to\ the\ line\ constraint = \frac{ET_{i,\Delta t}}{\Delta t \cdot capacity\ constraint\ of\ line\ i} \qquad (8)$$

This indicator is useful to evaluate the pressure of electricity transmission on the power grids.

Electricity price and generation costs are also given on hourly basis per region. To calculate the system value of both indicator and the average value over the study period, weighted average value concerning the relevant electricity quantity needs to be defined.

For weighted system average value, formula (9) can be applied:

$$\mathrm{avgX(t)} = \frac{\sum_i X_i(t) \cdot Q_i(t)}{\sum_i Q_i(t)} \qquad (9)$$

where $\mathrm{avgX(t)}$ is the weighted average value over the system; $X_i(t)$ denotes the hourly value per quantity, either the price or the cost for region i; and $Q_i(t)$ is the relevant electricity quantity. For electricity price, we use hourly demand load of the region. For generation cost, we use hourly electricity production of the region.

In terms of weighted average value over a certain period Δt, formula (10) is used:

$$\mathrm{avgX}_i = \frac{\sum_t^{t+\Delta t} X_i(t) \cdot Q_i(t)}{\sum_t^{t+\Delta t} Q_i(t)} \qquad (10)$$

where avgX_i is the weighted average value over over the period. The rest notations follow the above descriptions.

2.5 Assess the simulated results

2.5.1 Box-whisker diagram

Daily energy generation of iRES for the whole area is presented by the box-whisker diagram. The value of maximum, minimum, mean, median as well as quartiles and outliers can be displayed. In a box plot, the range between the first and the third quartile is called interquartile range (IQR). The minimum value is defined as 1.5 times of IQR below the first quartile and the maximum value is defined as 1.5 times of IQR above the third quartile. Values lay out of this range is the outlier. The box plot in this study is based on daily power generation of the iRES technology over the three winter months. It is useful to display the distribution and implied some information about the variation of the power generations of the iRES. The plots are compared against different weather years to observe the impact of NAO effect.

2.5.2 Capacity credits

Capacity credit is defined as the share of installed iRES capacity which reliably meets the electricity demands without compensation from other (thermal) generators. It represents the ability of iRES technology installation in replacing the capacity of non-intermittent renewable energy sources. It is calculated according to the mathematical definition proposed by OECD/IEA (2011):

$$\mathrm{CC} = \frac{max_t(Load(t)) - max_t(ResLoad(t))}{Capacity_{iRES}} \qquad (11)$$

where CC denotes the capacity credits; $Load(t)$ is the hourly demand over the whole year; $ResLoad(t)$ is the hourly residual demand over the whole year, and $Capacity_{iRES}$ is the installed capacity of iRES technology. Residual demand refers to the demand that must be fulfilled by non-interment renewables (OECD/IEA 2011) and is defined as:

$$ResLoad(t) = Load(t) - Generation_{iRES}(t) \qquad (12)$$

where $Generation_{iRES}(t)$ is the hourly power generation of certain iRES technology.

In the research of OECD/IEA (2011), a specific calculation method which uses the expected peak residual demand rather than the maximum residual demand to counteract interannual variation of iRES production, assuming that the residual load is normally distributed. However, we only used data in winter months and statistical test showed that the distribution of our residual load did not obey normal distribution. In that case, we adopted the initial definition to calculate capacity credits.

3. Data

3.1 Weather data of 2050

3.1.1 EC-Earth climate model and KNMI'14 scenario

Weather plays a key role in estimating the electricity output of wind turbine and solar panel. Here we use simulated weather data from simulations of the climate around 2050 done by KNMI. There are 16 runs of the EC-Earth V2.2 climate model to our disposal, each with a length of 30 years. The EC-Earth climate simulations include the day-to-day variations in weather and the low-frequency variations associated with climate dynamics - including the variations in the NAO (Hazeleger et al. 2010; Hazeleger et al. 2012). The simulations are downscaled to a 0.25°×0.25° resolution working grid (Ravestein et al. 2016) for the relevant output climate variables. Simulated winters are classified into four climate scenarios in a similar fashion as in the KNMI'14 scenarios. The simulated years are stratified in terms of two types of air circulation patterns as defined by the phases of the NAO (figure 5). The two climate phenomenon are assumed to function independently (van den Hurk et al. 2014). Air circulation pattern is represented by positive NAO (high value) and negative NAO (low value). Simulated winters from the 2035-2050 and the 2051-2085 periods are taken to represent a weak and strong warming scenario and are taken to represent the two GWEs of global mean temperature rise in 2050 relative to the period of 1981-2010, i.e. 1 °C (moderate scenario G) and 2 °C (warm scenario W), corresponding to RCP 4.5 and RCP 8.5 emission scenarios in IPCC (2013) report (KNMI 2014).

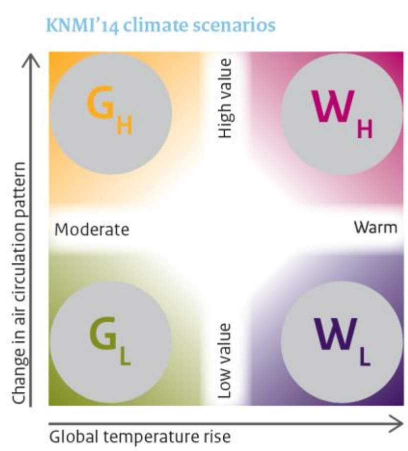


Figure 5. A sketch of KNMI'14 climate scenario. The horizontal direction denotes the global warming effect from moderate (1 °C increase) pathway to warm (2 °C increase) pathway. The vertical direction denotes the climate variation, i.e. the NAO effect from low (negative) value to high (positive)value. Four areas in the graph are separated for the simulated weather years. G and W represent the global warming against horizontal axis. H and L represent the climate variability against the vertical axis. For instance, the weather in W_H area suggests the climate context of high global temperature rise and high NAO index.

3.1.2 Sample year selection and pertinent climate variables

The scenario building sketched in section 3.1.1. produces four scenarios denoted by the sign of NAO index (negative or positive) and the path of climate change (warm or cold), i.e. -NAO & cold, -NAO & warm, +NAO & cold, +NAO & warm. In each scenario, we selected two weather years with maximum and minimum NAO index respectively, as a represent among the years with full range NAO index.

Table 2. Selection of the weather year.

Scenario category	Sample year	EC-earth model run	NAO index
Negative + cold	071	11	-0.0448
	029	4	-4.5650
Negative + warm	055	9	-0.0650
	010	2	-3.6405
Positive + cold	082	11	4.1919
	019	3	0.0223
Positive + warm	034	4	4.4441
	036	4	0.0455

Corresponding climate variables were gathered according to the method and technology setting, as shown in table 3. It should be noted that all outcome variables are either 6 hourly or daily value, whereas hourly values, especially for the wind speed at hub height and the SSRD, are necessary to calculate hourly electricity output of wind turbine and solar panel. Therefore, we conducted downscaling modification on variable 1 in line with Duffie and Beckman (2013, pp.37–40) and Craig (1984) and on variable 3 and 4 based on linear assumption of wind speed variation. A detailed information about the downscaling interpolation can be found in appendix C.

Table 3. Relevant climate variables of EC-earth model.

Variable Name	Unit
1. Daily shortwave surface radiation downward (SSRD)[4]	J/m^2
2. Daily average windspeed at 10 m height	m/s
3. 6 hourly windspeed at 100 m height	m/s
4. 6 hourly windspeed at 120 m height	m/s
5. Daily average temperature at 2 m height	°C
6. Daily maximum temperature at 2 m height	°C
7. Daily minimum temperature at 2 m height	°C

3.2 Geoinformation for capacity distribution

3.2.1 Landcover

Landcover information contains two types: the ocean data, which includes the water depth of sea, and the data of land which includes landcover class and the protected area. A bathymetry (ocean depth) data set from GEBCO[5] was used to obtain the water depth of the regions' Exclusive Economic Zone (EEZ) within 100km from shore. Corine Land Cover (CLC) 2012 (EEA 2012) at 250m resolution, combined with the nationally designated areas (CDDA)[6] which serves as the

[4] Both direct and diffuse radiation are included.
[5] http://www.gebco.net/data_and_products/gridded_bathymetry_data/
[6] https://www.eea.europa.eu/data-and-maps/data/nationally-designated-areas-national-cdda-11

forbidden area for iRES installation, was used to label the landcover types within each spatial grid. The CLC classified landcover into 44 classes (EEA 1990, pp.21–25), to which we set the land availability for wind turbine and solar panel (see Section 2.2.2).

3.2.2 Population

A predicted population in 2025[7] was used. The prediction is based on 1990 global population and the SRES B2 Scenario (Gaffin et al. 2004), with a working grid of 15 minutes, in accordance to the resolution of the spatial grid. Population density was also calculated according to the area of each spatial grid.

3.2.3 Historical weather records

Gridded wind records was obtained from the ERA-20C (Poli et al. 2016) reanalysis data simulated by ECMWF, in which the 3-hourly average wind speed was extracted. Solar radiation was collected from satellite observation of daily short wave incoming radiation published by EUMETSAT's CM SAF program (Posselt et al. 2012; EUMETSAT 2014). Both records cover a period of 30-year so that the effect of NAO in former years can be implicit.

3.3 Data for power system model

The PLEXOS requires techno-economic parameters and load patterns, pertaining to power generation, transmission and consumption, for all involved system options. For the wind turbines and the solar panels, the parameters were obtained from their manufactures (appendix A). Hourly production portfolio is needed as the input to the PLEXOS and this can be obtained in the methods (see Section 2.3). Parameters of other configurations were taken from Brouwer et al. (2016) as guaranteed, where biomass, geothermal, fossil fuel and nuclear power plants, demand response, transmission lines and demand loads are involved. A brief overview on the main components of the system configuration that selected from the previous research is given below. Detailed information can be found in Brouwer et al. (2016).

3.3.1 Power plants

Generators are classified into six groups as the input of the PLEXOS. Some important techno-economic parameters are displayed in table 4. As the vintage plants are disregarded, all parameters of the projection in 2035 are used to represent the average situation in 2050.

[7] http://sedac.ciesin.columbia.edu/data/set/sdp-downscaled-population-grid-b2-1990-2025/data-download#close

Table 4. Projected techno-economic parameters for 2035 (Brouwer et al. 2016).

Category	Power plant[a]	TCR[b] Investment	Fixed O&M	Variable O&M	Full load efficiency	Ramp rate
		€$_{2012}$/kW	€$_{2012}$/kW	€$_{2012}$/MWh	% LHV	% of max capacity/min
Non-intermittent renewables	Biothermal	1644	37	3.0	45%	3.0%
	Geothermal	2151	44	0.0	100%	3.0%
	Hydropower	2059	52	0.0	100%	8.3%
	Pumped hydropower	1410	0	0.2	80%	N.A.
Conventional thermal power	NGCC+CCS	1349	15	2.1	56%	4.5%
	Nuclear power	4841	103	1.0	33%	2.5%
Peak load power	NGCC	902	11	1.2	63%	4.5%
	Gas Turbine	438	10	0.8	42%	10.0%
Demand management	Air conditioning	17	4	N.A.	N.A.	N.A.
	Freezer/refrigerator	43	11			
	Heating	3	1			
	shift 1h by 2h load	3	1			
	shift 2h by 2h load	3	1			
	Washing machines & dryers	100	26			
Wind power	Onshore	1402	37	0.0	-[c]	
	Offshore	2655	83	0.0	-[c]	
Solar PV	Rooftop	700	17	0.0	-[c]	
	Utility					

[a] Power plants only generate electricity: no combined heat and power plants are included.
[b] The Total Capital Requirement (TCR) investment costs are calculated from the Total Overnight Costs (TOC) reported by the IEA (2014b). An interest percentage of 8% of is used
during construction. The capital expenditures occur linearly during the construction phase (Oxera 2011).
[c] Technical parameters for iRES technology are determined in this study (see table A-1).

3.3.2 Demand load

Demand load pattern for 2050 conditions had been estimated by extrapolating the historical electricity consumption records (ENTSO-E 2014) with respect to the IEA ETP'14 2DS scenario (IEA 2014a) which suggests an annual increases by 0.25% to 2800 TWh in 2050. Having realized the energy efficiency may improve and the structure of demand may alter, an alternative demand pattern was forecasted by van der Leij (2015). It projected efficiency developments in industry, transport, agriculture and energy sectors, together with per end-use demand of the residential and service sectors. Moreover, increased electrification of transport (to 23% of the passenger vehicle fleet) and heating (to 27–72% of residential and 15–58% of service sector heat demand, depending on the region) are included. Table 5 lists the annual demand loads per region as well as the demands in December, January and February.

Table 5. Regional demand loads.

	Annual demand	Load profile [GW]				Demand in DJF	Share of the year
	TWh	Max	Average	Minimum	Standard deviation	TWh	
British Isles	377	67	43	21	9	106	28%
France	547	105	62	30	15	173	32%
Germany & Benelux	737	114	84	48	13	192	26%
Iberian Peninsula	326	57	37	7	6	87	27%
Italy and Alpine States	478	85	55	29	11	126	26%
Scandinavia	334	63	38	20	8	103	31%
Total	2800	N.A.				787	28%

Demand load is set to be fixed for all simulated cases. Although the three winter months take up around 25% of annual times, their energy demands are all more than 25% of the annual. This verifies our reason for the time interval choice for this research.

3.3.3 Transmission and fuel prices

The transmission capacity (table 6) is based on the medium interconnection case of Brouwer et al. (2016). It is fixed over different energy scenario.

Table 6. Capacity of transmission lines.

Unit: GW	British Isles	France	Germany & Benelux	Iberian Peninsula	Italy and Alpine States	Scandinavia	Total outflow
British Isles	-	12.8	4.9	-	-	-	17.7
France	12.8	-	19.9	27.4	13.1	-	73.2
Germany & Benelux	4.9	19.9	-	-	6.6	9.8	41.2
Iberian Peninsula	-	27.4	-	-	-	-	27.4
Italy and Alpine States	-	13.1	6.6	-	-	-	19.8
Scandinavia	-	-	9.8	-	-	-	9.8
Total inflow	17.7	73.2	41.2	27.4	19.8	9.8	189.1

Fuel prices (table 7) are based on the low-carbon 2DS scenario of the IEA Energy Technology Perspectives 2014 (IEA 2014a). The study predicts the ranges of some fuel prices but we only fix on one medium case for simplification.

Table 7. Fuel prices in use.

Fuel type	Biomass	Gas with CCS	Gas for gas turbine	Gas for NGCC	Storage	Uranium
Price [€/GJ]	7.2	6.5	6.5	6.5	0.0	1.0

4. Results

4.1 Capacity distribution of iRES

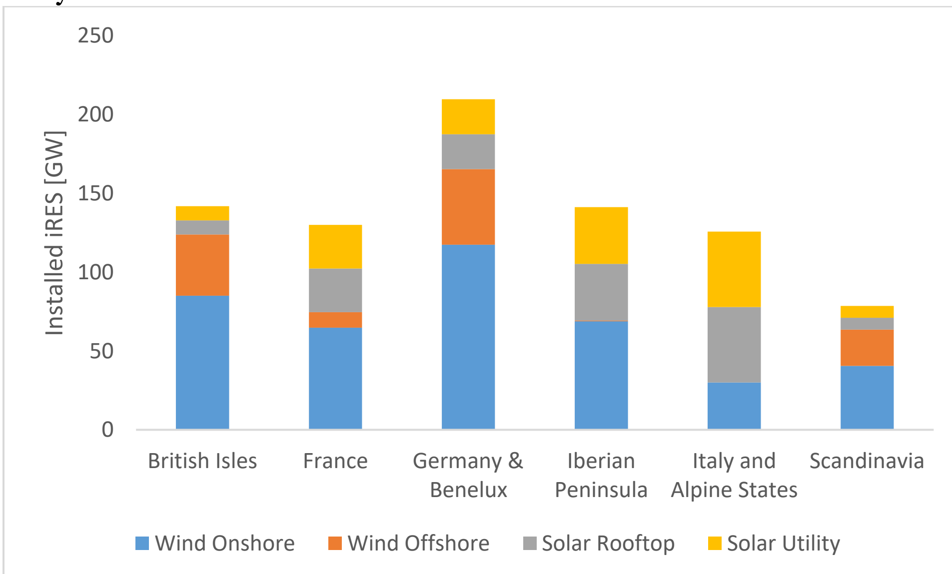


Figure 6. Regional iRES capacity installation in RES80 scenario.

Figure 6 presents the capacity installation of iRES technology in the six regions in RES80 scenario. The regions can be divided into two groups in terms of total iRES installation. Germany & Benelux owns the highest installation of more than 200 GW while the installations in the rest four areas, excluding Scandinavia, show similarly low levels at around 140 GW per region. The profile of installed iRES technology varies over regions. British Isles, Germany & Benelux and Scandinavia are dominated by wind power. France and Iberian Peninsula have equivalent installation between wind turbine and solar panel. Italy and Alpine States is dominated by solar power. Germany & Benelux has the most onshore wind capacity of about 120 GW. Although there is negligible capacity of offshore wind in Iberian Peninsula, its onshore wind capacity is even more than the total wind capacity in Scandinavia. Germany & Benelux and British Isles install most of offshore wind turbines, followed by Scandinavia. Regions can also be separated into two groups in terms of solar panel installation. Italy and Alpine States, Iberian Peninsula and France are the three hotpots for solar PV, where 50 to 100 GW capacity are installed per region. The second group has a lower level of solar capacity installation at 10 to 40 GW in each region.

Spatial features of the iRES capacity distribution are indicated in figure 7. Offshore wind turbines concentrate on the south-east coast of North Sea which is surrounded by British Isles, Germany & Benelux and Scandinavia. East and west coast of south British island and the north coast of France are also favorable to offshore wind capacity. Onshore wind turbines spread out over the whole Germany & Benelux and Irish. North-western France and north-eastern Spain are also diffused by wind turbines. Besides, it stretches along the coast of North Sea in Britain and Scandinavia. A quadrangle pattern around Tyrrhenian Sea is illustrated by the onshore wind turbine installation in Italy. The four corners which consist of two islands and two patches in the coastal zone are clustered with the capacity. Rooftop solar PV concentrates in the main cities over Europe continent. Utility solar PV prevails in the entire Italy and Alpine States and widely spread out in central Spain and Central France. Northern Germany and Ireland have clusters of utility solar capacity.

Full profiles of capacity allocation for all three energy scenarios can be found in appendix A and the full profiles of spatial distribution are illustrated in appendix E. The rank of regions in terms of installed capacity and the internal allocation of the technology do not change too much in different energy scenarios. An exception is Germany & Benelux where a sharp growth of onshore wind capacity in RES80 occurs. Because of this, Germany & Benelux transcends British Isles to be the area with the largest iRES capacity installation. In terms of spatial distribution, capacity distribution expands the general pattern with the increase of iRES installation plan but the core area for capacity installation remain the same. Although the regional allocation of iRES capacity is predefined, a specific spatial distribution of these allocated capacities could make difference on real power generation due to different weather conditions in each grid.

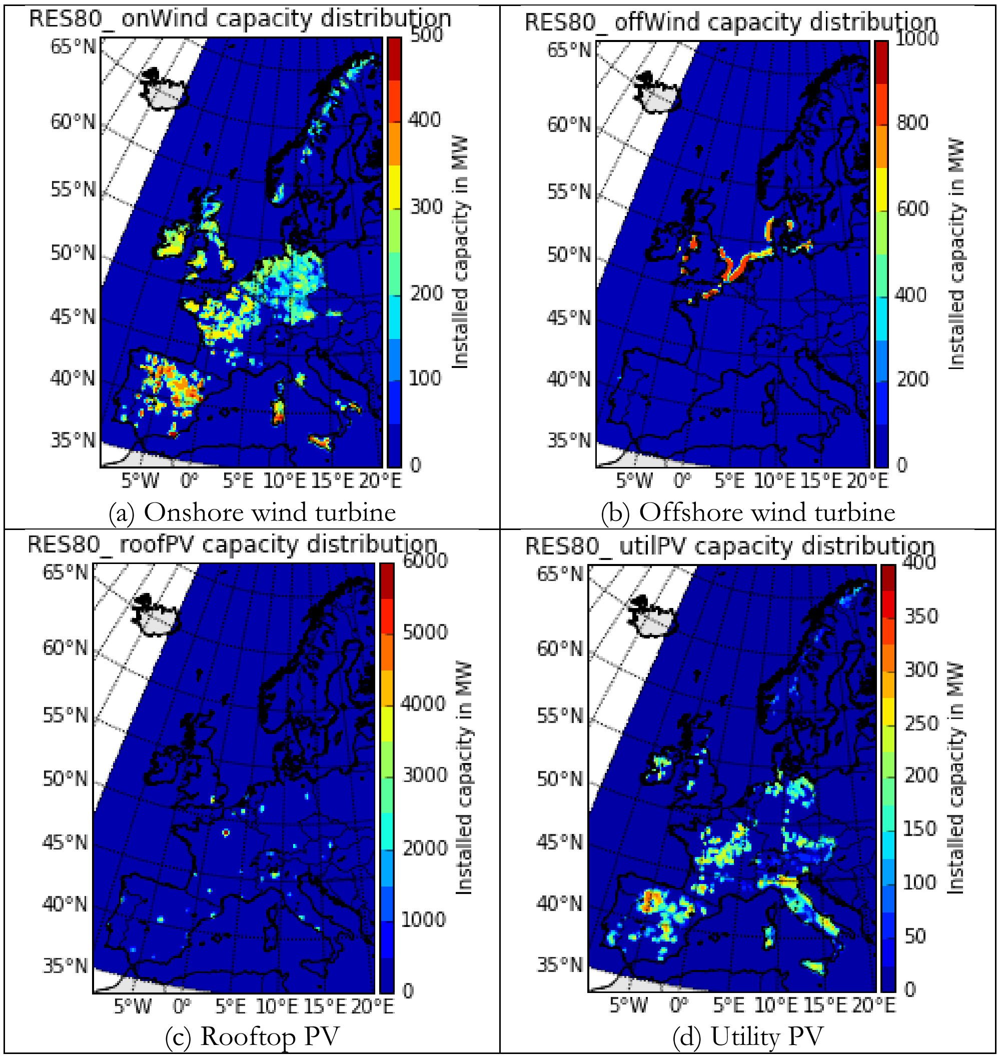


Figure 7. Spatial illustration of iRES capacity in RES80 Scenario.

4.2 Distribution and variation of iRES power generation

Daily power generation in winter is analyzed through box-whisker plot which shows the distribution of the results. In figure 8, the distribution of daily power generation per technology in RES80 energy pathway is presented and compared among the selected eight weather years. The boxes are arranged against years in increasing order of NAO index from minimum negative value to maximum positive value. A complete display of box-whisker plot for all three energy pathways is in appendix E.

Onshore wind can generate 1900-2800 GWh electricity within the system per day on average, as the variance of NAO years. The interquartile range of its system daily production takes up less than half of the whole range. There is a fluctuated growth trend of wind power daily outputs against the increase of NAO index. With the NAO index increasing, the generation raises in negative NAO phase. Then in the positive phase, the generation drops a little and grows to the highest in the year of maximum positive NAO index. Power generations in moderate NAO years (of which the NAO index is close to zero) usually hold wider range of distribution. The lower boundary declines until moderate weather years and ascends to the maximum level in extreme positive NAO years. The minimum generation in the year can reach 45-50% of its mean level, which is significantly higher than the other years. It is suggested that positive extreme NAO years are favorable for onshore wind power as severe shortage of its power supply may not happen.

Power generation from offshore wind of the system ranges from 1000 GWh to 1500 GWh per day on average in different NAO years. Its distribution follows a similar trend of variation as onshore wind despite its intra-period distribution is wider and more homogeneous. The boxes for offshore wind power are generally closer to both ends of the whisker. However, there is no outliers in offshore wind power production as in onshore wind power where there are ceiling outliers of production in weather years with extreme negative NAO index. The lower bound of the whiskers approaches to zero, indicating that severe shortage of offshore power supply during wintertime may occur.

Daily power generation of rooftop and utility solar PV are almost the same and stable at around 230 GWh per day on average, not changing with the variation of NAO year. Its daily production distribution is more concentrated in its lower half percentile but more widely distributed in the upper half percentile with some outliers. The variation of power generation distribution is not significant against weather years with NAO index, except that the power generations of both types of PV in extreme positive weather years are slight but significantly above the other years. There is also no observable difference of either the distribution or its variation between rooftop and utility technology. The lower boundaries of the solar power production in different weather years are rather high, which account for about 50% of the mean level and 20-40% of the maximum production. This suggests that a severe shortage of solar power supply is not likely to happen.

Climate variation is indicated to mainly influence the generation pattern of wind power among the iRES. Besides, the global warming effect and different volume of iRES capacity installation in different energy scenarios do not induce significant effect on the distribution and variation pattern of iRES power generation.

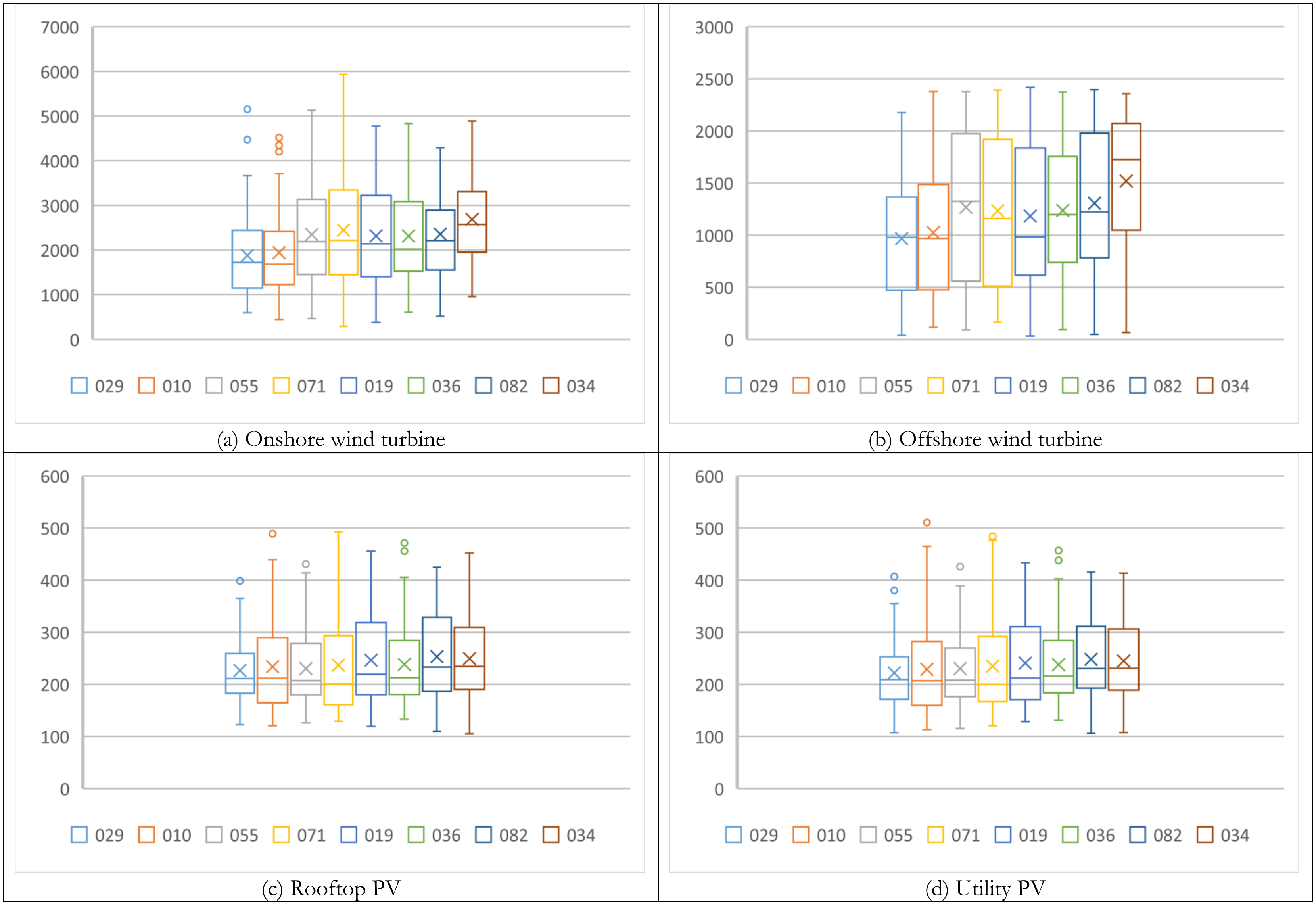


Figure 8. Distribution of daily power generation [GWh] per iRES in winter months (DJF). The box plots represent total electricity output available per day per iRES technology. A bar in the box shows the median. A cross in the box shows the mean. In each plot, boxes of weather years are ordered with increasing NAO index as shown below.

Chart for the order of weather years and their climate contexts.								
Weather Year	*029*	*010*	*055*	*071*	*019*	*036*	*082*	*034*
NAO index	*-4.5650*	*-3.6405*	*-0.0650*	*-0.0448*	*0.0223*	*0.0455*	*4.1919*	*4.4441*
GWE	*cold*	*warm*	*warm*	*cold*	*cold*	*warm*	*cold*	*warm*

4.3 Capacity credits of iRES power generation

As shown in figure 9, the capacity credits of total iRES power exhibit a strong trend of fluctuated growth as the variation of onshore wind power found in section 4.2. Values of the extreme positive years reach a high range between 12-18%. This means, for instance, that with 100GW installation of such iRES profiles, we can reliably support 12-18GW electricity demand through iRES without supplementary generators, namely, the same capacity of conventional generators can retire. On the other hand, the extreme negative year is unfavorable to iRES, of which the capacity credits can be as low as 4%. In general, iRES capacity has more profound effects of replacing non-renewables in positive NAO phase. In negative phase of climate variation, the global warming seems to affect the capacity credits. No matter the NAO index is higher or lower than its counterpart year with an index in the same level, the year in warm scenario shows a smaller credit. However, this situation cannot be clarified in positive phase since the NAO indexes of positive warm years are consistently higher than their counterpart cold years. Increasing the capacity installation of iRES drives down the capacity credits with 2-6%. One reason can be inferred that not all added capacity can coordinate with the demand load pattern due to the weather dependency of iRES power outputs. With the constraint of weather condition, a common situation should be that the larger volume of iRES power capacity, the lower its capacity credits.

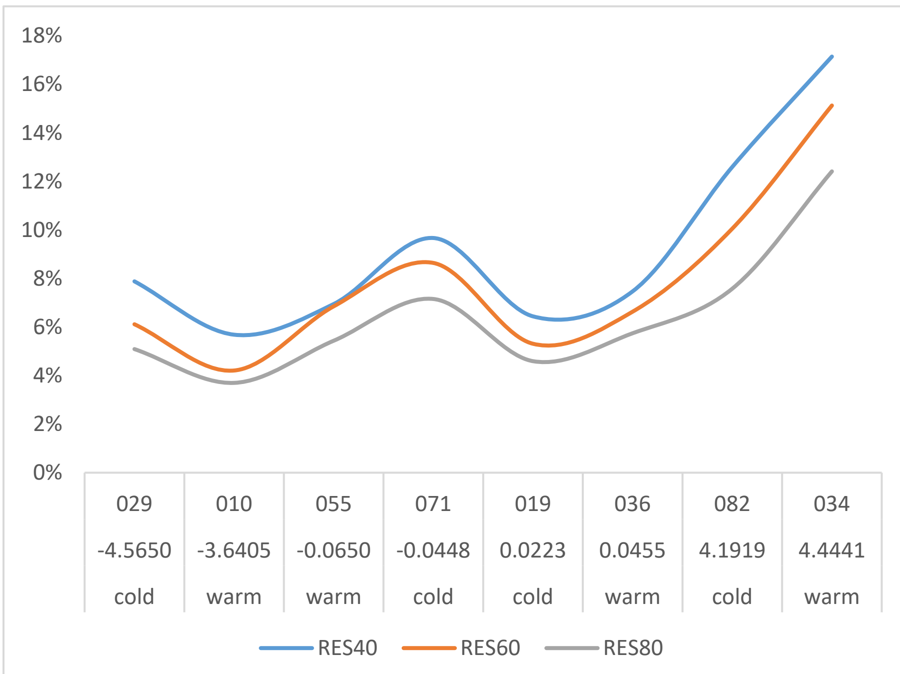


Figure 9. System capacity credits for total power generation of iRES technology over the year.

If the total capacity credits are decomposed into each iRES technology (figure 10), some different trends are revealed. The capacity credits of wind power lay between 5-40%, which are above that of total iRES in the same energy pathway. On the other hand, solar PV can hardly replace non-intermittent energy source and its credits approach zero.

Only offshore wind power follows the general trend of total iRES credits against climate variation. The capacity credits of onshore wind power stabilize within 8-20% in negative and moderate positive NAO phases, which do not seem to be strongly influenced by the climate variation. Onshore and offshore wind power share the same rise in the capacity credits from a bottom in moderate positive year to the peak in extreme positive year. Both technologies are advantageous in extreme positive weather year. The capacity credits of onshore wind power are generally higher than the offshore, despite the larger scale of onshore wind capacity installation.

Capacity credits of solar PV are almost insensitive to the change of capacity installation, except for the abnormal pattern of utility PV in RES80 scenario. The variation of capacity credits of both rooftop and utility PV against NAO effect is also different from total iRES. A common situation shared by both technology is that the capacity credits perform slightly better in the intervals between either of the extreme phases and the moderate phase, which is almost inverse to the total trend.

In conclusion, the NAO effect has influence on the efficacy of iRES in capacity substitution of non-intermittent energy. However, the influences on wind power and solar PV are opposite. Extreme positive and moderate NAO effects are preferable to wind power but are adverse to solar PV. Solar PV is more favorable in the two intervals between extreme and moderate NAO effects. Wind power dominates the variation trend of the total iRES capacity credits. It seems that offshore wind power shapes the total trend although both its capacity credits and capacity installation are smaller than onshore wind power. A complete profile of capacity credits including regional details is presented in table E-1 of appendix E.

Figure 10. System capacity credits per iRES technology over the year.

4.4 Outputs from the PLEXOS

Due to time constraint of the project, only two weather years were simulated in the PLEXOS platform. Year 010 with least NAO index (-3.6405) and year 034 with highest NAO index (4.4441), both in warm GWE pathway, were selected. They are used to represent the negative phase and the positive phase of the NAO. In the following sections, we just name these two years 'negative NAO year' and 'positive NAO year' respectively. The selection is based on the common believe on the severe global warming and serves for comparing the impacts of NAO the effect from both phases. There are in total six cases that were simulated, as the combination of two weather years (010 and 034) and three ECF energy pathways (RES40, RES60 and RES80). Although the PLEXOS runs the ST plan for UCED over the entire 2050, we are going to discuss the output indicators during winter months, except for the constant capacity installation over the year.

4.4.1 Capacity installation portfolio

The LT plan was first used to determine the optimal capacity installation of all types of power plants, including demand management capacity. The profiles were obtained from optimization in each case according the planned target in the energy scenarios where 40%, 60% and 80% of the electricity are supplied by the renewables. Figure 9 shows the proportion of each power plant category among the total capacity in the case. Table 8 shows the amount of capacity installation.

As the capacity of renewable power is predefined, both its installation capacity and the capacity share of the total do not change in different weather years. Demand management keeps the same capacity of 36GW in no matter different weather years or energy scenarios. On the other hand, this means its proportion of total installed capacity shrinks as the total capacity rises. The proportions are the same against two NAO phases. With more iRES implemented, relatively less demand management is needed. The electricity demand can thus be better met. Climate variation does not seem to affect the status of demand response.

In positive NAO year, there are always more peak load capacity and less conventional thermal power capacity than in negative NAO year. In the RES80 scenario where the most iRES capacity is installed, the difference of peak load capacity between the two weather years is also the largest. The share of peak load capacity remains at about 20% of the system total capacity with different iRES configurations, but that of conventional thermal power significantly shrinks from 25% to less than 5%. This phenomenon indicates that the iRES technology can replace conventional thermal power but the power for peak load cannot be removed.

Power generation of the iRES is variable, intermittent and undispatchable since it relies on weather conditions, on which the climate variation has influence. Its pattern cannot coordinate with the demand load pattern all the time. As a result, introducing larger volume of iRES may replace conventional thermal power for base load but it cannot cope with the elastic peak loads. Peak load generators which are flexible are thus requisite to compensate the demands during the shortage of iRES electricity supply. Climate variation seems to be able to alter the extent of the phenomenon. In positive NAO year, the importance of peak load power seems to be reinforced whereas it is weakened in negative NAO year. Further mechanism of the impact and the roles of wind power and solar PV will be explored in the following sections.

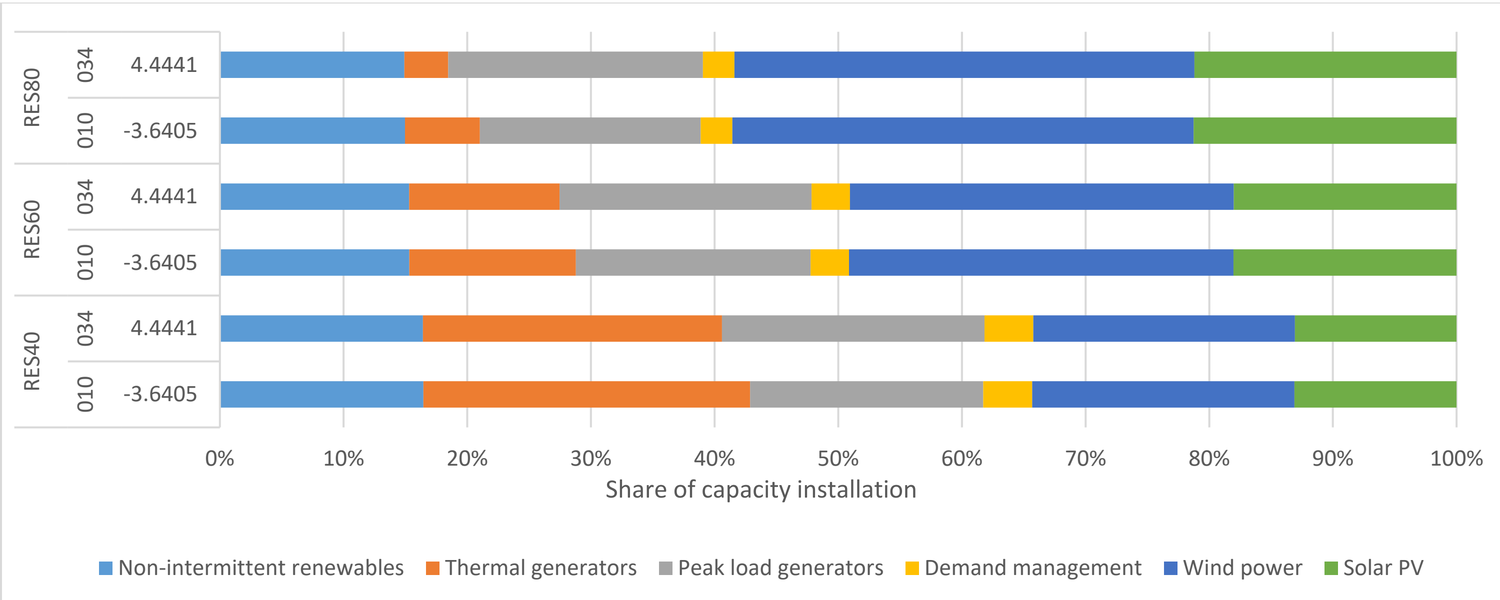


Figure 9. Share of capacity installation.

Table 8. Capacity installation per category of technologies.

Installed Capacity [GW]	RES40		RES60		RES80	
	010	034	010	034	010	034
	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441
Non-intermittent renewables	150	150	178	178	211	211
Conventional thermal power plants	242	222	157	142	85	50
Peak load power plants	172	195	221	237	252	292
Demand management	36	36	36	36	36	36
Wind power	194	194	362	362	527	527
Solar PV	120	120	210	210	300	300
Total	914	917	1163	1165	1412	1416

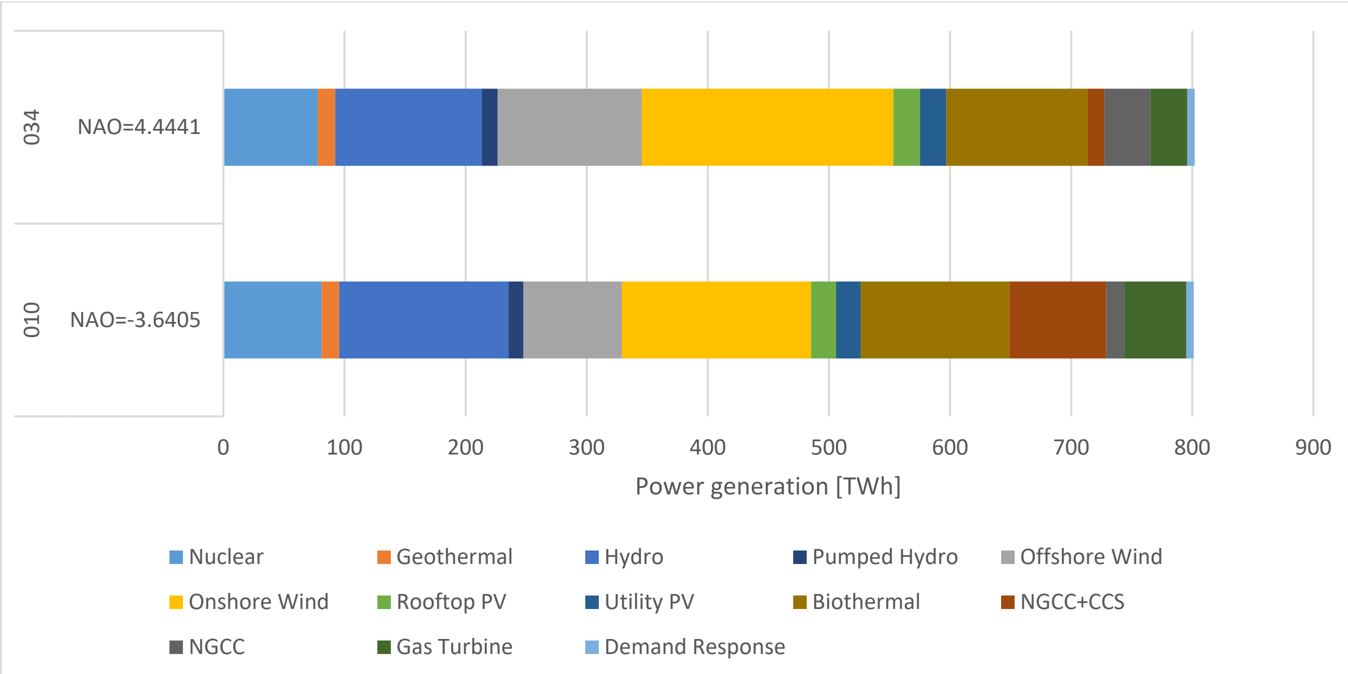
4.4.2 Overview of system power generation mix

As the demand loads are constant in all cases, the annual electricity generations of power system should also be the same if it is met. The PLEXOS outputs show that in all cases, the annual system power generation is 2831 TWh with the same quantity of system demand fulfilled. In winter months (DJF), both the supply and the demand are 801 TWh, taking up 28.3% of the annual. This result is higher than the demand inputs with 31 TWh over the year and 14 TWh in winter. The difference is probably due to the demand management in the system. Demand increase in winter months accounts for 45% of the total growth, which again verifies the importance of winter in the power system.

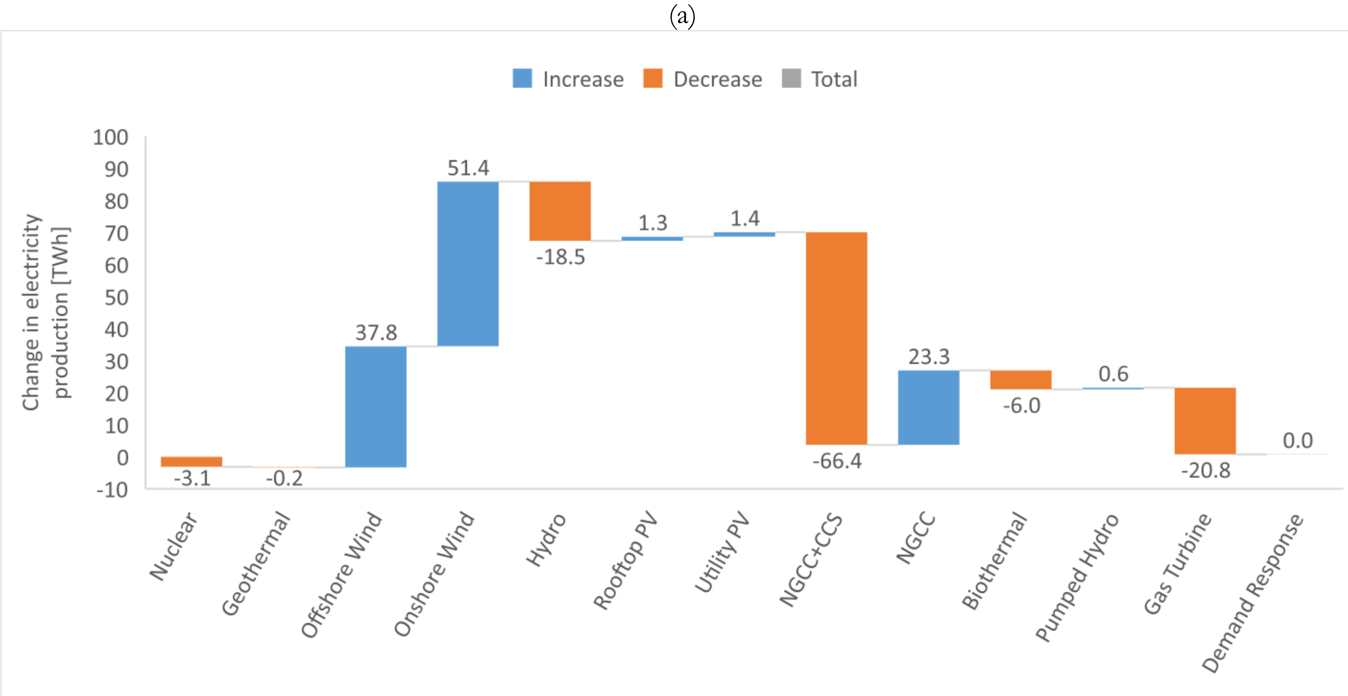
Figure 10 (a) shows the system generation mix and (b) shows the change of its components over the winter month (DJF) in the RES80 ECF scenario. Recall that the system power generations and the capacity installations of either iRES technology in both years are the same. With the switch from negative NAO phase to the positive NAO phase, the power system reinforces its electricity production of both onshore and offshore wind power with 37.8 TWh and 51.5 TWh respectively, while the difference of solar PV between the two years is negligibly 2.7 TWh for both technologies. In addition, the NGCC with CCS and gas turbine reduce their productions with 66.4 TWh and 20.8 TWh whereas the NGCC raise 23.3 TWh of its production.

Hydropower and the NGCC with CCS are normally for base load supply. Gas turbine and the NGCC serve the peak load due to their flexibility. Note that the total peak load generations supported by the NGCC and gas turbine in either of the weather years are the same. With more wind power generation, base load generators can be replaced. The flexible peak load demand remains unchanged. However, more electricity from gas turbine, and accordingly, less from the NGCC, in negative NAO year with fewer wind power. Gas turbine is more flexible than the NGCC. It is usually employed when there are severe variation or shortage as during peak load hours. This suggests that the wind power generation is more variable in negative NAO phase.

Positive NAO effect is suggested to be more favorable to wind power generation than the negative whereas the production of solar power does not seem to be strongly affected. Wind power can replace the base load generators. Negative NAO effect brings the power system with fewer wind power, which increases the base load supply from other generators. In addition, the more flexible gas turbine is needed in negative NAO phase with fewer iRES power supply.



(a)



(b)

Figure 10. (a) System power generation mix over winter months (DJF) in RES80. (b) Electricity production change of the generators in winter from negative NAO year (010) to the positive year (034). The total electricity produced by the system in winter is 801 TWh for both weather years.

Figure 11 zooms into the regional electricity production over the wintertime. The NAO has different impact on the regional productions. Positive NAO effect elevates the total power generation in north regions (British Isles, Germany & Benelux and Scandinavia). The elevation is primarily rendered through the increase in wind power production. The impact on Scandinavia is not apparent because there is hydropower as a strong supplement. On the contrary, less electricity is produced in south regions (Iberian Peninsula and Italy and Alpine States) together with a reduction in wind power generation. As France locates in the middle of Europe, the impact of the NAO sways in between. Positive NAO effect diminishes its total electricity production as for south regions but increase its wind power output, though the growth is weak. No significant change of solar power output can be found with different NAO effects.

Internal structures of regional electricity production are different in terms of the NAO effect. In British Isles, the shrink in both total and wind power electricity during negative NAO phase adds the supply from gas turbine. In France, where the other generators keep the same when switch from positive NAO phase to the negative phase, power supply by gas turbine is raised and the region introduces the NGCC with CCS. In Germany & Benelux, reduced production in wind power in negative NAO phase is taken by large amount of the NGCC with CCS. Besides, the NGCC output in positive NAO phase is removed. Scandinavia uses more hydropower and biothermal power in negative NAO year to compensated wind power decline. The electricity production structure in Iberian Peninsula does not change with different NAO effects. In Italy and Alpine States, with more wind power production in negative NAO year, about half of the NGCC electricity is replaced by the NGCC with CCS.

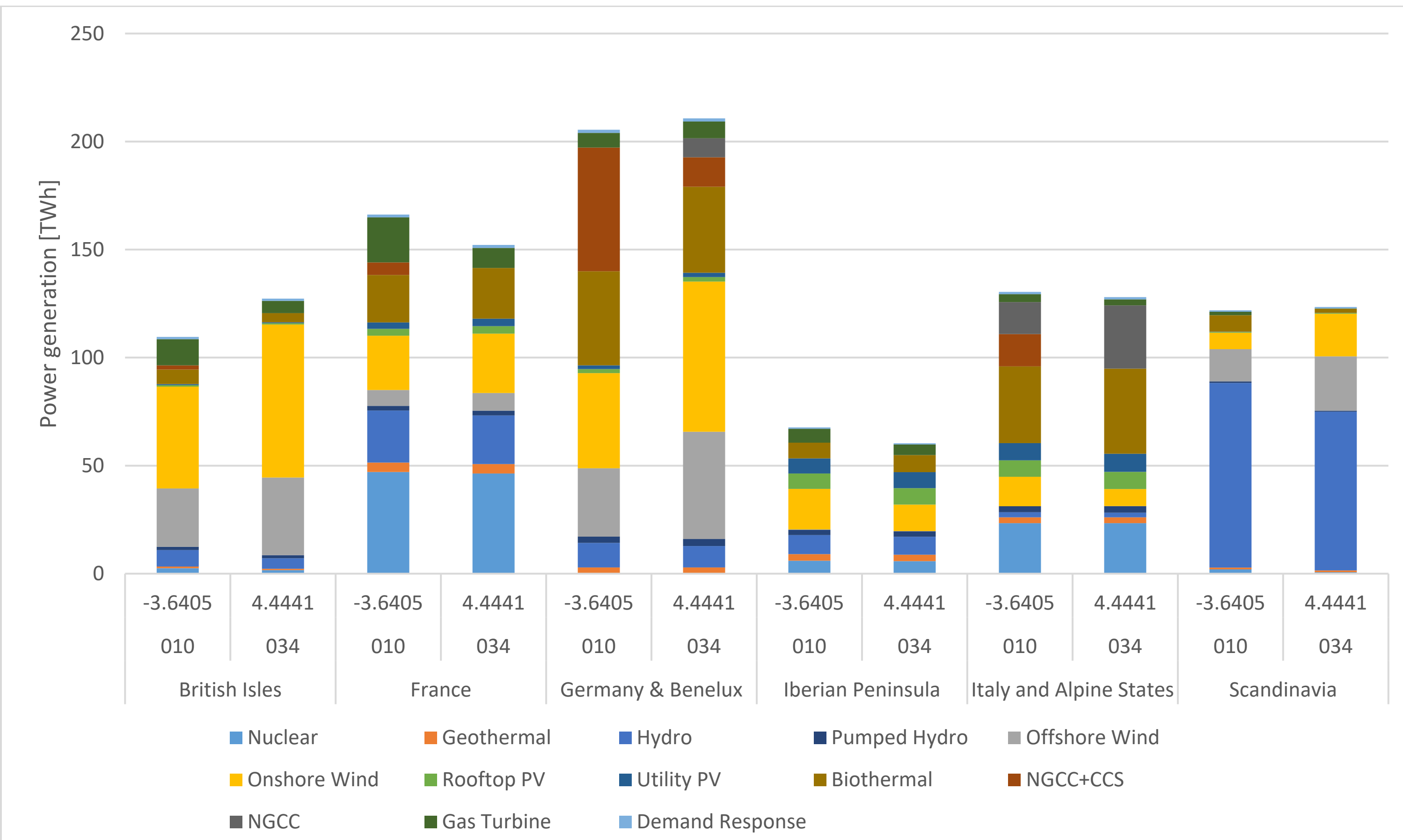


Figure 11. Regional power generation mix over winter months (DJF) in RES80.

4.4.3 Adequacy of electricity supply and demand

As suggested by table 9, there is no unserved or dumped energy in all cases. The power system can perfectly balance energy supply and demand by mathematical optimization. Nevertheless, either demand capacity or generation capacity may be curtailed, which is influenced by the NAO. In RES40 scenario, there are 25.9% of total hours in winter may have demand curtailment in negative NAO phase. Once it happens, on average 0.2% of the capacity at the hour to be discarded. However, in positive NAO phase, the trouble is thoroughly solved. If we have more renewables power like in RES60 and RES80 scenarios, curtailment may appear in generation but with rather low probability and low share to the total capacity. In positive NAO year, there are more times in winter with curtailments on generation (up to 4.8% vs. 2.2% in RES80) but smaller share of capacity (0.1% vs. 2.2% in RES80) to be discarded compared with the situation of negative NAO phase. In this sense, the RES60 scenario is more adaptive than the others to climate variation as its generation curtailment level is the lowest and there is no demand curtailment.

Table 9. System adequacy and shortage in winter months (DJF).

Category		Year	NAO	RES40	RES60	RES80
Unserved Energy [MWh]		010	-3.6405	0	0	0
		034	4.4441	0	0	0
Dump Energy [MWh]		010	-3.6405	0	0	0
		034	4.4441	0	0	0
Demand Curtailed	Time share[a]	010	-3.6405	25.9%	0.0%	0.0%
		034	4.4441	0.0%	0.0%	0.0%
	Average rate[b]	010	-3.6405	0.2%	0.0%	0.0%
		034	4.4441	0.0%	0.0%	0.0%
Generation Capacity Curtailed	Time share[a]	010	-3.6405	0.0%	0.4%	2.2%
		034	4.4441	0.0%	1.2%	4.8%
	Average rate[b]	010	-3.6405	0.0%	0.4%	2.2%
		034	4.4441	0.0%	0.1%	0.1%

[a] The share of curtailment hours to the total hours in winter.

[b] The average rate of curtailed capacity to the total demand/generation capacity of the hour when the curtailment happens.

Detailed information can be found in table E-3, where the regional distribution of capacity curtailment is shown. It is suggested that demand curtailments are evenly distributed among all regions whereas the generation capacity curtailment concentrates in British Isles and Scandinavia where wind power is vastly introduced. Positive NAO effect has the same impact as for the system that it raises the opportunity of curtailment in the two regions but reduces the curtailed volume.

4.4.4 Storage and transmission

Storage and transmission are two measures in a power system to balance demand and supply. Storage can deal with the temporal imbalance between supply and demand by storing electricity when the supply is surplus and releasing power when supply shortage occurs. Power transmission grids balance the supply and demand from spatial dimension, by exporting surplus production and importing electricity when a shortage happens.

Storage capacity is useful and essential to compensate the intermittency and undispatchability of the iRES. An energy system with higher iRES penetration should need more storage capacity. In the power system model of this research, storage is assumed to be offered by pumped-hydropower and thus the cost is set to zero. The energy system can use as much storage capacity as it needs within the available limit. Table 10 presents the profile of system capacity that is used over the winter months.

Table 10. Usage of system storage capacity in winter (DJF).

Weather year	010		034		010		034	
NAO index	-3.6405		4.4441		-3.6405		4.4441	
Category	Total stored electricity [TWh]	Share of total production	Total stored electricity [TWh]	Share of total production	Peak load [GW]	Share of total capacity	Peak load [GW]	Share of total capacity
RES40	67.3	8.4%	68.4	8.5%	125	13.7%	120	13.0%
RES60	68.2	8.5%	68.6	8.6%	121	10.4%	116	9.9%
RES80	68.5	8.6%	70.1	8.7%	118	8.4%	117	8.2%

System storage does not variate too much in each case. In positive NAO year, there are more storage needed but the peak load is lower, compared with the negative NAO year. With more renewable energy introduced, more storage is used, in terms of both quantity and the share to the total production. However, the peak load declines in both quantity and the share.

Power system with large share of iRES, especially the wind power, in positive NAO phase usually needs more capacity of supply-demand balance measures. In positive NAO phase, the storm track drifts northwards, bringing more winds to North Sea area where most of the wind turbines are installed. Higher wind power output may add to the variability and dispatchability of local power systems. More storage capacity is needed for the temporal variation and more transmission capacity is used to balance interregional demand and supply.

Figure 11 shows the load of electricity transmission for the system over the winter period. More transmission load is required in positive NAO year., together with larger shares of the electricity online to either total energy production or the capacity constraints of the lines. The gap enlarges with increasing the RES electricity supply. Detailed information about interregional transmission lines can be found in table E-2 in appendix E. The positive NAO condition may strengthen the transmission load of outflow for north regions, such as Scandinavia, British Isles and Germany & Benelux, while relieve the outflow burden for south regions, including Iberian Peninsula and Italy and Alpine States. As France locates in the middle of the continent, the impact of NAO on its transmission load sways in between.

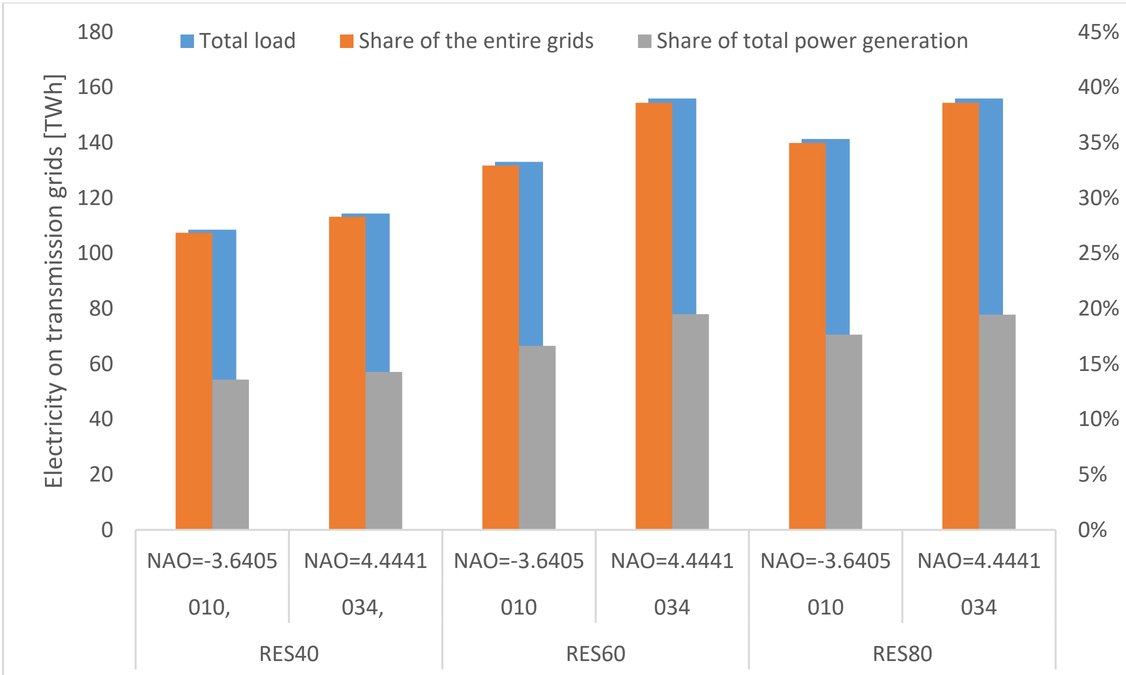


Figure 11. System electricity transmissions over the winter months (DJF).

Regional electricity transportation is displayed in figure 12. The shift of NAO effect from negative to positive adds the electricity exports in Scandinavia and Germany & Benelux in all three ECF scenarios. Either of the three regions maintains its export at 15 TWh. For Italy and Alpine States, the effect is elusive. In the RES40 scenario, the NAO has no impact on its import status. In the RES60 and the RES80 scenarios, the NAO switch from negative to positive alters the transmission status of the region from export 12 TWh to import 10 TWh. Although the transmission status of either Iberian Peninsula and British Isles is different with the ECF scenarios, effects of the NAO shift from negative to positive phase on them have the same direction. For Iberian Peninsula, electricity export is reduced by 4 TWh while the imports in RES60 and RES80 is dramatically raised by 15 TWh and 8 TWh respectively. British Isles is altered in a contrary way in which its tiny electricity import is reduced while the export is largely enhanced to 19 TWh in RES80 and 13 TWh in RES60. The same NAO shift on the status in France relies on the ECF scenario, i.e. the iRES installation. It needs 11-16 TWh more electricity import in the RES40 and the RES80 but 10 TWh less in the RES60.

In negative NAO phase, interregional imbalance of power generation is relatively mild. This means more electricity demand can be locally supplied. On the other hand, positive NAO may result in a severe lack of electricity supply as 34 TWh as in Iberian Peninsula. Recall its total electricity production in winter (see section 4.4.2) which is about 60 TWh. The shortage accounts for half of the local production, i.e. one-thirds of its demand cannot be locally supported.

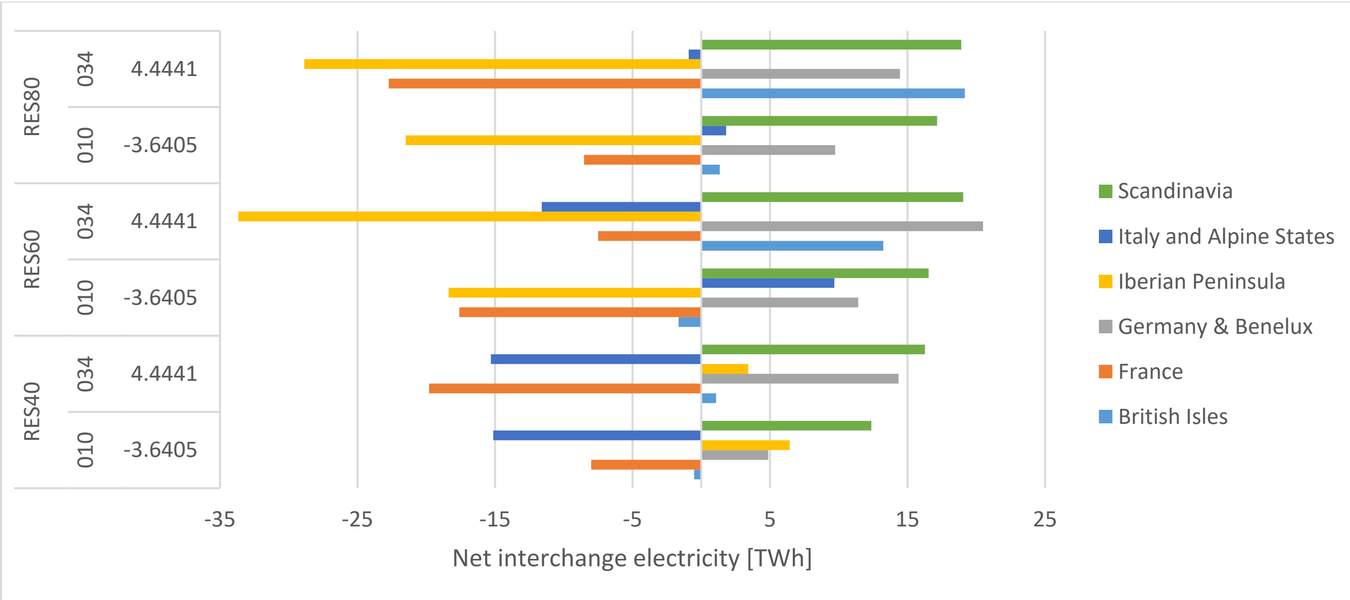


Figure 12. Regional total net electricity exchange over the winter months (DJF). The negative value denotes the local shortage in supply which needs net import. The positive value denotes the excessive local power supply that is exported.

4.4.5 Generation costs and electricity prices

Figure 13 presents the composition of generation costs. Total cost of per unit electricity generation consists of emission costs, the cost for start and shutdown the generators and the pure cost for energy generation. In positive NAO year, the total generation cost is significantly lower than in the negative year (17-22 €/MWh vs. 22-26 €/MWh). Its components in generation and emission shrink too whereas the generator start and shutdown cost increases slightly. The phenomenon is probably owing to that positive NAO effect brings more wind power to the system, with no charge in energy production. The slightly increase in generator start and shutdown costs implicates that the generation by thermal generators, for either base load or peak load, becomes more fluctuated.

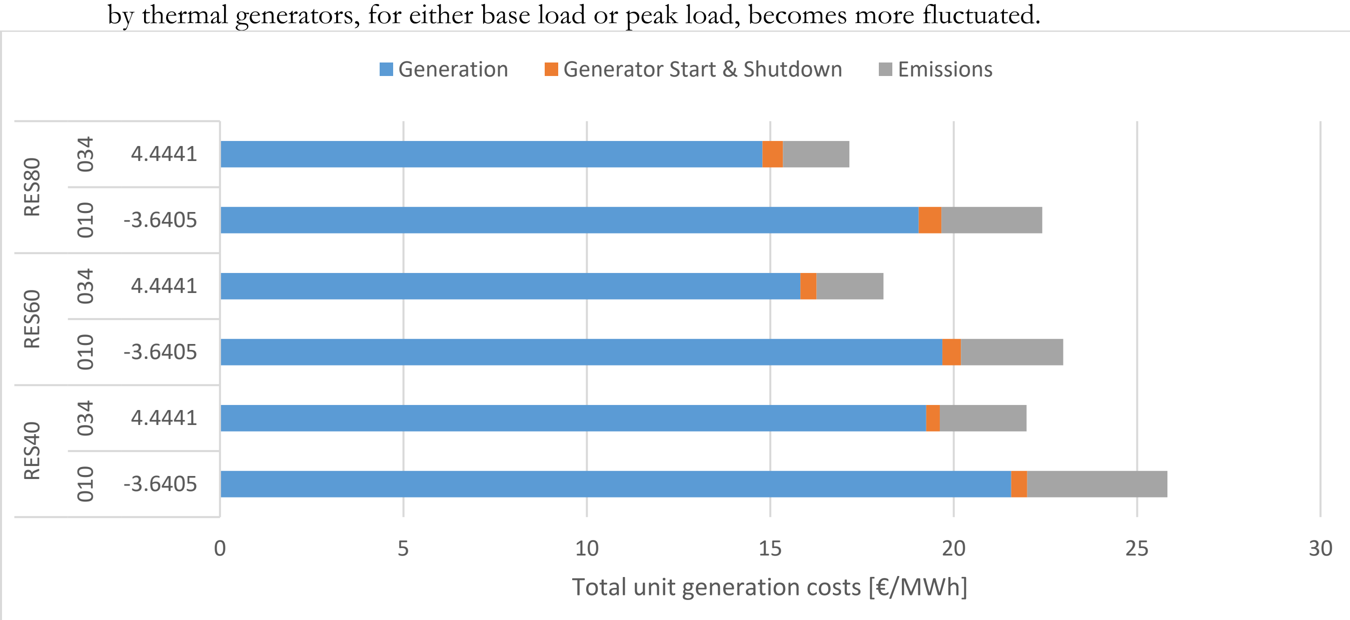


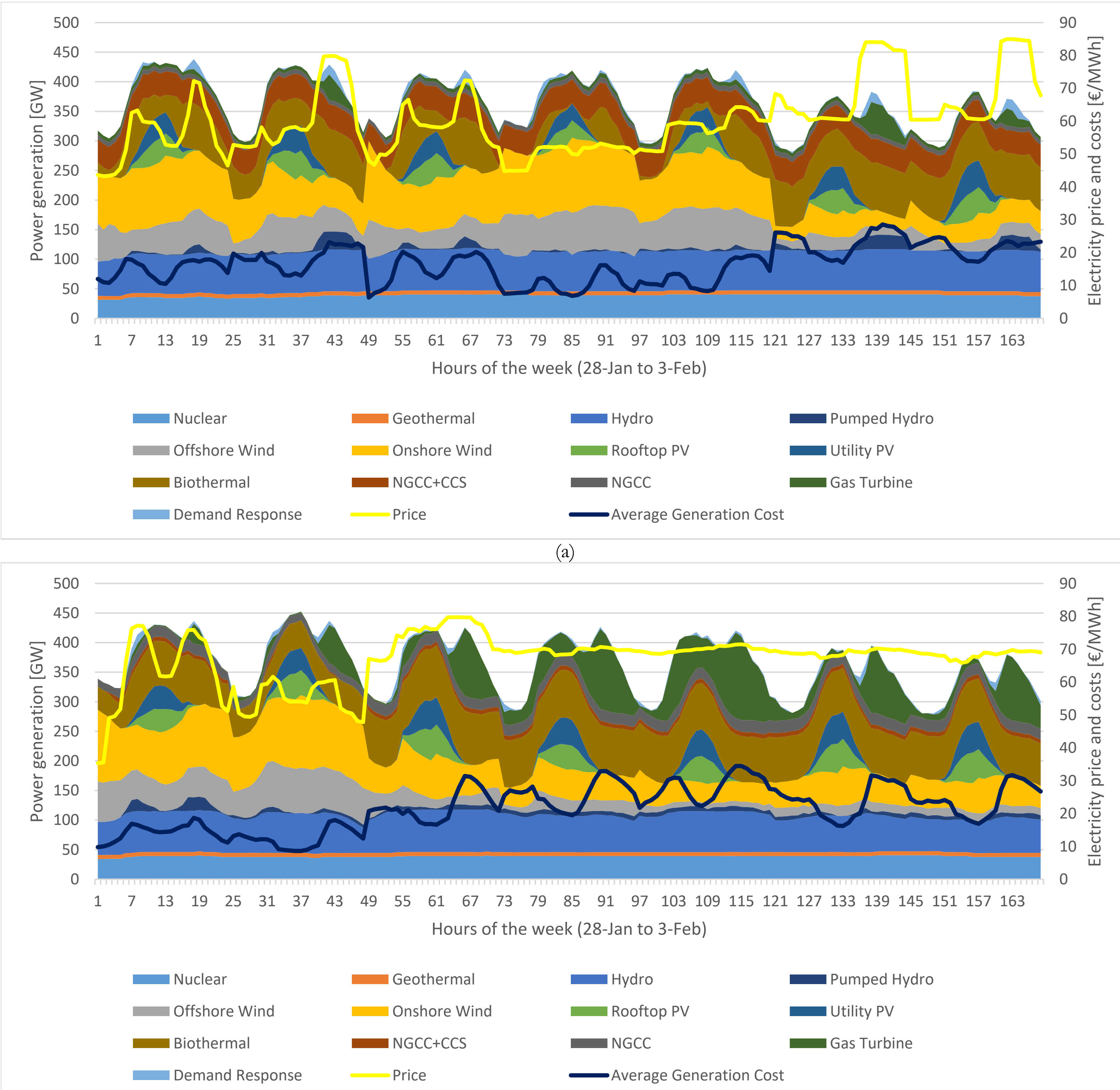
Figure 13. Profile of generation costs during winter months (DJF).

System electricity prices over the winter months (DJF) are presented in table 11. In positive NAO year, the average price can reach as low as 56.4 €/MWh with standard deviation of 16.1 €/MWh, either of which is smaller than that of the negative year, which is 65.4 €/MWh and 17.6 €/MWh respectively. Positive NAO effect lowers the price and stabilizes it as well. With the growth in the exploitation of the renewables, prices in both years falls considerably by about 8 units from RES40 to RES60 and then slip by about 3 units at RES80. However, the standard deviations change in a different way. In the positive year, it ascends slowly from RES40 to RES60 by 0.5 unit and then upraise 3.6 units from 12.5 €/MWh to 16.1 €/MWh in RES80. In negative NAO phase, it first drops dramatically 8.7 units to the minimum level at 13.8 €/MWh in RES60 and then is lifted to 17.6 €/MWh. As a result, with RES60 energy scenario, the price gap between NAO phases remains the same as in the other scenarios but gap of stability narrows.

Table 11. Profile of electricity price [€/MWh].

Indicator	Standard deviation		Weighted average		Minimum	
Year	010	034	010	034	010	034
NAO	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441
RES40	22.5	12.0	76.1	67.5	10.7	10.7
RES60	13.8	12.5	68.9	59.8	0.0	0.0
RES80	17.6	16.1	65.4	56.4	0.0	0.0

The cause of the price difference could mainly because of the extended exploitation of wind power in positive NAO phase. As presented in figure 14 about the generation/price/cost pattern, electricity price drops when vast wind electricity is supplied and it rises when wind power production decreases. Solar PV also has profound influence on system electricity price. It can drive down the price through its generation growth. However, as there seems no sensible change on the generation pattern of solar power caused by climate variation, it does not belong to the impact path of the NAO effect. Power generation by biothermal generator and gas turbine during peak hours is expensive, driving the price to as high as 85 €/MWh. The variability of wind power production may render the frequent use of biothermal generator and gas turbine for peak load. As presented in section 4.4.2, energy outputs from biothermal are equal between the two NAO years but the power system in positive NAO year has less gas turbine outputs. This implies a steadier wind electricity production and explains the lower price and costs in the positive phase.



(a)

(b)

Figure 14. Patterns of system price and generation cost in the sample week for (a) weather year 010 (NAO index = -3.6405) in the RES80 scenario, and (b) weather year 034 (NAO index = 4.4441) in the RES80 scenario. The weighted average electricity price over the regions is used to calculate the system average. Note that the hourly power generation of wind and solar is derived from 6 hourly/ daily climate model data projected for 2050.

4.4.6 System CO2 emissions

Carbon dioxide is produced from burning fossil fuels without CCS measure. As illustrated in figure 15, the power system in positive NAO phase which brings more wind power, has less CO2 production as well as emission than in the negative phase. The gaps of CO2 production lay at about 20 million tons in total over the winter months, which is mainly caused by the reduction of CO2 storage. Taking the RES80 scenario for instance, the system in positive NAO phase largely expels the electricity supply from NGCC with CCS as discussed in section 4.4.2. That is why the stored carbon dioxide is much lower than in the negative phase. Nevertheless, with more wind power being introduced, the system CO2 production has already been mitigated from source.

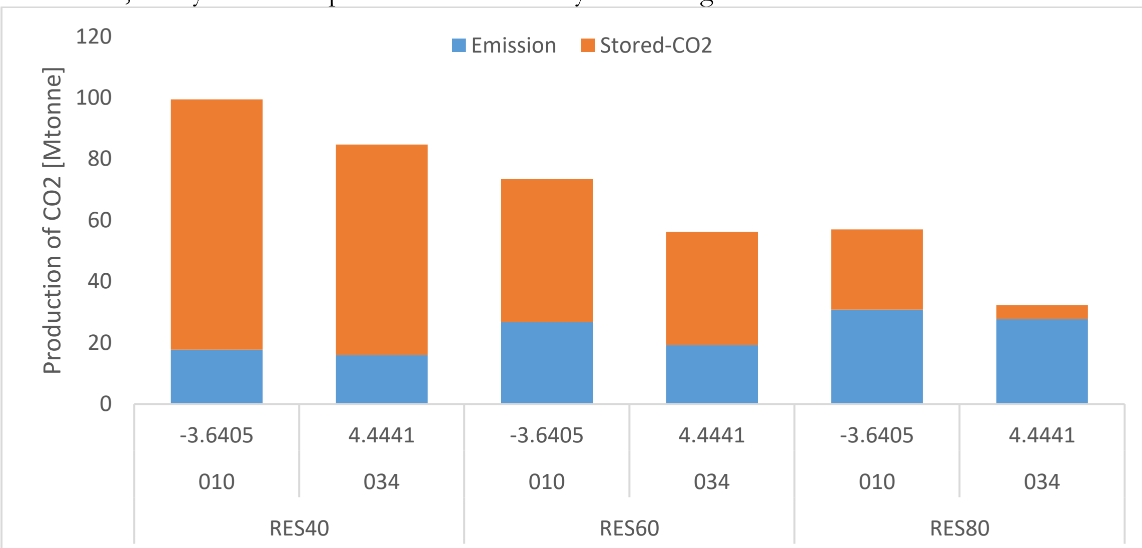


Figure 15. System CO2 production during the winter months (DJF).

5. Discussion

5.1 Limitations

5.1.1 Limitations of research scope

This research involves the NAO effect to the European power system with high penetration of iRES such as onshore/offshore wind power and rooftop/utility solar PV. The most profound effect of NAO that happens during winter months is considered, as well as the main components of the power system. However, despite the limitations of the power system constructed by Brouwer et al. (2016), several important and interesting parts are lacking due to the restriction of the project.

Float wind turbine and concentrated solar power are excluded. These two types of renewable generator are suggested to play an important role in 2050. With float wind turbines installed, a larger area in North Sea can be available for offshore wind power (EWEA 2013), which can considerably add to the wind power supply. Solar CSP is a rather continuous renewable energy technology. It is more sensitive to temperature variation than solar PV due to its mechanism of work. This feature could result in that the NAO to be more influential on it than on solar PV. As most of the capacity of CSP is to be installed in Spain (Khetarpal 2016), Iberian Peninsula could substantially filled its lack in supply (see section 4.4.4).

Temperature pattern variation, as a critical consequence of the NAO effect, is roughly interpolated into hourly data. Its impact on generation is also not thoroughly investigated. Thermal generators, no matter conventional or renewable, are dependent on temperature patterns in terms of thermal-power efficiency due to the restriction of thermodynamic laws. Besides, temperature variation could affect the demand of heat, which is also a pivotal component in energy consumption. Investigating the parallel variation of demand and supply as well as the interaction between them of the power system caused by the NAO must be more inspiring.

In this research, only the impact of the NAO in winter months was examined. The sNAO that happens in summer is not studied. It is inferred that the sNAO should have sensible impact on solar PV as its electricity output becomes higher. Besides, the status of Iberian Peninsula and Italy and Alpine States where large fleet of solar PV is installed can be more fairly evaluated if we consider the peak season for solar power harvest.

Last but the most, we only investigated eight weather years in terms of iRES power production and simulated two weather years for the entire power system. The full range of power system performance in relative to NAO effect variation cannot be sufficiently revealed.

5.1.2 Limitations of the assumptions

The linear interpolation on wind data may underestimate the variation of wind power output. In downscaling of the solar resource, cloud effect is ignored. This may result in overestimate of its stability in power output. The treatment on temperature data is coarse, which undermines the estimation of NAO effect.

In deploying the iRES technologies, only one model is applied for each. For wind power, resources at different hub heights are not counted, which can undermine the estimation of power generation and the representativeness of the impact from the NAO. The mechanism of capacity distribution that all available land in the grid are occupied if it has the priority may cause bias. Locating capacity installation is also determined by local demands. The bias on the distribution of rooftop solar panels is among the most apparent. Besides, solar PV production is estimated according to empirical formula, of which the tile effect as well as the shed effect are not explicit.

5.2 Comparison to other literatures

Our research confirms to the conclusion made by Curtis et al. (2016b) about the dependency of the NAO on the level of wind capacity within an electricity system. In that research on Irish power market, the shift of NAO from negative to positive could reduce the electricity price by 1.5 €/MWh. In this study, we find the reduction of the price can be 9 €/MWh. Curtis et al.(2016b) investigated the present power market where the installation of wind power is not as high as in our study. The impact of NAO is hence weakened.

Variation of carbon emission was also reported to be as much as 10% in Irish power market (Curtis et al. 2016a). Our findings in carbon emission coincides with the research, especially in RES40 scenario where the variation of carbon emission is around 15% relative to the change of NAO phase. Considering 40% renewable energy in a power system is higher than the 20% penetration (European Commission 2014) in present proportion in Ireland.

5.3 Suggestion on further research

Simulating the performance of the power system with the full profile of NAO years will be of great value to analyze the impact of this atmospheric circulation. Climate model data for the whole year is suggested to estimate the generation profile of the iRES so that the full profile of NAO effect of the year can be assessed. Once we find the boundary of the NAO effect on power system performance, a further research can be conducted to explore the optimal configuration of the power system to adapt to the variation of NAO.

6. Conclusion

By analyzing the results of Europe power system with large share of iRES power installation, we find the following conclusions regarding to the impact of the NAO effect on the system.

- In wintertime, the NAO mainly influences electricity outputs from wind power. Electricity produced by solar PV is not significantly affected.
- Positive NAO phase is more favorable to the power system with high iRES penetration than the negative. It introduces more electricity supply from wind power than in the negative phase. Thermal generators are vastly replaced. As a result, the price and cost falls, carbon emission decreases, and more demand of the region can be locally supplied.
- The effect of NAO is spatially variated. reinforces on wind power production occur in north regions of Europe (British Isles, Germany & Benelux and Scandinavia). In south regions (Iberian Peninsula and Italy and Alpine States), the inverse effect occurs, diminishing wind power production with slightly raise in solar power. For regions in the middle of Europe (France), the NAO impact elusively sways around.
- Increasing the proportion of iRES power supply in the power system, especially the amount of onshore/offshore wind power, strengthens the impact of NAO phase variation.

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Appendix

Appendix A. Technical parameters of iRES technology and the capacity distribution

Table A-1 The iRES technical specifications

	Wind turbines			Solar PV panels	
Parameter	Onshore	Offshore	Parameter	Rooftop	Utility
Manufacture & Model	Vestas V117	Vestas V164	Manufacture & Model	Sunpower X21-345	TrinaSolar TSM-PD14
Hub height (m)	120	100	Technology	Monocrystalline Silicon	Polycrystalline Silicon
Rated power capacity (MW)	3.3	8.0	Nominal power capacity at STC[a] (W)	345	325
Operational efficiency	88%	88%	Module efficiency	21.5%	16.8%
Roter diameter - D (m)	117	164	Power temperature coefficient (% $°C^{-1}$)	-0.30%	-0.41%
Module dimensions[b]	10D*5D = 0.68 (km^2)	10D*5D = 1.34 (km^2)	Module dimensions	1.559m*1.046m = 1.63m^2	1.956m*0.992m = 1.94m^2
Power density (W m^{-2})	4.82	5.95	Power density (W m^{-2})	212	167
Operational temperature range (°C)	-20 to 30	-10 to 25	Operational temperature range (°C)	-40 to 85	-40 to 86
a: Standard Test Conditions: 1000 W m^{-2} irradiance, air mass coefficient 1.5, temperature 25° C					
b: Counting for wake effects					

Table A-2 iRES capacity distributions [GW]

ECF Scenarios	Technology		British Isles	France	Germany & Benelux	Iberian Peninsula	Italy and Alpine States	Scandinavia	Total
RES40	Wind	Onshore	38.0	16.3	27.1	32.6	10.9	21.7	146.5
		Offshore	15.1	3.8	18.7	0.2	0.0	9.0	46.8
	Solar	Rooftop	6.7	11.1	8.9	14.4	14.4	4.4	59.9
		Utility	6.7	11.1	8.9	14.4	14.4	4.4	59.9
RES60	Wind	Onshore	72.5	31.1	51.8	62.1	20.7	41.4	279.7
		Offshore	26.5	6.7	32.7	0.3	0.0	15.7	81.9
	Solar	Rooftop	11.7	19.4	15.5	25.2	25.2	7.8	104.9
		Utility	11.7	19.4	15.5	25.2	25.2	7.8	104.9
RES80	Wind	Onshore	85.0	64.8	117.4	68.8	30.0	40.5	406.6
		Offshore	38.8	9.8	47.9	0.4	0.0	23.1	120.1
	Solar	Rooftop	9.0	27.7	22.2	36.0	47.9	7.5	150.1
		Utility	9.0	27.7	22.2	36.0	47.9	7.5	150.1

Appendix B Assumptions to land availability

Table B-1 Available land factor assumptions

CLC Classification				Land availability assumption			
Level 1 Class	Level 2 Class	Level 3 Class	Class Code	Onshore Wind	Offshore Wind	Rooftop PV	Utility PV
Artificial surfaces	Urban fabric	Continuous urban fabric	111			10%	
		Discontinuous urban fabric	112			6%	
	Industrial, commercial and transport units	Industrial or commercial units	121			7%	
		Road and rail networks and associated land	122				
		Port areas	123				
		Airports	124				
	Mine, dump and construction sites	Mineral extraction sites	131				
		Dump sites	132				
		Construction sites	133				
	Artificial, non-agricultural vegetated areas	Green urban areas	141				
		Sport and leisure facilities	142				
	Arable land	Non-irrigated arable land	211	15%			0.34%
		Permanently irrigated land	212	15%			0.34%
		Rice fields	213	15%			
	Permanent crops	Vineyards	221	15%			
		Fruit trees and berry plantations	222	15%			
		Olive groves	223	15%			
	Pastures	Pastures	231	15%			0.34%
	Heterogeneous agricultural areas	Annual crops associated with permanent crops	241	15%			
		Complex cultivation patterns	242	15%			
		Land principally occupied by agriculture, with significant areas of natural vegetation	243	15%			0.34%
		Agro-forestry areas	244				
Forest and semi natural areas	Forests	Broad-leaved forest	311				
		Coniferous forest	312				
		Mixed forest	313				
	Scrub and/or herbaceous vegetation associations	Natural grasslands	321	20%			
		Moors and heathland	322	20%			
		Sclerophyllous vegetation	323	20%			
		Transitional woodland-shrub	324				
	Open spaces with	Beaches, dunes, sands	331				

	little or no vegetation	Bare rocks	332				
		Sparsely vegetated areas	333	20%			0.34%
		Burnt areas	334				
		Glaciers and perpetual snow	335				
Wetlands	Inland wetlands	Inland marshes	411				
		Peat bogs	412				
	Maritime wetlands	Salt marshes	421				
		Salines	422				
		Intertidal flats	423				
Water bodies	Inland waters	Water courses	511				
		Water bodies	512				
	Marine waters	Coastal lagoons	521				
		Estuaries	522				
		Sea and ocean	523		30%		
*National designated area is not included where no technology can be installed.							

Table B-2 Literature survey on available land for iRES installation

Technology	Land (sea) availability factor [%]					
	Deng et al. (2015) (Low/Mid/High)	Hoogwijk et al. (2004)	Mainzer et al. (2014)	Ordóñez et al. (2010)	Hoefnagels & Junginger (2011)	Bruninx et al. (2014)
Onshore Wind	Agricultural, Desert Grassland, Barren land: 3%/6%/10%	Agricultural: 70% Grassland: 80% Forest: 10%			Agricultural: 10%-35% Grassland: 50% Forest: 10%	6%
Offshore Wind	0-10 km: 4%/5%/5% 10-50 km: 0%/30%/40% 50-200 km: 25%/60%/80%					3%[b]
Utility PV (ground based)	Agricultural: 0.1%/0.5%/2% Grassland & Barren Land: 0.5%/1%/3%				Agricultural: 0.5%	Agricultural: 0.1% Other free land: 2%
Rooftop PV[a]	33%		Flat: 27% Pitched: 58%	Flat: 51-55% Pitched: 16-21%	50%	40%

a: Availability for rooftop PV is on the basis of roof area, not land area.

b: 3% of the total area deemed suitable in an earlier study of approx. 750,000 km2 compared with 634,000 km2 in this study. However, a much higher capacity density is assumed (15 MW km^{-2}) for offshore wind which partly compensates for this.

Appendix C Interpolating climate model data into hourly value

Downscaling process emphasizes on revealing the tendency of diurnal variation pattern of solar irradiation and wind which is substantial to the integration of iRES into power grids. Some subordinate effect would be ignored due to insufficient information.

C.1 6-hour average wind speed

Wind speed within the 6-hour time step is interpolated into hourly value by a simplified assumption of linear relation of the variation trend between time steps. This method is initiated from that wind speed is inclined to variate towards its future statue. Pressure gradience between atmosphere levels is one of the principal factors affecting surface wind speed. Air flows faster in high level of atmosphere than on the earth surface. During daytime, the air is heated up by absorbing infrared radiation from ground of which energy is supplied by solar radiation. Warm slow-moving air ascends while cold fast-moving air descends, raising the surface wind speed. When it comes to the wind over sea surface, a similar effect happens predominantly in the evening. Owing to the high heat capacity of water, the solar energy radiated to the sea does not release but accumulates during daytime. After a whole day of sunshine, the absorbed energy releases at night to heat the air above sea surface so that explicit pressure gradience emerges. Therefore, although the variation patterns of surface wind speed differ from ground to sea, diurnal solar irradiation accounts for the change. To conclude, the tendency of wind variation during late night of the day can be inferred based on the wind statue in the previous late afternoon.

In this research, the hourly variation of wind speeds during 00:00 to 06:00, 06:00 to 12:00 and 12:00 to 18:00 are calculated according to the linear trend towards the next period, whereas the wind speeds in 18:00 to 24:00 is determined based on the variation trend from 12:00 to 18:00. The original average value is set to be the wind speed in the middle of its 6-hour period.

$$u_i = \begin{cases} \dfrac{(\overline{u_{i1}} - \overline{u_{i0}})}{6-1} \times \left(n - \dfrac{6-1}{2}\right) + \overline{u_{i0}}, & for\ 00:00-06:00, 06:00-12:00, 12:00-18:00 \\ \dfrac{(\overline{u_{i0}} - \overline{u_{i-1}})}{6-1} \times \left(n - \dfrac{6-1}{2}\right) + \overline{u_{i0}}, & for\ 18:00-24:00 \end{cases}$$

where:

u_i : average wind speed of hour i, $i \in [0, 23]\ and\ i \in R$;

$\overline{u_{i0}}$: average wind speed in the period when the hour i involved;

$\overline{u_{i1}}$: average wind speed in the period after that of hour i;

$\overline{u_{i-1}}$: average wind speed in the period before that of hour i;

n : the order of hour i in its period, $n = i\ mod\ 6$.

Chaos effect which renders wind speed stochastic is important but it is not applicable to this research due to lacking data.

C.2 Daily total SSRD

The SSRD is interpolated hourly value according to the diurnal hourly distribution of extraterrestrial radiation which can be calculated per grid. Cloudiness effect is neglected in this circumstance because of the lack of cloud data.

$$R_i = R_d \times \frac{R_{ah}}{R_a}$$

where:

R_i : surface solar irradiation in hour i;

R_{ah} : extraterrestrial radiation in hour i;

R_a : extraterrestrial radiation of the day.

The extraterrestrial radiations R_{ah} and R_a for a specific date are determined using the formulas proposed by Duffie and Beckman (2013, pp.37–40), along with the method proposed by Craig (1984) to determine the day in the year.

Appendix D Power curves for the turbines

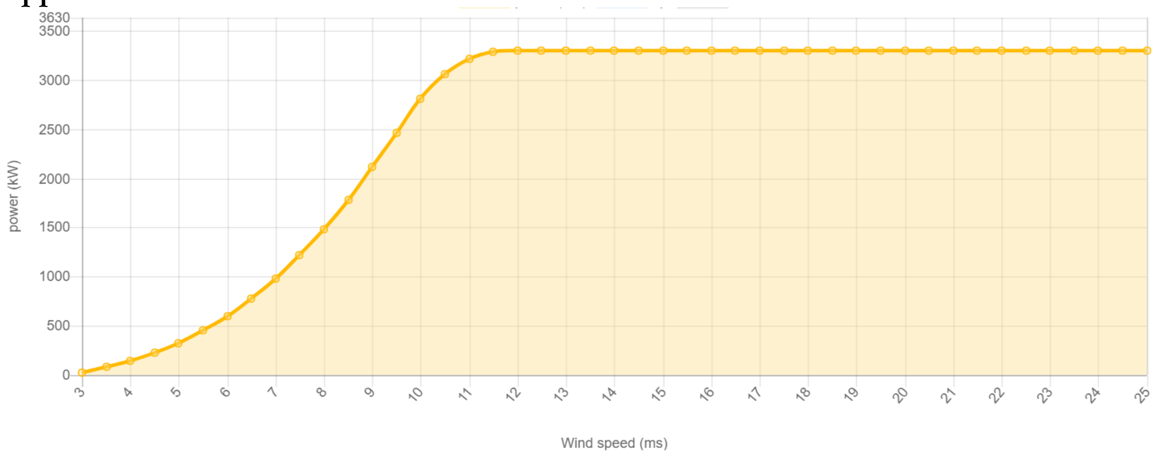


Figure D-1. Power curve of onshore wind turine.
Source: https://en.wind-turbine-models.com/turbines/694-vestas-v-117-3.3

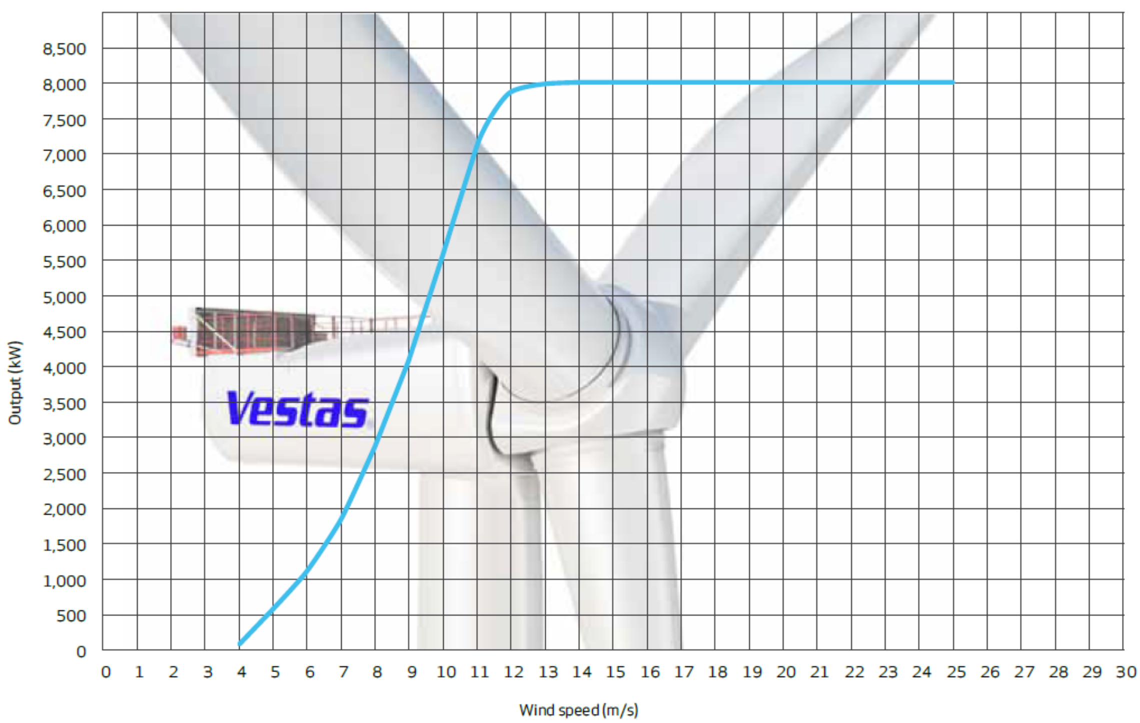


Figure D-2. Power curve of offshore wind turbine (Vestas 2011).

Appendix E Supplementary to the results

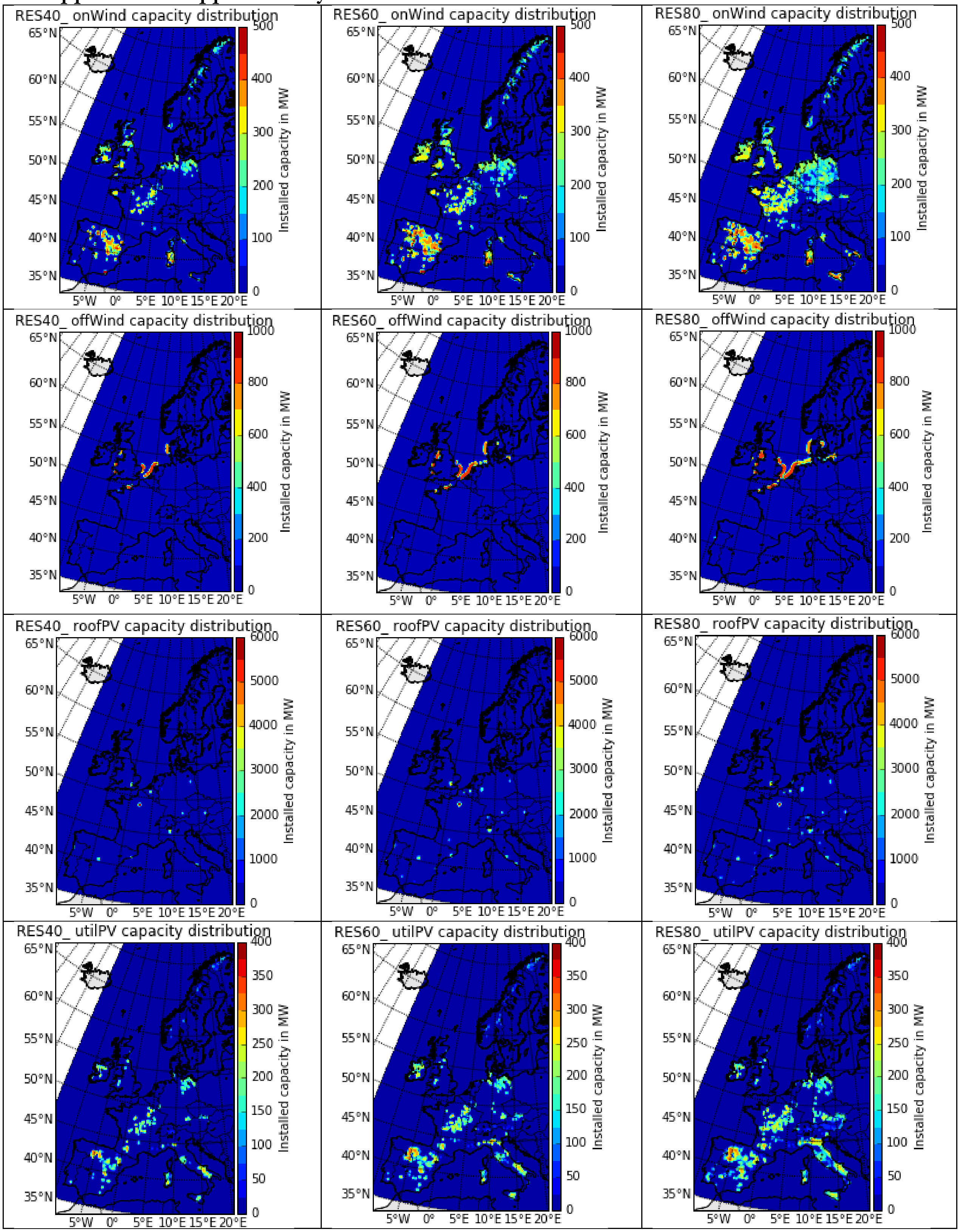
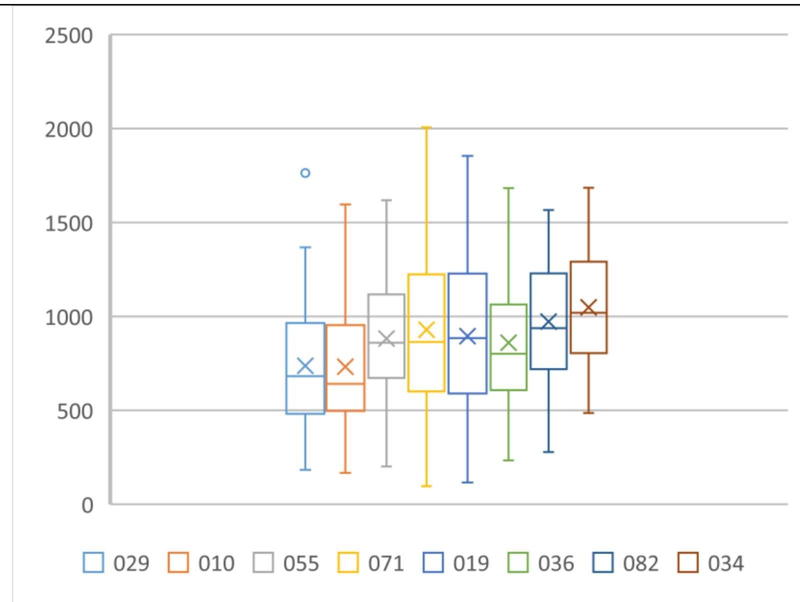
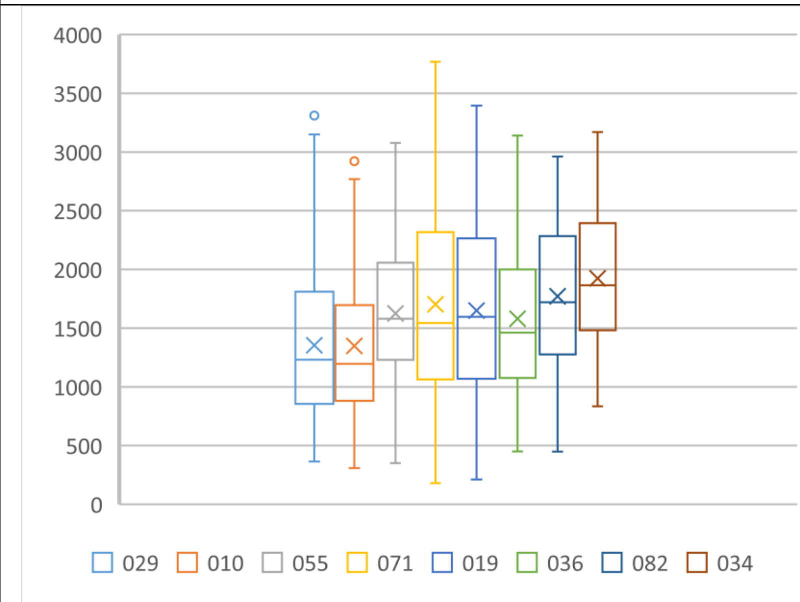
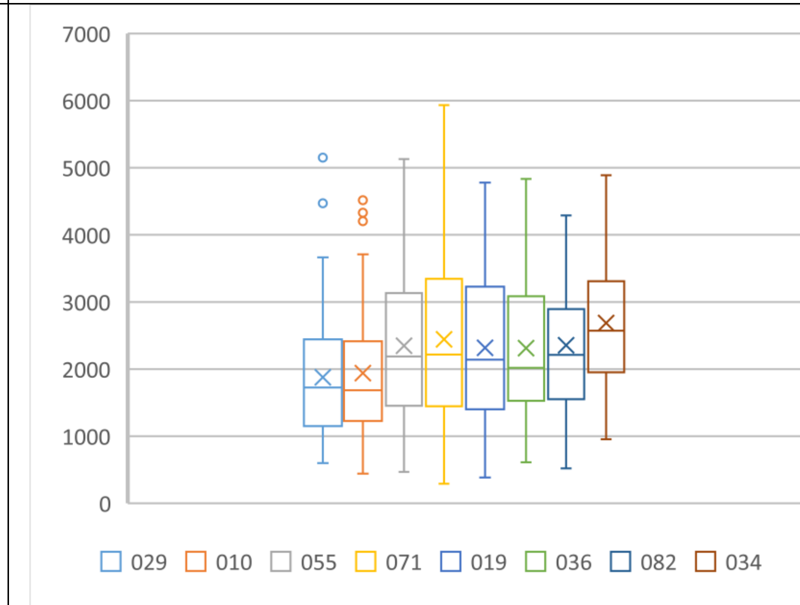
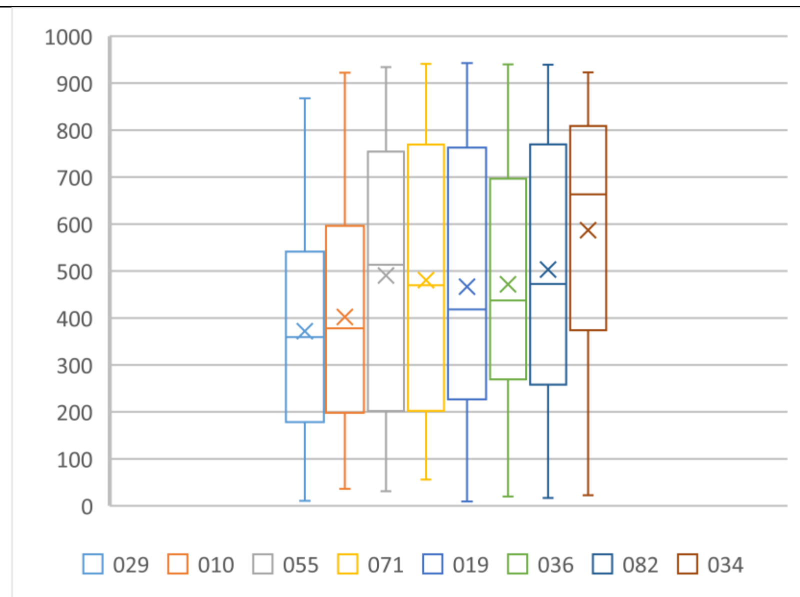
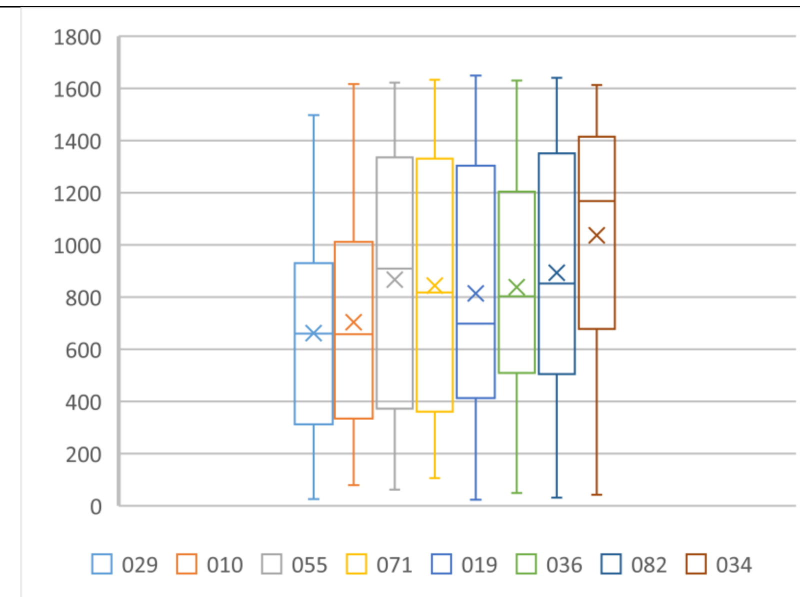
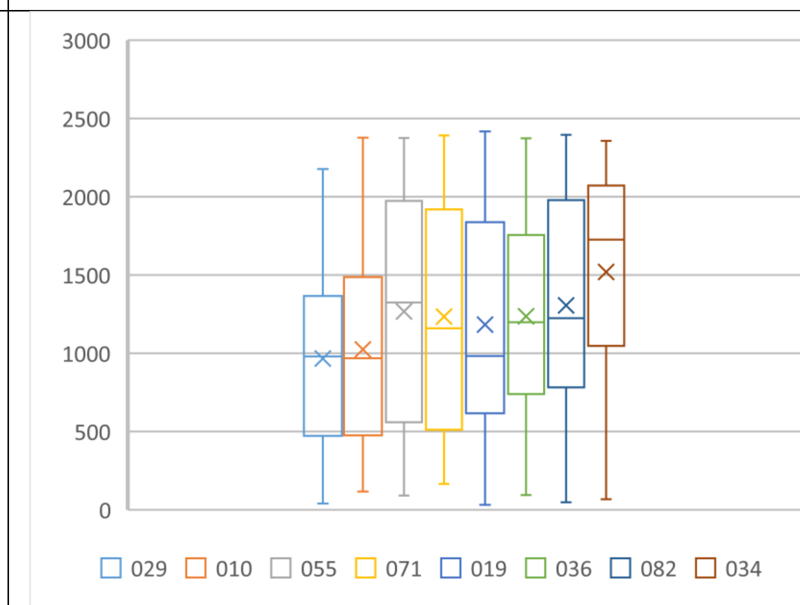


Figure E-1. Spatial distribution of iRES installed capacity per energy GWEway.

<table>
<tr><th colspan="2">Unit: GWh</th><th>RES40</th><th>RES60</th><th>RES80</th></tr>
<tr><td rowspan="2">Wind power</td><td>Onshore</td><td>
</td><td>
</td><td>
</td></tr>
<tr><td>Offshore</td><td>
</td><td>
</td><td>
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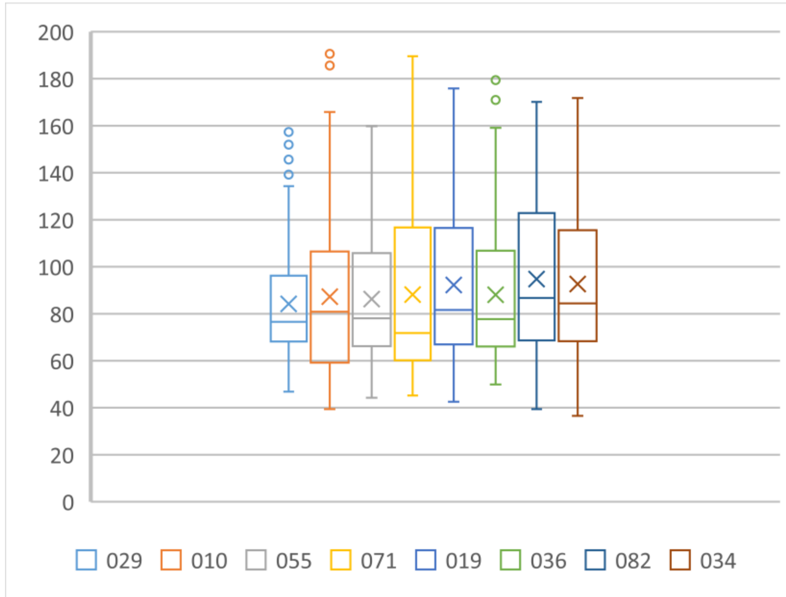
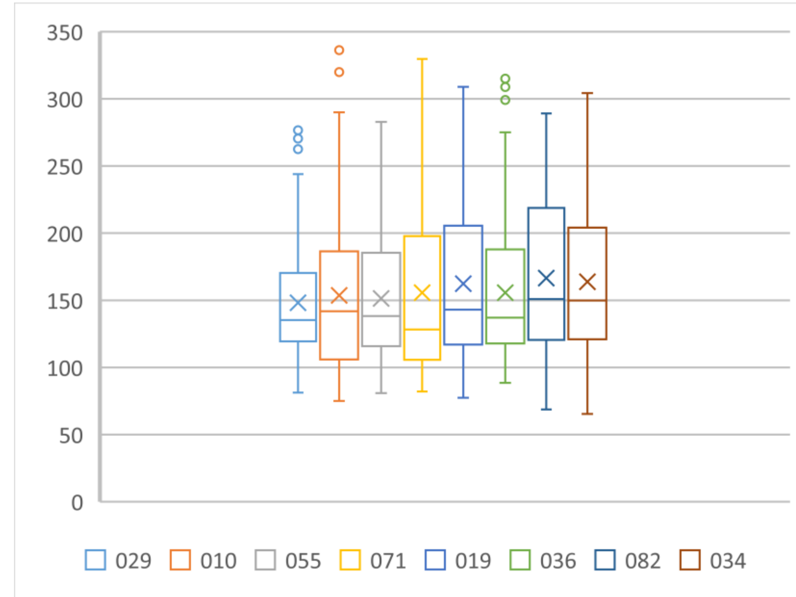
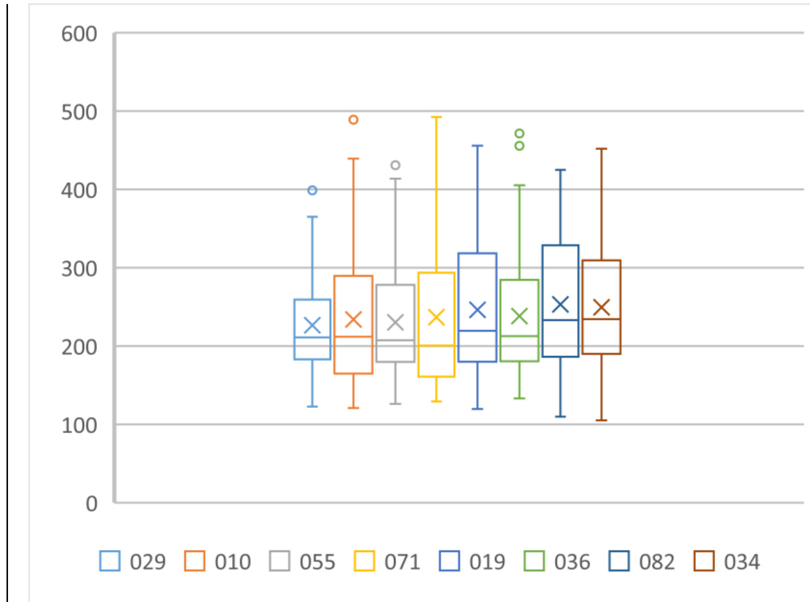
</table>

Solar PV

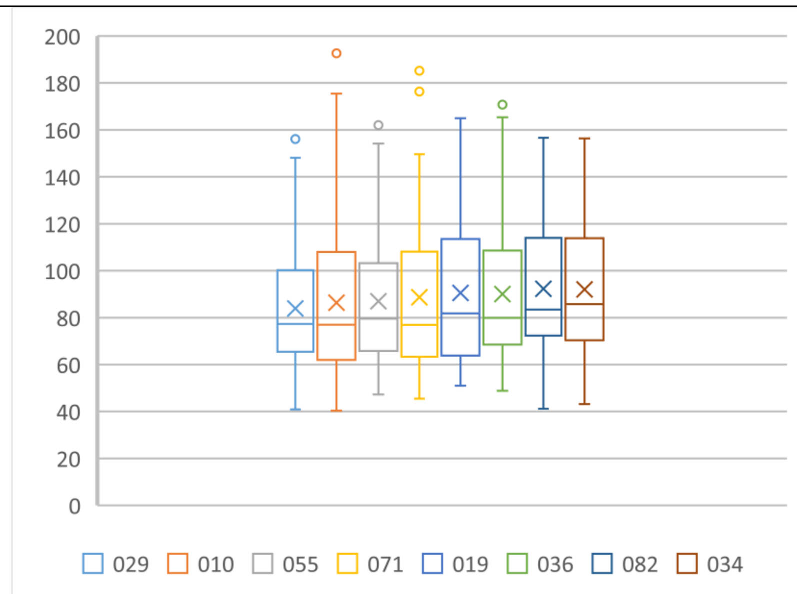
Rooftop

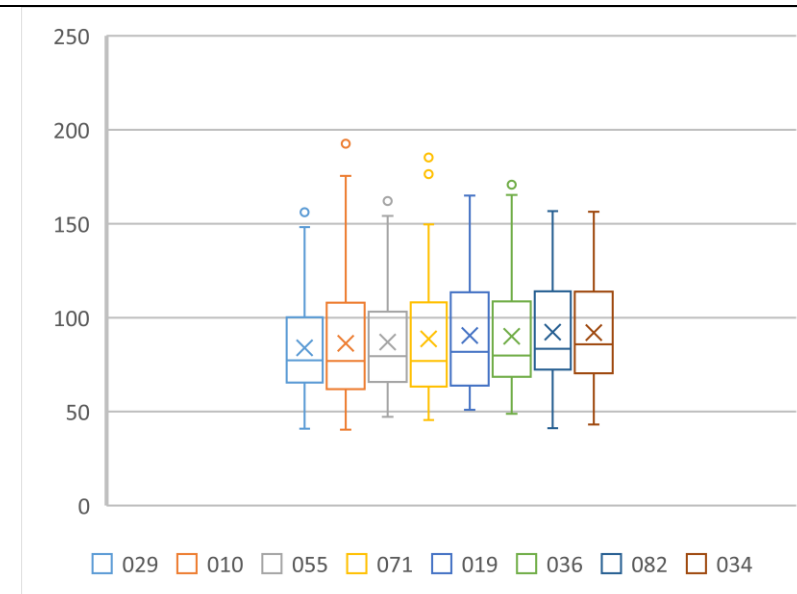






Utility





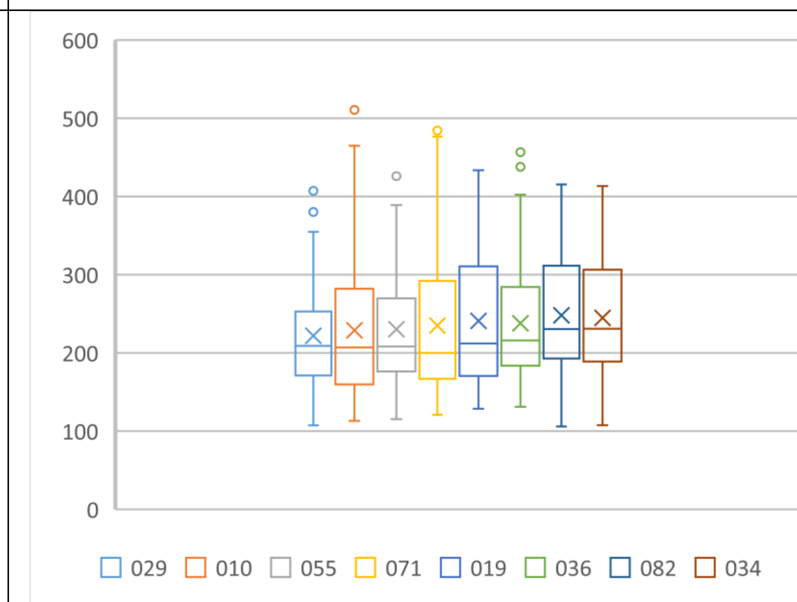


Figure E-2. Distribution of daily power generation per iRES in winter months (DJF) for all three energy pathways.

Chart for the order of weather years and their climate contexts.								
Weather Year	029	010	055	071	019	036	082	034
NAO index	-4.5650	-3.6405	-0.0650	-0.0448	0.0223	0.0455	4.1919	4.4441
GWE	cold	warm	warm	cold	cold	warm	cold	warm

Table E-1. Detailed capacity credits for all cases

		RES40						RES60						RES80					
NAO	-4.5650	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES
GWE	cold	Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total	
	BR	6.05%	10.53%	0.00%	0.75%	0.37%	5.17%	4.76%	7.56%	0.00%	0.78%	0.39%	4.61%	4.86%	6.25%	0.00%	0.78%	0.39%	5.00%
	FR	11.05%	3.72%	0.00%	0.00%	0.00%	4.59%	9.94%	3.95%	0.00%	0.00%	0.00%	4.16%	6.90%	3.99%	0.00%	0.00%	0.00%	3.46%
	GE	3.70%	7.26%	0.00%	0.00%	0.00%	2.98%	3.11%	5.55%	0.00%	0.00%	0.00%	2.43%	2.64%	4.49%	0.00%	0.00%	0.00%	2.04%
029	IB	6.05%	0.00%	0.02%	0.02%	0.02%	3.87%	4.00%	0.00%	0.02%	0.02%	0.02%	2.60%	3.66%	0.00%	0.02%	0.02%	0.02%	2.10%
	IT	25.49%	N.A.	0.00%	0.00%	0.00%	6.97%	23.08%	N.A.	0.00%	0.00%	0.00%	6.72%	21.72%	N.A.	0.00%	0.00%	0.00%	5.18%
	SC	1.25%	0.00%	0.00%	0.00%	0.00%	0.69%	1.71%	0.00%	0.00%	0.00%	0.00%	0.98%	1.72%	0.41%	0.00%	0.00%	0.00%	1.00%
	TOT	16.04%	13.23%	0.64%	0.11%	0.38%	7.88%	10.86%	9.31%	0.59%	0.11%	0.35%	6.11%	8.24%	8.69%	0.57%	0.12%	0.35%	5.09%
NAO	-3.6405	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES
GWE	warm	Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total	
	BR	5.52%	12.30%	0.00%	0.87%	0.44%	4.46%	4.12%	9.28%	0.00%	0.92%	0.46%	3.62%	4.22%	8.70%	0.00%	0.92%	0.46%	4.20%
	FR	7.34%	0.00%	0.00%	0.00%	0.00%	2.82%	7.38%	0.00%	0.00%	0.00%	0.00%	2.99%	5.36%	0.75%	0.00%	0.00%	0.00%	2.74%
	GE	3.64%	3.47%	0.00%	0.00%	0.00%	1.88%	3.13%	2.44%	0.00%	0.00%	0.00%	1.71%	2.77%	2.00%	0.00%	0.00%	0.00%	2.01%
010	IB	4.22%	0.00%	0.02%	0.02%	0.02%	2.53%	2.27%	0.00%	0.02%	0.02%	0.02%	1.51%	2.06%	0.00%	0.02%	0.02%	0.02%	1.30%
	IT	25.49%	N.A.	0.00%	0.00%	0.00%	6.97%	23.08%	N.A.	0.00%	0.00%	0.00%	6.72%	18.65%	N.A.	0.00%	0.00%	0.00%	4.45%
	SC	4.72%	0.03%	0.00%	0.00%	0.00%	2.60%	4.71%	0.37%	0.00%	0.00%	0.00%	2.76%	4.73%	0.54%	0.00%	0.00%	0.00%	2.60%
	TOT	18.68%	10.80%	0.63%	0.14%	0.39%	5.68%	13.97%	7.21%	0.61%	0.15%	0.38%	4.21%	12.48%	6.01%	0.57%	0.19%	0.38%	3.70%
NAO	-0.0650	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES
GWE	warm	Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total	
	BR	0.85%	7.52%	0.00%	0.92%	0.46%	2.55%	1.18%	5.80%	0.00%	0.95%	0.47%	2.84%	1.86%	5.21%	0.00%	0.95%	0.48%	3.72%
	FR	10.49%	0.82%	0.00%	0.00%	0.00%	4.11%	10.36%	0.59%	0.00%	0.00%	0.00%	4.25%	9.17%	0.43%	0.00%	0.00%	0.00%	4.60%
	GE	9.41%	18.62%	0.00%	0.00%	0.00%	7.27%	7.92%	13.49%	0.00%	0.00%	0.00%	5.39%	5.97%	11.06%	0.00%	0.00%	0.00%	3.66%
055	IB	4.24%	0.00%	0.02%	0.02%	0.02%	2.51%	2.27%	0.00%	0.02%	0.02%	0.02%	1.49%	2.06%	0.00%	0.02%	0.02%	0.02%	1.29%
	IT	25.49%	N.A.	0.00%	0.00%	0.00%	6.97%	23.08%	N.A.	0.00%	0.00%	0.00%	6.72%	22.27%	N.A.	0.00%	0.00%	0.00%	5.31%
	SC	5.97%	24.44%	0.00%	0.00%	0.00%	8.83%	6.02%	16.74%	0.00%	0.00%	0.00%	7.05%	6.05%	12.52%	0.00%	0.00%	0.00%	6.80%
	TOT	19.04%	8.29%	1.02%	0.16%	0.59%	6.95%	13.47%	8.64%	0.99%	0.16%	0.57%	6.85%	10.76%	9.77%	0.93%	0.23%	0.58%	5.44%
NAO	-0.0448	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES
GWE	cold	Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total	
	BR	3.99%	5.35%	0.00%	1.03%	0.52%	2.67%	3.40%	3.65%	0.00%	1.07%	0.53%	2.35%	3.34%	3.30%	0.00%	1.07%	0.53%	2.51%
	FR	20.97%	41.55%	0.00%	0.00%	0.00%	14.25%	16.43%	56.92%	0.00%	0.00%	0.00%	9.66%	12.28%	60.82%	0.00%	0.00%	0.00%	6.50%
	GE	9.41%	6.45%	0.00%	0.00%	0.00%	6.96%	8.53%	8.53%	0.00%	0.00%	0.00%	6.21%	6.34%	7.49%	0.00%	0.00%	0.00%	4.24%
071	IB	7.89%	0.00%	0.02%	0.02%	0.02%	4.60%	4.47%	0.00%	0.02%	0.02%	0.02%	2.86%	4.08%	0.00%	0.02%	0.02%	0.02%	2.41%
	IT	25.49%	N.A.	0.00%	0.00%	0.00%	6.97%	23.08%	N.A.	0.00%	0.00%	0.00%	6.72%	18.53%	N.A.	0.00%	0.00%	0.00%	4.42%
	SC	10.96%	20.64%	0.00%	0.00%	0.00%	10.70%	10.20%	16.85%	0.00%	0.00%	0.00%	9.46%	10.28%	11.81%	0.00%	0.00%	0.00%	8.77%
	TOT	19.19%	18.32%	0.19%	0.13%	0.16%	9.67%	15.88%	13.89%	0.18%	0.13%	0.16%	8.64%	15.57%	11.96%	0.17%	0.11%	0.14%	7.15%
NAO	0.0223	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES
GWE	cold	Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total	

019	BR	8.39%	14.56%	0.00%	0.43%	0.21%	5.34%	5.54%	8.48%	0.00%	0.45%	0.23%	3.90%	5.17%	5.90%	0.00%	0.45%	0.22%	3.86%
	FR	18.81%	5.78%	0.00%	0.00%	0.00%	7.57%	14.98%	6.06%	0.00%	0.00%	0.00%	6.40%	9.76%	5.82%	0.00%	0.00%	0.00%	4.90%
	GE	9.41%	19.55%	0.00%	0.00%	0.00%	6.81%	7.86%	12.88%	0.00%	0.00%	0.00%	4.78%	4.46%	10.03%	0.00%	0.00%	0.00%	2.96%
	IB	4.51%	0.00%	0.02%	0.02%	0.02%	2.63%	2.61%	0.00%	0.02%	0.02%	0.02%	1.66%	2.39%	0.00%	0.02%	0.02%	0.02%	1.43%
	IT	25.49%	N.A.	0.00%	0.00%	0.00%	6.97%	23.08%	N.A.	0.00%	0.00%	0.00%	6.72%	18.82%	N.A.	0.00%	0.00%	0.00%	4.49%
	SC	17.72%	37.43%	0.00%	0.00%	0.00%	16.69%	14.14%	36.12%	0.00%	0.00%	0.00%	9.82%	14.46%	26.56%	0.00%	0.00%	0.00%	9.21%
	TOT	19.27%	11.89%	0.99%	0.10%	0.54%	6.44%	12.70%	9.21%	0.91%	0.10%	0.50%	5.31%	9.68%	7.78%	0.87%	0.16%	0.52%	4.59%
NAO	0.0455	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES
GWE	warm	Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total	
036	BR	2.18%	0.93%	0.00%	1.17%	0.58%	1.58%	2.41%	1.19%	0.00%	1.24%	0.62%	1.81%	2.39%	1.89%	0.00%	1.23%	0.61%	2.10%
	FR	13.86%	17.99%	0.00%	0.00%	0.00%	7.48%	9.61%	19.31%	0.00%	0.00%	0.00%	5.59%	6.69%	24.71%	0.00%	0.00%	0.00%	4.26%
	GE	4.87%	5.73%	0.00%	0.00%	0.00%	3.76%	4.38%	6.98%	0.00%	0.00%	0.00%	3.94%	3.95%	7.78%	0.00%	0.00%	0.00%	3.99%
	IB	4.46%	0.00%	0.02%	0.02%	0.02%	2.66%	2.44%	0.00%	0.02%	0.02%	0.02%	1.60%	2.32%	0.00%	0.02%	0.02%	0.02%	1.43%
	IT	25.49%	N.A.	0.00%	0.00%	0.00%	6.97%	23.08%	N.A.	0.00%	0.00%	0.00%	6.72%	18.20%	N.A.	0.00%	0.00%	0.00%	4.34%
	SC	6.68%	26.49%	0.00%	0.00%	0.00%	9.48%	5.99%	21.82%	0.00%	0.00%	0.00%	5.45%	6.00%	15.16%	0.00%	0.00%	0.00%	5.13%
	TOT	9.53%	12.58%	0.88%	0.18%	0.53%	7.47%	10.27%	9.22%	0.84%	0.18%	0.51%	6.63%	10.30%	7.80%	0.81%	0.20%	0.50%	5.74%
NAO	4.1919	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES
GWE	cold	Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total	
082	BR	14.16%	8.95%	0.00%	0.26%	0.13%	8.64%	9.80%	10.89%	0.00%	0.28%	0.14%	6.45%	8.84%	9.33%	0.00%	0.27%	0.14%	6.06%
	FR	30.75%	7.85%	0.00%	0.00%	0.00%	13.11%	19.76%	8.29%	0.00%	0.00%	0.00%	8.02%	12.06%	10.61%	0.00%	0.00%	0.00%	6.01%
	GE	9.41%	19.67%	0.00%	0.00%	0.00%	8.08%	6.64%	17.51%	0.00%	0.00%	0.00%	6.13%	4.13%	14.65%	0.00%	0.00%	0.00%	4.61%
	IB	7.49%	0.00%	0.02%	0.02%	0.02%	5.04%	4.03%	0.00%	0.02%	0.02%	0.02%	3.18%	3.69%	0.00%	0.02%	0.02%	0.02%	2.58%
	IT	25.49%	N.A.	0.00%	0.00%	0.00%	6.97%	23.08%	N.A.	0.00%	0.00%	0.00%	6.72%	17.69%	N.A.	0.00%	0.00%	0.00%	4.22%
	SC	4.85%	40.12%	0.00%	0.00%	0.00%	14.71%	6.71%	25.53%	0.00%	0.00%	0.00%	12.27%	6.72%	27.30%	0.00%	0.00%	0.00%	12.32%
	TOT	21.15%	21.90%	1.43%	0.09%	0.76%	12.59%	25.02%	18.16%	1.34%	0.09%	0.72%	10.05%	19.10%	13.09%	1.28%	0.21%	0.74%	7.58%
NAO	4.4441	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES	Wind power		Solar PV			iRES
GWE	warm	Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total		Onshore	Offshore	Rooftop	Utility	Total	
034	BR	17.14%	28.85%	0.00%	0.05%	0.02%	13.00%	11.40%	26.60%	0.00%	0.05%	0.02%	8.38%	11.21%	21.83%	0.00%	0.05%	0.03%	7.76%
	FR	6.84%	24.73%	0.00%	0.00%	0.00%	2.63%	4.12%	14.14%	0.00%	0.00%	0.00%	1.67%	2.41%	9.66%	0.00%	0.00%	0.00%	1.21%
	GE	9.41%	16.17%	0.00%	0.00%	0.00%	8.40%	8.53%	13.54%	0.00%	0.00%	0.00%	6.82%	6.07%	13.07%	0.00%	0.00%	0.00%	4.21%
	IB	2.36%	0.00%	0.02%	0.02%	0.02%	2.21%	2.24%	0.00%	0.02%	0.02%	0.02%	2.07%	2.21%	0.00%	0.02%	0.02%	0.02%	1.74%
	IT	25.49%	N.A.	0.00%	0.00%	0.00%	6.97%	23.08%	N.A.	0.00%	0.00%	0.00%	6.72%	20.51%	N.A.	0.00%	0.00%	0.00%	4.89%
	SC	18.64%	30.53%	0.00%	0.00%	0.00%	12.54%	11.87%	41.85%	0.00%	0.00%	0.00%	11.90%	12.05%	37.32%	0.00%	0.00%	0.00%	12.63%
	TOT	38.91%	27.13%	0.92%	0.06%	0.49%	17.14%	30.06%	19.38%	0.86%	0.05%	0.46%	15.12%	26.10%	15.85%	0.81%	0.15%	0.48%	12.41%

Table E-2. Load profile of transmission lines.

RES40															
	Unit	British Isles		France		Germany & Benelux		Iberian Peninsula		Italy and Alpine States		Scandinavia		Total outflow	
		010	034	010	034	010	034	010	034	010	034	010	034	010	034
British Isles	Load [TWh]	-		8.1	9.9	4.7	4.1	-		-		-		12.8	14.0
	Share to line capacity			30%	36%	44%	39%							34%	37%
France	Load [TWh]	8.6	7.8	-		4.8	2.0	2.9	4.3	15.6	13.7	-		31.9	27.8
	Share to line capacity	31%	29%			11%	5%	5%	7%	56%	49%			20%	18%
Germany & Benelux	Load [TWh]	4.8	5.2	19.6	27.2	-		-		7.3	8.2	1.5	0.8	33.1	41.4
	Share to line capacity	45%	49%	46%	64%					51%	57%	7%	4%	38%	47%
Iberian Peninsula	Load [TWh]	-		9.3	7.7	-		-		-		-		9.3	7.7
	Share to line capacity			16%	13%									16%	13%
Italy and Alpine States	Load [TWh]	-		2.9	2.7	4.9	3.8	-		-		-		7.8	6.6
	Share to line capacity			10%	10%	34%	27%							18%	15%
Scandinavia	Load [TWh]	-		-		13.7	16.9	-		-		-		13.7	16.9
	Share to line capacity					66%	81%							66%	81%
Total inflow	Load [TWh]	13.3	13.0	39.8	47.5	28.0	26.9	2.9	4.3	22.9	21.9	1.5	0.8	108.5	114.3
	Share to line capacity	35%	34%	25%	30%	32%	30%	5%	7%	54%	52%	7%	4%	27%	28%
RES60															
	Unit	British Isles		France		Germany & Benelux		Iberian Peninsula		Italy and Alpine States		Scandinavia		Total outflow	
		010	034	010	034	010	034	010	034	010	034	010	034	010	034
British Isles	Load [TWh]	-		9.9	19.8	3.8	6.7	-		-		-		13.7	26.5
	Share to line capacity			36%	72%	36%	63%							36%	70%
France	Load [TWh]	9.6	4.1	-		3.3	2.6	22.2	32.0	3.5	6.6	-		38.6	45.3
	Share to line capacity	35%	15%			8%	6%	38%	55%	12%	23%			25%	29%
Germany & Benelux	Load [TWh]	5.7	3.2	27.6	32.8	-		-		6.8	9.9	0.3	0.5	40.4	46.3
	Share to line capacity	54%	30%	65%	77%					47%	69%	1%	2%	46%	53%
Iberian Peninsula	Load [TWh]	-		3.9	3.2	-		-		-		-		3.9	3.2
	Share to line capacity			7%	6%									7%	6%
Italy and Alpine States	Load [TWh]	-		14.6	12.1	5.1	3.2	-		-		-		19.8	15.3
	Share to line capacity			52%	43%	36%	22%							47%	36%
Scandinavia	Load [TWh]	-		-		16.6	19.3	-		-		-		16.6	19.3
	Share to line capacity					80%	93%							80%	93%
Total inflow	Load [TWh]	15.3	7.3	56.1	67.9	28.8	31.7	22.2	32.0	10.2	16.4	0.3	0.5	133.0	155.9
	Share to line capacity	40%	19%	36%	43%	33%	36%	38%	55%	24%	39%	1%	2%	33%	39%
RES80															
	Unit	British Isles		France		Germany & Benelux		Iberian Peninsula		Italy and Alpine States		Scandinavia		Total outflow	
		010	034	010	034	010	034	010	034	010	034	010	034	010	034
British Isles	Load [TWh]	-		12.0	19.8	4.0	6.7	-		-		-		16.0	26.5

	Share to line capacity			44%	72%	38%	63%							42%	70%
France	Load [TWh]	8.9	4.1	-		4.5	2.6	26.0	32.0	6.8	6.6	-		46.2	45.3
	Share to line capacity	33%	15%			11%	6%	44%	55%	24%	23%			30%	29%
Germany & Benelux	Load [TWh]	5.7	3.2	26.2	32.8	-		-		8.0	9.9	0.5	0.5	40.5	46.3
	Share to line capacity	54%	30%	62%	77%					56%	69%	2%	2%	46%	53%
Iberian Peninsula	Load [TWh]	-		4.5	3.2	-		-		-		-		4.5	3.2
	Share to line capacity			8%	6%									8%	6%
Italy and Alpine States	Load [TWh]	-		12.0	12.1	4.6	3.2	-		-		-		16.5	15.3
	Share to line capacity			42%	43%	32%	22%							39%	36%
Scandinavia	Load [TWh]	-		-		17.5	19.3	-		-		-		17.5	19.3
	Share to line capacity					84%	93%							84%	93%
Total inflow	Load [TWh]	14.6	7.3	54.7	67.9	30.6	31.7	26.0	32.0	14.9	16.4	0.5	0.5	141.3	155.9
	Share to line capacity	39%	19%	35%	43%	35%	36%	44%	55%	35%	39%	2%	2%	35%	39%

Table E-3. Regional capacity curtailment profile.

Category	Indicator	Year	NAO	Britannica	Gallia	Germania	Hispania	Italia	Scandinavia
RES40									
Demand curtailment	Time share	010	-3.6405	27%	26%	27%	26%	26%	23%
		034	4.4441	0%	0%	0%	0%	0%	0%
	Average rate	010	-3.6405	0.13%	0.20%	0.69%	0.24%	0.07%	0.08%
		034	4.4441	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Generation curtailment	Time share	010	-3.6405	0%	0%	0%	0%	0%	0%
		034	4.4441	0%	0%	0%	0%	0%	0%
	Average rate	010	-3.6405	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
		034	4.4441	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
RES60									
Category	Indicator	Year	NAO	Britannica	Gallia	Germania	Hispania	Italia	Scandinavia
Demand curtailment	Time share	010	-3.6405	0%	0%	0%	0%	0%	0%
		034	4.4441	0%	0%	0%	0%	0%	0%
	Average rate	010	-3.6405	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
		034	4.4441	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Generation curtailment	Time share	010	-3.6405	1%	0%	0%	0%	0%	1%
		034	4.4441	6%	0%	0%	0%	0%	0%
	Average rate	010	-3.6405	1.45%	0.00%	0.00%	0.00%	0.00%	1.22%
		034	4.4441	0.14%	0.00%	0.00%	0.18%	0.00%	0.08%
RES80									
Category	Indicator	Year	NAO	Britannica	Gallia	Germania	Hispania	Italia	Scandinavia
Demand curtailment	Time share	010	-3.6405	0%	0%	0%	0%	0%	0%
		034	4.4441	0%	0%	0%	0%	0%	0%
	Average rate	010	-3.6405	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
		034	4.4441	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Generation curtailment	Time share	010	-3.6405	2%	0%	2%	0%	0%	9%
		034	4.4441	7%	0%	4%	0%	0%	18%
	Average rate	010	-3.6405	2.25%	0.00%	1.69%	0.19%	0.00%	9.04%
		034	4.4441	0.15%	0.00%	0.21%	0.25%	0.00%	0.13%

Table E-4. The profile of electricity prices and generation costs.

Unit: €/MWh	RES40													
Category	Generation Costs								Price					
Indicator	Generation		Generator Start & Shutdown		Emissions		Total unit cost		Standard deviation		Weighted average		Minimum	
Year	010	034	010	034	010	034	010	034	010	034	010	034	010	034
NAO	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441
British Isles	18.7	11.2	0.5	0.4	5.1	1.9	24.4	13.6	22.8	13.1	76.8	69.3	52.5	45.5
France	13.1	9.6	0.3	0.2	1.9	0.5	15.2	10.4	22.7	12.8	76.0	68.2	52.7	50.9
Germany & Benelux	36.3	34.9	0.5	0.5	6.3	4.9	43.1	40.3	22.7	12.8	76.6	68.7	52.7	50.9
Iberian Peninsula	23.5	23.7	0.5	0.4	4.1	3.0	28.1	27.1	22.7	12.8	76.4	68.5	52.7	50.9
Italy and Alpine States	23.3	23.9	0.5	0.5	4.0	2.6	27.8	27.1	22.7	12.8	76.6	68.8	52.7	50.9
Scandinavia	7.9	5.4	0.3	0.2	0.9	0.4	9.0	6.0	22.5	10.6	73.5	60.1	10.7	10.7
System	21.6	19.3	0.4	0.4	3.8	2.4	25.8	22.0	22.5	12.0	76.1	67.5	10.7	10.7
Unit: €/MWh	RES60													
Category	Generation Costs								Price					
Indicator	Generation		Generator Start & Shutdown		Emissions		Total unit cost		Standard deviation		Weighted average		Minimum	
Year	010	034	010	034	010	034	010	034	010	034	010	034	010	034
NAO	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441
British Isles	12.5	5.6	0.5	0.4	2.9	1.0	15.8	6.9	22.1	31.6	66.5	47.7	0.0	0.0
France	12.6	14.1	0.4	0.3	2.0	2.4	15.1	16.8	12.0	9.8	71.1	66.4	50.9	39.8
Germany & Benelux	33.8	29.3	0.6	0.6	3.6	2.9	38.0	32.8	12.4	10.0	70.3	64.4	50.9	39.8
Iberian Peninsula	14.3	8.3	0.7	0.4	3.9	0.9	18.9	9.7	12.0	10.1	71.3	66.8	50.9	14.3
Italy and Alpine States	27.3	21.5	0.5	0.5	3.7	2.3	31.5	24.3	11.9	9.7	70.8	66.8	50.9	45.2
Scandinavia	5.6	2.0	0.3	0.2	0.6	0.1	6.5	2.4	23.5	23.7	60.3	37.9	0.0	0.0
System	19.7	15.8	0.5	0.4	2.8	1.8	23.0	18.1	13.8	12.5	68.9	59.8	0.0	0.0
Unit: €/MWh	RES80													
Category	Generation Costs								Price					
Indicator	Generation		Generator Start & Shutdown		Emissions		Total unit cost		Standard deviation		Weighted average		Minimum	
Year	010	034	010	034	010	034	010	034	010	034	010	034	010	034
NAO	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441	-3.6405	4.4441
British Isles	11.3	5.7	0.5	0.4	3.4	1.3	15.2	7.5	27.2	35.7	62.6	39.2	0.0	0.0
France	18.7	15.0	0.7	0.6	3.1	1.3	22.4	17.0	12.9	12.3	70.4	69.5	10.7	2.2
Germany & Benelux	27.1	18.5	0.7	0.7	2.8	2.0	30.6	21.2	19.7	22.6	66.5	61.7	0.0	0.0
Iberian Peninsula	13.1	12.3	0.7	0.7	2.8	1.8	16.6	14.8	13.0	13.1	70.7	69.6	4.9	0.0
Italy and Alpine States	29.7	30.3	0.9	0.8	3.8	4.1	34.3	35.2	12.0	9.2	70.1	69.6	11.7	50.0
Scandinavia	4.8	1.1	0.3	0.1	0.4	0.0	5.5	1.3	32.8	24.5	47.7	14.9	0.0	0.0
System	19.0	14.8	0.6	0.6	2.8	1.8	22.4	17.2	17.6	16.1	65.4	56.4	0.0	0.0

All values are calculated over the winter months (DJF). For system values, the weighted average method defined in section 2.4 is applied.

Appendix F Samples of Python codes used in the study

F.1 Select weather years

```
#!/usr/bin/env python3
# -*- coding: utf-8 -*-

' Select sample years with two ideas '  #文档注释

"""
__author__ ='Huang, Jiangyi'

Created on 2017/06/18
"""
import numpy as np
import re
from netCDF4 import Dataset

def __extract_val(x): #extract the character of digit in the string
   return re.findall('[-+]?\d+[\.]?\d*',x)

def __chr2digit(x):
   try:
      x = int(x)
   except ValueError:
      x = float(x)
   return x

'''1. Select years in terms of NAO index'''

### extract text from file ###
def removeEmpty(list):
   new_list = []
   for val in list:
      if val:
         new_list.append(val)
   return new_list

with open('/net/bhw509/nobackup/users/huang/Data/Temp/NAO_index/Neg_DJF_cold.txt','r') as nc:
#
# D:\Workspace\Develop\Data\\Neg_DJF_cold.txt
   neg_cold_r = nc.read()
   neg_cold_r = neg_cold_r.split('\n')
   neg_cold_r = removeEmpty(neg_cold_r)
with open('/net/bhw509/nobackup/users/huang/Data/Temp/NAO_index/Neg_DJF_warm.txt','r') as nw:
   neg_warm_r = nw.read()
   neg_warm_r = neg_warm_r.split('\n')
   neg_warm_r = removeEmpty(neg_warm_r)
with open('/net/bhw509/nobackup/users/huang/Data/Temp/NAO_index/Pos_DJF_cold.txt','r') as pc:
   pos_cold_r = pc.read()
   pos_cold_r = pos_cold_r.split('\n')
   pos_cold_r = removeEmpty(pos_cold_r)
with open('/net/bhw509/nobackup/users/huang/Data/Temp/NAO_index/Pos_DJF_warm.txt','r') as pw:
   pos_warm_r = pw.read()
   pos_warm_r = pos_warm_r.split('\n')
   pos_warm_r = removeEmpty(pos_warm_r)

### convert plain text into data table ###

def NAOindextable(x):
   table_str = []
   for s in x:
      table_str.append(__extract_val(s))
   table_digit = []
   for s in table_str:
      s.pop(3)
      sample = []
      for k in s:
         k = __chr2digit(k)
         sample.append(k)
      # sample = dict(zip(['N', 'Member', 'Year', 'NAO'], sample))
```

```
      table_digit.append(sample)
   return table_digit

neg_cold = NAOindextable(neg_cold_r)
neg_warm = NAOindextable(neg_warm_r)
pos_cold = NAOindextable(pos_cold_r)
pos_warm = NAOindextable(pos_warm_r)
total = [neg_cold, neg_warm, pos_cold, pos_warm]

### Select process ###
def search(table, *NAO):
    y = []
    for n in NAO:
        #group = []
        for i in range(len(table)):
            if n == table[i][3]:
                y.append(table[i])  # to avoid the same NAO index in different samples #
        #y.append(group)
    return y

def getrange(table, lb, ub): #lb = lower boundary, ub = upper boundary
    if lb>ub:
        lb, ub = ub, lb
    group = []
    for i in range(len(table)):
            if ((table[i][3]>=lb)and(table[i][3]<=ub)):
                group.append(table[i])
    return group,len(group)

def maxNAO(table):
    x = []
    for i in range(len(table)):
        x.append(table[i][3])
    return max(x)

def minNAO(table):
    x = []
    for i in range(len(table)):
        x.append(table[i][3])
    return min(x)

### For selection 1: max and min for each scenario ###
def select1(table):
    return search(table, maxNAO(table), minNAO(table))

def getN(selection):
    N = []
    for i in range(len(selection)):
        n = []
        for j in range(len(selection[i])):
            n.append(selection[i][j][0])
        N.append(n)
    return N

def num2char(s):
    if s<100 and s>-100:
        return '0%d'%s
    else:
        return '%d'%s

selection_1 = list(map(select1,total))
N = getN(selection_1)
selected_N = [] # format selected years
for s in N:
    selected_N.append(list(map(num2char,s)))


'''2. Copy and unzip relevant datafiles'''

# full directory from other work stations: /net/bhw509/nobackup/...
```

```
import os

def cpsamples(data,scenario, *N): # only for solar and wind so far
    name =
[['BC_Neg_DJF_cold','Neg_cold'],['BC_Neg_DJF_warm','Neg_warm'],['BC_Pos_DJF_cold','Pos_cold'],['BC_
Pos_DJF_warm','Pos_warm']]
    for i in range(len(name)):
        if scenario == name[i][0]:
            for j in N:
                os.system("cp /nobackup/users/huang/Data/Raw_data/Weather_data/%s/%s_*%s_*.nc*
/nobackup/users/huang/Data/Selection_1/%s/"%(name[i][0],data,j,name[i][1]))
                os.system("gunzip /nobackup/users/huang/Data/Selection_1/%s/*"%name[i][1])
    return None
'''In Neg_warm, all relevant files are in .nc format already'''

data = ['msl','T2','TN','TX','wind10','wind','SSRD']
scenarios = ['BC_Neg_DJF_cold','BC_Neg_DJF_warm','BC_Pos_DJF_cold','BC_Pos_DJF_warm']

for i in range(len(scenarios)):
    cpsamples(data[5],scenarios[i],*[N for N in selected_N[i]])
    cpsamples(data[6],scenarios[i],*[N for N in selected_N[i]])
```

F.2 Interpolate weather data into hourly values

F.2.1 SSRD

```
#!/usr/bin/env python3
# -*- coding: utf-8 -*-

' a test module '  #文档注释

"""
__author__ ='Huang, Jiangyi'

Created on 2017/06/21
"""

from netCDF4 import Dataset
import numpy as np
import math, time, sys # , os


### 1. Create time zone ###
def getLm(x): # for longitude between -180 to 180
   if x<=0:
      return abs(x)
   elif x>0:
      return 360-x

def getLz(lon): #longitude: degree west of Greenwich
   if (lon>=352.5)or(lon<7.5):
      return 0
   else:
      for y in range(15,360,15):
         if ((360-lon)>=(y-7.5))and((360-lon)<(y+7.5)):
            return y

d = sys.argv[1]
'''
'/net/bhw509/nobackup/users/huang/Data/Temp/Weather/Neg_cold/SSRD_Samp_080_month_01.nc'
'D:\Workspace\Develop\Data\SSRD_Samp_080_month_01.nc'
'''
with Dataset(d, 'r') as rd:
    time0 = rd.variables['time'][:]
    lat0 = rd.variables['lat'][:]
    lon0 = rd.variables['lon'][:]
    rd0 = rd.variables['SSRD'][:]

Lm = [] # longitude of the measurement site
Lz = [] # longitude of the center of the local time zone
for i in range(len(lon0)):
```

```python
    Lm.append(getLm(lon0[i]))
    Lz.append(getLz(Lm[i]))
Lm = np.asarray(Lm)
Lz = np.asarray(Lz)

### 2. Daily extraterrestrial radiation R_a (MJ/d/m2) ###
G = 0.0820 # solar constant, unit: MJ/d/min

def getJ(dd,mm): # Is the sample year 2050 a leap year?
    g = 9.016
    p = 2  # constants
    if mm<3:
        p = 0
    D = (dd-18)/24+1 # number of the day in the month
    k = 275*mm/g-30+D
    J = k.astype(int)-p # number of the day in the year
    return J

def mlp(new_axis,origin_array):
     a = []
     for i in range(len(new_axis)):
         a.append(new_axis[i]*origin_array)
     return np.asarray(a)

J = getJ(time0,1)

dr = 1+0.033*np.cos(2*math.pi/365*J) # relative distance earth-sun
delta = 0.409*np.sin(2*math.pi/365*J-1.39) # solar declination (rad)
lat = 2*math.pi/360*lat0
temp_var = -1*mlp(np.tan(delta),np.tan(lat))

def modify_arc(val): # modify the value to be valid for arc input
    if val > 1:
        return 1
    elif val < -1:
        return -1
    else:
        return val

for i in range(len(temp_var)):
    for j in range(len(temp_var[0,:])):
        temp_var[i,j]=modify_arc(temp_var[i,j])

omgs = np.arccos(temp_var) # sunset hour angel (rad)

R_a = 24*60/math.pi*G*\
np.transpose(dr*np.transpose((omgs*mlp(np.sin(delta),np.sin(lat))+\
np.sin(omgs)*mlp(np.cos(delta),np.cos(lat)))))

### 3. Extraterrestrial radiation per hour of the day R_ah (MJ/hr/m2) ###

t1 = 1 # time step = 1 hr

def mad(new_axis,origin_array):
    a = []
    for i in range(len(new_axis)):
        a.append(new_axis[i]+origin_array)
    return np.asarray(a)
hr = np.asarray([i+0.5 for i in range(24)]) # standard clock time in the midpoint of the period
# calculate omg
b = 2*math.pi*(J-81)/364
Sc = 0.1645*np.sin(2*b)-0.1255*np.cos(b)-0.025*np.sin(b)

omg = math.pi/12*(mad(hr,mad(Sc,0.06667*(Lz-Lm)))-12)

omg1 = omg - math.pi*t1/24
omg2 = omg + math.pi*t1/24

temp1 = np.transpose(mlp(np.sin(lat),(omg2-omg1)),(1,0,3,2))*np.sin(delta)
temp2 = np.transpose(mlp(np.cos(lat),(np.sin(omg2)-np.sin(omg1))),(1,0,3,2))*np.cos(delta)
```

```
R_ah = np.transpose(12*60/math.pi*G*dr*(temp1+temp2),(0,3,1,2))
R_ah[R_ah<0] = 0

### 4. general distribution ###
distr = []
for i in range(len(lon0)):
    lon = []
    for j in range(len(hr)):
        r = R_ah[j,:,:,i]/R_a
        r[np.isnan(r)]=0
        lon.append(r)
    distr.append(lon)
distr = np.transpose(np.asarray(distr),(1,2,3,0))

### 5. decompose the original SSRD ###
SSRD = []
for i in range(len(hr)):
    SSRD.append(distr[i,:,:,:]*rd0)
SSRD = np.asarray(SSRD)

### 6. create netCDF file ###
print('writing netcdf file...')
d_new = sys.argv[2]
'''
'D:\Workspace\Develop\Data\\New\SSRD_Samp_080_month_01_hr.nc'
'/nobackup/users/huang/Data/Temp/New/SSRD_Samp_080_month_01_hr.nc'
'''
with Dataset(d_new, 'w') as rd_new:
    rd_new.createDimension('hour', len(hr))
    rd_new.createDimension('day', len(time0))
    rd_new.createDimension('lat', len(lat0))
    rd_new.createDimension('lon', len(lon0))
    rd_new.createDimension('SSRD', len(rd0))

    hour = rd_new.createVariable('hour', hr.dtype.char,('hour',))
    day = rd_new.createVariable('day', time0.dtype.char,('day',))
    lat = rd_new.createVariable('lat', lat0.dtype.char, ('lat',))
    lon = rd_new.createVariable('lon', lon0.dtype.char, ('lon',))
    rd_new.createVariable('SSRD', rd0.dtype.char, ('hour','day','lat','lon'))

    hour[:] = hr-0.5 # start time of the hour
    day[:] = (time0-18)/24 + 1
    lat[:] = lat0
    lon[:] = lon0
    rd_new.variables['SSRD'][:] = SSRD

    rd_new.description = "hourly SSRD"
    rd_new.history = "Created " + time.ctime(time.time())
    rd_new.source = "daily SSRD from EC-earth"
    lat.units = "degrees north"
    lon.units = "degrees east"
    hour.units = "hours from 00:00 to 23:00"
    day.units = "date of the month"
    rd_new.units = "J/hr/m2"

rd_new = Dataset(d_new, 'r')
rd_new.variables['SSRD'][:]
rd_new.close()

# os.remove(d_new)
```

F.2.2 Windspeeds

```
# -*- coding: utf-8 -*-
"""
Created on Fri Jun 16 14:06:05 2017

@author: huang
"""
```

```
#Calculate hourly data for wind speed

import numpy as np
from netCDF4 import Dataset
import time, os, sys

### import data from netCDF file ###
'''
dxx = '/nobackup/users/huang/Data/Temp/Weather/Neg_cold/wind_100_Samp_080_month_01_HH_xx.nc'
dxx = 'D:\Workspace\Develop\Data\wind_100_Samp_080_month_01_HH_xx.nc'
'''
d00, d06, d12, d18 = sys.argv[1], sys.argv[2], sys.argv[3], sys.argv[4]
d = [d00, d06, d12, d18]

def readfile(d):
    with Dataset(d, 'r') as ws:
        windspeed = np.squeeze(ws.variables['speed'][:], axis=(1))
        time0 = ws.variables['time'][:]
        lat0 = ws.variables['lat'][:]
        lon0 = ws.variables['lon'][:]
    return [windspeed, time0, lat0, lon0]

# linear estimation for hourly wind speed
def linear(sp1,sp2,interval = 6, mode = 'b'): # b = backwards, retrospective: obtain detailed sp1 
based on sp2
    base = sp1                             # f = forwards, projective: obtain detailed sp2 based on 
sp1
    if mode=='f':
        base = sp2
    sp = []
    k = (sp2 - sp1)/(interval-1)
    for n in range(interval):
        sp.append(base + (n-(interval-1)/2)*k)
    return np.asarray(sp)

# calculate the data files
winddata = []
for s in d:
    winddata.append(readfile(s))
winddata_00, winddata_06, winddata_12, winddata_18 = winddata

windspeed_hr = np.concatenate((linear(winddata_00[0],winddata_06[0]),\
                               linear(winddata_06[0],winddata_12[0]),\
                               linear(winddata_12[0],winddata_18[0]),\
                               linear(winddata_12[0],winddata_18[0], mode='f')),0)
windspeed_hr[windspeed_hr<0]=0
# print('shape windspeed_hr:', np.shape(windspeed_hr))
# print('type windspeed_hr:', type(windspeed_hr))
# print(windspeed_hr.flags)

### create netCDF file ###
print('writing netcdf file...')
hr = np.asarray([t for t in range(24)])
d_new = sys.argv[5]
'''
'D:\Workspace\Develop\Data\\New\wind_100_Samp_080_month_01_hr.nc'
'/nobackup/users/huang/Data/Temp/New/wind_100_Samp_080_month_01_hr.nc'
'''
with Dataset(d_new, 'w') as ws:
   ws.createDimension('hour', len(hr))
   ws.createDimension('day', len(winddata_00[1]))
   ws.createDimension('lat', len(winddata_00[2]))
   ws.createDimension('lon', len(winddata_00[3]))
   ws.createDimension('speed', len(windspeed_hr))

   hour = ws.createVariable('hour', hr.dtype.char,('hour',))
   day = ws.createVariable('day', winddata_00[1].dtype.char,('day',))
   lat = ws.createVariable('lat', winddata_00[2].dtype.char, ('lat',))
   lon = ws.createVariable('lon', winddata_00[3].dtype.char, ('lon',))
   ws.createVariable('speed', windspeed_hr.dtype.char, ('hour','day','lat','lon'))
```

```
    hour[:] = hr
    day[:] = winddata_00[1]/24+1
    lat[:] = winddata_00[2]
    lon[:] = winddata_00[3]
    ws.variables['speed'][:] = windspeed_hr

    ws.description = "hourly wind speed"
    ws.history = "Created " + time.ctime(time.time())
    ws.source = "6 hourly wind speed from EC-earth"
    lat.units = "degrees north"
    lon.units = "degrees east"
    hour.units = "hours from 00:00 to 23:00"
    day.units = "date of the month"
    ws.units = "m/s"

ws = Dataset(d_new, 'r')
ws.variables['speed'][:]
ws.__dict__
ws.close()
```

F.2.3 Temperature interpolation

```
# -*- coding: utf-8 -*-
"""
Created on Thu Aug 10 13:24:08 2017

@author: huang
"""

#Interpolate hourly temperature of the day

import numpy as np
from netCDF4 import Dataset
import time, os, sys

### import data from netCDF file ###
'''
dxx = '/nobackup/users/huang/Data/Temp/Weather/Neg_cold/T2_Samp_029_month_01.nc'
dxx = 'D:\Workspace\Develop\Data\T2_Samp_029_month_01.nc'
'''
davg = sys.argv[1]

# davg = '/nobackup/users/huang/Data/Temp/Weather/Neg_cold/T2_Samp_029_month_01.nc'
# dmax = '/nobackup/users/huang/Data/Temp/Weather/Neg_cold/TX_Samp_029_month_01.nc'
# dmin = '/nobackup/users/huang/Data/Temp/Weather/Neg_cold/TN_Samp_029_month_01.nc'

# davg, dmax, dmin = sys.argv[1], sys.argv[2], sys.argv[3]

def readfile(d,name):
    with Dataset(d, 'r') as tp:
        temperature = tp.variables[name][:]
        time0 = tp.variables['time'][:]
        lat0 = tp.variables['lat'][:]
        lon0 = tp.variables['lon'][:]
    return [temperature, time0, lat0, lon0]

# make up missing values (oncean) with the max temperature at the same latitude
def makeup(T):
    T_new = []
    lat = T[2]; time = T[1]
    for i in range(len(time)):
        T_lat = []
        for j in range(len(lat)):
            T_latmax = np.ma.max(T[0][i,j])
            T_lat.append(np.ma.filled(T[0][i,j],T_latmax))
        T_new.append(T_lat)
    return [np.asarray(T_new),time,lat,T[3]]

# calculate the data files
T_new = makeup(readfile(davg,'T2'))
```

```
### create netCDF file ###
print('writing netcdf file...')
hr = np.asarray([t for t in range(24)])
d_new = sys.argv[2]
'''
'D:\Workspace\Develop\Data\\New\wind_100_Samp_080_month_01_hr.nc'
'/nobackup/users/huang/Data/Temp/New/T2_Samp_080_month_01_hr.nc'
'''
with Dataset(d_new, 'w') as ws:

   ws.createDimension('day', len(T_new[1]))
   ws.createDimension('lat', len(T_new[2]))
   ws.createDimension('lon', len(T_new[3]))
   ws.createDimension('T2', len(T_new[0]))

   day = ws.createVariable('day', T_new[1].dtype.char,('day',))
   lat = ws.createVariable('lat', T_new[2].dtype.char, ('lat',))
   lon = ws.createVariable('lon', T_new[3].dtype.char, ('lon',))
   ws.createVariable('T2', T_new[0].dtype.char, ('day','lat','lon'))

   day[:] = T_new[1]
   lat[:] = T_new[2]
   lon[:] = T_new[3]
   ws.variables['T2'][:] = T_new[0]

   ws.description = "daily average temperature, use in hourly input"
   ws.history = "Created " + time.ctime(time.time())
   ws.source = "daily T2 from EC-earth"
   lat.units = "degrees_north"
   lon.units = "degrees_east"
   day.units = "date of the month"
   ws.units = "K"
```

F.2.4 Downscale to hourly values

```
# -*- coding: utf-8 -*-
"""
Created on Fri Jun 30 10:23:13 2017

@author: huang
"""

import os, glob, GWElib

subfile = ['Neg_cold/','Neg_warm/','Pos_cold/','Pos_warm/']
subfile_hr = ['hr_Neg_cold/hr_','hr_Neg_warm/hr_','hr_Pos_cold/hr_','hr_Pos_warm/hr_']
d0 = '/nobackup/users/huang/Data/Selection_1/'

def delfile(list,*char): # delete specific file
    for c in char:
        i = 0
        while i < len(list):
            if c in list[i]:
                list.remove(list[i])
            else:
                i+=1
    return list

# create folder if it doesn't exist
for s in subfile:
    GWElib.GWE(d0 + 'hr_' + s).mkdir(parents=True, exist_ok=True)

### 1. obtain hourly solar irradiation ###
expy1 = 'python /nobackup/users/huang/Data/Python/Completed/SSRD_hr.py '
for i in range(len(subfile)):
    initial = glob.glob(d0+subfile[i]+'SSRD_*')
    GWElib.GWE(d0 + 'hr_' + subfile[i]).mkdir(parents=True, exist_ok=True)
    for s in initial:
        target = s.replace(subfile[i],subfile_hr[i])
        cmd_SSRD = expy1 + s + ' ' + target
```

```
        os.system(cmd_SSRD)

### 2. obtain hourly windspeed ###
expy2 = 'python /nobackup/users/huang/Data/Python/Completed/windspeed_hr.py '
for i in range(len(subfile)):
    initial = glob.glob(d0+subfile[i]+'wind_*_00.nc')
    initial = delfile(initial,'month_11_','month_03_')
    GWElib.GWE(d0 + 'hr_' + subfile[i]).mkdir(parents=True, exist_ok=True)
    for s in initial:
        source00 = s + ' '
        source06 = s.replace('_00','_06') + ' '
        source12 = s.replace('_00','_12') + ' '
        source18 = s.replace('_00','_18') + ' '
        target = (s.replace(subfile[i],subfile_hr[i])).replace('_00','')
        cmd_windspeed = expy2 + source00 + source06 + source12 + source18 + target
        os.system(cmd_windspeed)
for i in range(len(subfile)):
    initial = glob.glob(d0+subfile[i]+'wind10_*.nc')
    for s in initial:
        target = (s.replace(subfile[i],subfile_hr[i]))
        os.system('cp {0} {1}'.format(s,target))

### 3. obtain modified daily T2 for hourly use ###
expy3 = 'python /nobackup/users/huang/Data/Python/Completed/daily_T2.py '
for i in range(len(subfile)):
    initial = glob.glob(d0+subfile[i]+'T2_*')
    GWElib.GWE(d0 + 'hr_' + subfile[i]).mkdir(parents=True, exist_ok=True)
    for s in initial:
        target = s.replace(subfile[i],subfile_hr[i])
        cmd_T2 = expy3 + s + ' ' + target
        os.system(cmd_T2)
```

F.3 Distribution of installed capacity

F.3.1 Estimate iRES resources from previous weather records for capacity installation

```
# -*- coding: utf-8 -*-
"""
Created on Tue Aug 15 14:30:05 2017

@author: huang
"""

"""Evaluate solar and wind resource for each grid"""

import numpy as np
import pandas as pd
from netCDF4 import Dataset
from datetime import date, timedelta
import time, csv

# Abundency of solar radiation
start_time = time.time()    # record time consumption
## import data from netCDF file
def coordinate_solar(d):
    with Dataset(d, 'r') as crd:
        lat = crd.variables['lat'][:]
        lon = crd.variables['lon'][:]
    return [lat,lon]

def radiation(d):
    with Dataset(d, 'r') as sr:
        SSRD = np.squeeze(sr.variables['SIS'][:],axis=0)
    return SSRD

## mass operation
d0_solar = '/nobackup/users/huang/Data/Historical/SSRD/'
dtarget = '/nobackup/users/huang/Data/Historical/Output/'

### generate time dateset
```

```
def timespan(start, end, delta):
    curr = start
    while curr <= end:
        yield curr
        curr += delta

period = []
for result in timespan(date(1982, 1, 1), date(2015, 12, 31), timedelta(days=1)):
    period.append(result.strftime('%Y%m%d'))

latlon_solar = coordinate_solar(d0_solar+'SISdm'+period[0]+'0000002UDAVPOS01UD.nc')
SSRD0 = radiation(d0_solar+'SISdm'+period[0]+'0000002UDAVPOS01UD.nc')
SSRDf = radiation(d0_solar+'SISdm'+period[len(period)-1]+'0000002UDAVPOS01UD.nc')

### Solar irradiation resource W/m2, daily average over the timespan (19820101-20151231)
#SSRD = np.zeros(SSRD0[1].shape,dtype=SSRD0[1].dtype)
d = []
for t in period:
    d.append(d0_solar+'SISdm'+t+'0000002UDAVPOS01UD.nc')

SSRD_mask = np.ma.array(list(map(radiation,d))).mean(axis=0)   #averaging values of several masked 
ndarrays
SSRD = SSRD_mask.filled(0)

std = np.std(SSRD)
maxvalue = np.amax(SSRD)
minvalue = np.amin(SSRD)

## write to netCDF file
with Dataset(dtarget+'SSRD', 'w') as rd_new:
    rd_new.createDimension('lat', len(latlon_solar[0]))
    rd_new.createDimension('lon', len(latlon_solar[1]))

    lat = rd_new.createVariable('lat', latlon_solar[0].dtype.char, ('lat',))   #float64
    lon = rd_new.createVariable('lon', latlon_solar[1].dtype.char, ('lon',))   #float64
    rd_new.createVariable('SSRD', SSRD.dtype.char, ('lat','lon'))

    lat[:] = latlon_solar[0]
    lon[:] = latlon_solar[1]
    rd_new.variables['SSRD'][:] = SSRD

    rd_new.description = "daily average SSRD capacity over 19820101-20151231"
    rd_new.history = "Created " + time.ctime(time.time())
    rd_new.source = "daily observational SSRD from 
https://wui.cmsaf.eu/safira/action/viewProduktSearch"
    lat.units = "degrees north"
    lon.units = "degrees east"
    rd_new.units = "W/m2"
    rd_new.max = maxvalue
    rd_new.min = minvalue
    rd_new.std = std
'''
f = Dataset(dtarget+'SSRD', 'r')
a = f.variables['SSRD'][:]
f.close()
'''
print("--- %s seconds ---" % (time.time() - start_time))   # record time consumption
## write specific value to excel files
with pd.ExcelFile('D:\Workspace\Develop\Data\Cap_distribution.xlsx') as xlsx:
   grids = pd.read_excel(xlsx, 'Population_2025+Resource', index_col=0, parse_cols=[0,5,6,9])
#dtype of lat and lon are by default float64

f = Dataset('D:\Workspace\Develop\Data\weather_records\SSRD', 'r')
lat = f.variables['lat'][:]
lon = f.variables['lon'][:]
SSRD = f.variables['SSRD'][:]
f.close()

grids=grids.assign(SSRD=0.000)
```

```
for i in grids.index:
    for y in range(len(lat)):
        if lat[y]==grids.lat[i]:
            break
    for x in range(len(lon)):
        if lon[x]==grids.lon[i]:
            break
    grids.SSRD[i]=SSRD[y,x]

grids.to_excel('D:\Workspace\Develop\Data\hist_solar.xlsx', sheet_name='Solar_resource')


# Capacity factor of wind speeds
start_time = time.time()
## import data from netCDF file
def coordinate_wind(d):
    with Dataset(d, 'r') as crd:
        lat = crd.variables['latitude'][:]
        lon = crd.variables['longitude'][:]
    return [lat,lon]

def hour(d):
    with Dataset(d, 'r') as hr:
        hour = hr.variables['time'][:]
    return hour

def windspeed(d,start,interval):
    with Dataset(d, 'r') as ws:
        u = ws.variables['u100'][start:start+interval]
        v = ws.variables['v100'][start:start+interval]
        speed = np.power(u**2+v**2,0.5,dtype = np.float32)
    return speed

def prd(x,ui,ur,uo,ax=0):
    return ((x>=ur)*(x<uo)+(x>=ui)*(x<ur)*np.power(x,3)/np.power(ur,3)).sum(axis=ax)

## calculation
d0_wind = '/nobackup/users/huang/Data/Historical/Wind/'

latlon_wind = coordinate_wind(d0_wind+'windspeed_u+v_ERA-20C.nc')
t = hour(d0_wind+'windspeed_u+v_ERA-20C.nc')

n = 1000; start = 0; hr = 0
while n == 1000:
    u = windspeed(d0_wind+'windspeed_u+v_ERA-20C.nc',start,n)
    if start==0:
        Pon = np.zeros((u[0].shape),dtype = np.float32)
        Poff = np.zeros((u[0].shape),dtype = np.float32)
    n = len(u); start += n; hr += n
    Pon = Pon + prd(u,3,13.5,25)
    Poff = Poff + prd(u,4,14,25)

CFon = Pon/hr; CFoff = Poff/hr

CFon_max = np.amax(CFon); CFon_min = np.amin(CFon); CFon_std = np.std(CFon)
CFoff_max = np.amax(CFoff); CFoff_min = np.amin(CFoff); CFoff_std = np.std(CFoff)
## adjust grid
CFon = np.delete(np.delete(CFon,0,0),220,1)
CFoff = np.delete(np.delete(CFoff,0,0),220,1)
lat_wind = np.delete(latlon_wind[0],0)+0.125
lon_wind = np.delete(latlon_wind[1],220)+0.125

## write to netCDF file
with Dataset(dtarget+'windCF', 'w') as ws_new:
    ws_new.createDimension('lat', len(lat_wind))
    ws_new.createDimension('lon', len(lon_wind))

    lat = ws_new.createVariable('lat', lat_wind.dtype.char, ('lat',))   #float32
    lon = ws_new.createVariable('lon', lon_wind.dtype.char, ('lon',))   #float32
    CF_onshore = ws_new.createVariable('CF_onshore', CFon.dtype.char, ('lat','lon'))
```

```
    CF_offshore = ws_new.createVariable('CF_offshore', CFoff.dtype.char, ('lat','lon'))

    lat[:] = lat_wind
    lon[:] = lon_wind
    ws_new.variables['CF_onshore'][:] = CFon
    ws_new.variables['CF_offshore'][:] = CFoff

    ws_new.description = "average capacity factor per 3 hour over 19810101-20101231"
    ws_new.history = "Created " + time.ctime(time.time())
    ws_new.source = "ERA-20C from ECMWF"
    lat.units = "degrees north"
    lon.units = "degrees east"
    ws_new.units = "-"
    CF_onshore.max = CFon_max; CF_onshore.min = CFon_min; CF_onshore.std = CFon_std
    CF_offshore.max = CFoff_max; CF_offshore.min = CFoff_min; CF_offshore.std = CFoff_std


print("--- %s seconds ---" % (time.time() - start_time))

## write specific value to excel files
with pd.ExcelFile('D:\Workspace\Develop\Data\Cap_distribution.xlsx') as xlsx:
   grids = pd.read_excel(xlsx, 'Population_2025+Resource', index_col=0, parse_cols=[0,5,6,9])
#dtype of lat and lon are by default float64

f = Dataset('D:\Workspace\Develop\Data\weather_records\windCF', 'r')
lat = f.variables['lat'][:]
lon = f.variables['lon'][:]
CFon = f.variables['CF_onshore'][:]
CFoff = f.variables['CF_offshore'][:]
f.close()

grids=grids.assign(CFonshore=0.000); grids=grids.assign(CFoffshore=0.000)
for i in grids.index:
    for y in range(len(lat)):
        if lat[y] == grids.lat[i]:
            break
    for x in range(len(lon)):
        if lon[x] == grids.lon[i]:
            break
    grids.CFonshore[i] = CFon[y,x]
    grids.CFoffshore[i] = CFoff[y, x]

grids.to_excel('D:\Workspace\Develop\Data\hist_windCF.xlsx', sheet_name='Wind_resource')

# write info for distribution to csv file
with pd.ExcelFile('D:\Workspace\Develop\Data\Cap_distribution.xlsx') as xlsx:
   scenario = pd.read_excel(xlsx, 'Region_plan', index_col=0, dtype={'num': 'int'})
   cap = pd.read_excel(xlsx, 'Capacity_distribution', index_col=0, dtype={'OID *':'int'})    #dtype
of lat and lon are by default float64
cap.loc[1:len(cap.index),'RES40_onWind':'RES80_utilPV']=0.
# or use cap.ix() as a more general way bu is not deprecated
scenario.to_csv('D:\Workspace\Develop\Data\scenario.csv')
cap.to_csv('D:\Workspace\Develop\Data\cap_distr_info.csv')
```

F.3.2 Distribute capacities

```
# -*- coding: utf-8 -*-
"""
Created on Mon Aug 28 13:29:48 2017

@author: huang
"""

from netCDF4 import Dataset
import numpy as np
import pandas as pd
import time

scenario = pd.read_csv('D:\Workspace\Develop\Data\scenario.csv', index_col = 1)
grids = pd.read_csv('D:\Workspace\Develop\Data\cap_distr_info.csv', index_col = 0)
# '/nobackup/users/huang/Data/Cap_distribution/scenario.csv'
```

```
# '/nobackup/users/huang/Data/Cap_distribution/cap_distr_info.csv'

tech_name = ['onWind','offWind','roofPV','utilPV']
scen_name = ['RES40','RES60','RES80']

rank_onWind = grids.nomi_onWind.sort_values(axis=0, ascending=False).reset_index().values
rank_offWind = grids.nomi_offWind.sort_values(axis=0, ascending=False).reset_index().values
rank_roofPV = grids.nomi_roofPV.sort_values(axis=0, ascending=False).reset_index().values
rank_utilPV = grids.nomi_utilPV.sort_values(axis=0, ascending=False).reset_index().values

tech_rank = np.transpose(np.asarray(\
   [rank_onWind, rank_offWind, rank_roofPV, rank_utilPV]),(1,0,2))

for sce in sce_name:
   for i in range(len(tech_rank)):
      for j in range(len(tech_rank[i])):
         # info from tech score rank
         num = tech_rank[i,j,0]; score = tech_rank[i,j,1]
         # info from grids
         ISO = grids.ISO[num]
         tech_land = getattr(grids, 'Land_'+tech_name[j]+'_m2')[num]
         # info from scenario
         total_cap = getattr(scenario, ISO)[sce+'_'+tech_name[j]]
         unit_P_nomi = getattr(scenario, 'unit_nominal_P_W')[sce+'_'+tech_name[j]]
         unit_A = getattr(scenario, 'unit_area_m2')[sce+'_'+tech_name[j]]
         # allocation
         if total_cap > 0:
            install_cap = unit_P_nomi * int(tech_land/unit_A) * pow(10,-6) # in MW
            if total_cap > install_cap:
               grids.set_value(num, sce + '_' + tech_name[j], install_cap)
            else:
               install_cap = (int(total_cap * pow(10,6)/unit_P_nomi)+1) * unit_P_nomi * pow(10,-6)
               grids.set_value(num, sce + '_' + tech_name[j], install_cap)
            scenario.set_value(sce + '_' + tech_name[j], ISO, total_cap - install_cap)
         else:
            grids.set_value(num, sce + '_' + tech_name[j], 0)

# write data to csv file
grids.to_csv('D:\Workspace\Develop\Data\cap_distr.csv')
scenario.to_csv('D:\Workspace\Develop\Data\scenario_end.csv')

start_time = time.time()   # record time consumption
# write data to netCDF
d1_win = 'D:\Workspace\Develop\Data\scenario.csv'
d1_lin = '/nobackup/users/huang/Data/Cap_distribution/scenario.csv'
scenario = pd.read_csv(d1_lin, index_col = 1)
d2_win = 'D:\Workspace\Develop\Data\cap_distr.csv'
d2_lin = '/nobackup/users/huang/Data/Cap_distribution/cap_distr.csv'
distr = pd.read_csv(d2_lin, index_col = 0)
d3_win = 'D:\Workspace\Develop\Data\distr_netCDF\\'
d3_lin = '/nobackup/users/huang/Data/Cap_distribution/distr_netCDF/'
d_target = d3_lin
lat0 = np.arange(35.125,75.0,0.25); lon0 = np.arange(-14.875,40.0,0.25)
for sce in sce_name:
      for tech in tech_name:

           d_new = d_target + sce + '_' + tech +'_'+ 'cap_distr.nc'
           cap0 = np.zeros((len(lat0),len(lon0)))
           for i in range(1,len(distr.index)+1):
                 cap = getattr(distr, sce + '_' + tech)[i]
                 if cap > 0:
                     print(sce,tech,i,'/',len(distr.index))
                     for y in range(len(lat0)):
                         for x in range(len(lon0)):
                             if (lat0[y]==distr.lat[i] and lon0[x]==distr.lon[i]):
                                 cap0[y,x] = cap

           with Dataset(d_new, 'w') as f:
               f.createDimension('lat', len(lat0))
               f.createDimension('lon', len(lon0))
```

```
                f.createDimension('CAP', 1)

                lat = f.createVariable('lat', lat0.dtype.char, ('lat',))
                lon = f.createVariable('lon', lon0.dtype.char, ('lon',))
                CAP = f.createVariable('CAP', cap0.dtype.char, ('lat', 'lon'))

                lat[:] = lat0
                lon[:] = lon0
                f.variables['CAP'][:] = cap0

                f.description = "Capacity distributin of " + tech + 'in' + sce
                f.history = "Created " + time.ctime(time.time())
                f.source = "cap_distr.csv"
                lat.units = "degrees_north"
                lon.units = "degrees_east"
                f.units = "MW"

print("--- %s seconds ---" % (time.time() - start_time))

f = Dataset('directory', 'r')
f.variables['CAP'][:]
f.close()
```

F.3.3 Plot the spatial distribution of installed capacity

```
from netCDF4 import Dataset
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.basemap import Basemap
import pylab as pl

#DEFINE FUNCTION """Replace every 0 with 'nan' and return a copy."""
def zero_to_nan(deltaT):
   if deltaT == 0:
      return float('nan')
   else:
      return deltaT



### IMPORT NETCDF DATA ############################
scenarios = ['RES40_','RES60_','RES80_']
techs = ['onWind','offWind','roofPV','utilPV']

clevs_onWind = [x for x in range(0,501,50)]
clevs_offWind = [x for x in range(0,1001,100)]
clevs_roofPV = [x for x in range(0,6001,500)]
clevs_utilPV = [x for x in range(0,401,25)]

for scen in scenarios:
    for tech in techs:
        CapacityDistribution = 
'/nobackup/users/huang/Data/Cap_distribution/distr_netCDF/{0}{1}_cap_distr.nc'.format(scen,tech)
        print(CapacityDistribution)

        fh = Dataset(CapacityDistribution, mode='r')

        lons = fh.variables['lon'][:]; lats = fh.variables['lat'][:]; cap = fh.variables['CAP'][:]
        print('lons', np.shape(lons)); print('lats', np.shape(lats)); print('CAP', np.shape(cap))
        fh.close()

        ######## PLOT DATA ####################################
        plotvar = np.full((len(lats),len(lons)),0)
        for i in range(len(lats)):
            for j in range(len(lons)):

                plotvar[i,j] = cap[i,j]

        lon_0 = lons.mean()
        lat_0 = lats.mean()
```

```
        m = Basemap(projection = 'stere', lat_0=lat_0, lon_0=lon_0, llcrnrlon=-9,
                    llcrnrlat=33, urcrnrlon = 33, urcrnrlat = 72, resolution='i')

        lon, lat = np.meshgrid(lons, lats)
        x, y = m(lon, lat)

        cs = m.contourf(x,y,plotvar,eval('clevs_'+tech)) #clevs

        m.drawcoastlines()
        #m.drawstates()
        m.drawcountries()
        #m.drawparallels(np.arange(-80.,81.,20.))
        #m.drawmeridians(np.arange(-180.,181.,20.))
        #m.drawmapboundary(fill_color='white', zorder=-1)
        m.fillcontinents(color='0.9', lake_color='white', zorder=0)

        cbar = m.colorbar(cs)
        cbar.set_label('Installed capacity in MW')
        #cbar = m.colorbar(cs,ticks=[0, 50, 100, 150, 200, 250, 300])
        # Add Grid Lines
        m.drawparallels(np.arange(-80., 81., 5.), labels=[1,0,0,0], fontsize=10)
        m.drawmeridians(np.arange(-180., 181., 5.), labels=[0,0,0,1], fontsize=10)

        plt.title('{0} {1} capacity distribution'.format(scen,tech))

        savedir =
'/nobackup/users/huang/Data/Cap_distribution/pictures/{0}{1}_cap_distr.png'.format(scen,tech)
        plt.savefig(savedir)
        print('savedir:', savedir)
        plt.savefig(savedir)
        plt.close()
```

F.4 Prepare inputs of iRES for the PLEXOS

F.4.1 Hourly power generation from iRES

```
#!/usr/bin/env python3
# -*- coding: utf-8 -*-

"""
__author__ ='Huang, Jiangyi'

Created on 2017/09/05
"""

from netCDF4 import Dataset
import numpy as np
import pandas as pd
import time, GWElib

# Read technical profile
'''
with pd.ExcelFile('D:\Workspace\Develop\Data\Cap_distribution.xlsx') as xlsx:
   turbine = pd.read_excel(xlsx, 'turbine', index_col=0)
   panel = pd.read_excel(xlsx, 'panel', index_col=0)

turbine.to_csv('D:\Workspace\Develop\Data\\turbine.csv')
panel.to_csv('D:\Workspace\Develop\Data\\panel.csv')
'''
turbine = pd.read_csv('/nobackup/users/huang/Data/Cap_distribution/turbine.csv', index_col=0)
panel = pd.read_csv('/nobackup/users/huang/Data/Cap_distribution/panel.csv', index_col=0)
selection = pd.read_csv('/nobackup/users/huang/Data/Selection_1/sample.csv',index_col=0, dtype=str)

d_weather = '/nobackup/users/huang/Data/Selection_1/hr_'
d_cap = '/nobackup/users/huang/Data/Cap_distribution/distr_netCDF/'

NAO = ['Neg_cold','Neg_warm','Pos_cold','Pos_warm']
tech_name = ['onWind','offWind','roofPV','utilPV']
scen_name = ['RES40','RES60','RES80']
# functions for technology
```

```
def onWind_month(scen,nao,year,month):
    opt = 0.88  # operational efficiency
    u_ci = turbine.Cut_in[tech_name[0]]
    u_co = turbine.Cut_out[tech_name[0]]
    u_r = turbine.Rated[tech_name[0]]
    T_low = turbine.low_T[tech_name[0]]
    T_high = turbine.high_T[tech_name[0]]
    H = turbine.Hub_height[tech_name[0]]

    with Dataset(d_cap+'{0}_{1}_cap_distr.nc'.format(scen,tech_name[0]),'r') as fp:
        cap = fp.variables['CAP'][:]
    with Dataset(d_weather+'{0}/hr_TN_Samp_{1}_month_{2}.nc'.format(nao,year,month),'r') as fp:
        TN = fp.variables['Tn'][:]
    with Dataset(d_weather+'{0}/hr_TX_Samp_{1}_month_{2}.nc'.format(nao,year,month),'r') as fp:
        TX = fp.variables['Tx'][:]
    with Dataset(d_weather+'{0}/hr_wind_{1}_Samp_{2}_month_{3}_HH.nc'.format(nao,H,year,month),'r')
as fp:
        u0 = fp.variables['speed'][:]
        hr0 = fp.variables['hour'][:]
        day0 = fp.variables['day'][:]
        lat0 = fp.variables['lat'][:]
        lon0 = fp.variables['lon'][:]

    eff = (TN>=T_low)*(TX<=T_high)*((u0>=u_r)*(u0<u_co)*1 + \
        (u0>=u_ci)*(u0<u_r)*((np.power(u0,3)-np.power(u_ci,3))/(np.power(u_r,3)-np.power(u_ci,3))))
    P = cap * eff * opt # MWh per grid

    GWElib.GWE(d_weather + 'Egen/{0}/'.format(scen)).mkdir(parents=True, exist_ok=True)
    with Dataset(d_weather +
'Egen/{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,year,month,tech_name[0]), 'w') as f:
        f.createDimension('hour', len(hr0))
        f.createDimension('day', len(day0))
        f.createDimension('lat', len(lat0))
        f.createDimension('lon', len(lon0))
        f.createDimension('Gen', )

        hour = f.createVariable('hour', hr0.dtype.char, ('hour',))
        day = f.createVariable('day', day0.dtype.char, ('day',))
        lat = f.createVariable('lat', lat0.dtype.char, ('lat',))
        lon = f.createVariable('lon', lon0.dtype.char, ('lon',))
        f.createVariable('Gen', P.dtype.char, ('hour','day','lat', 'lon'))

        hour[:] = hr0
        day[:] = day0
        lat[:] = lat0
        lon[:] = lon0
        f.variables['Gen'][:] = P

        f.description = "hourly electricity generation of onWind"
        f.history = "Created " + time.ctime(time.time())
        hour.units = "hours from 00:00 to 23:00"
        day.units = "date of the month"
        lat.units = "degrees_north"
        lon.units = "degrees_east"
        f.units = "MWh"

    return '{0} {1} Samp_{2} {3} {4} complete'.format(scen,nao,year,month,tech_name[0]) #
[hr0,day0,lat0,lon0,P]

def offWind_month(scen,nao,year,month):
    opt = 0.88 # operational efficiency
    u_ci = turbine.Cut_in[tech_name[1]]
    u_co = turbine.Cut_out[tech_name[1]]
    u_r = turbine.Rated[tech_name[1]]
    T_low = turbine.low_T[tech_name[1]]
    T_high = turbine.high_T[tech_name[1]]
    H = turbine.Hub_height[tech_name[1]]

    with Dataset(d_cap+'{0}_{1}_cap_distr.nc'.format(scen,tech_name[1]),'r') as fp:
        cap = fp.variables['CAP'][:]
```

```
    with Dataset(d_weather+'{0}/hr_TN_Samp_{1}_month_{2}.nc'.format(nao,year,month),'r') as fp:
        TN = fp.variables['Tn'][:]
    with Dataset(d_weather+'{0}/hr_TX_Samp_{1}_month_{2}.nc'.format(nao,year,month),'r') as fp:
        TX = fp.variables['Tx'][:]
    with Dataset(d_weather+'{0}/hr_wind_{1}_Samp_{2}_month_{3}_HH.nc'.format(nao,H,year,month),'r')
as fp:
        u0 = fp.variables['speed'][:]
        hr0 = fp.variables['hour'][:]
        day0 = fp.variables['day'][:]
        lat0 = fp.variables['lat'][:]
        lon0 = fp.variables['lon'][:]

    eff = (TN>=T_low)*(TX<=T_high)*((u0>=u_r)*(u0<u_co)*1 + \
        (u0>=u_ci)*(u0<u_r)*((np.power(u0,3)-np.power(u_ci,3))/(np.power(u_r,3)-np.power(u_ci,3))))
    P = cap * eff * opt # MWh per grid

    GWElib.GWE(d_weather + 'Egen/{0}/'.format(scen)).mkdir(parents=True, exist_ok=True)
    with Dataset(d_weather +
'Egen/{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,year,month,tech_name[1]), 'w') as f:
        f.createDimension('hour', len(hr0))
        f.createDimension('day', len(day0))
        f.createDimension('lat', len(lat0))
        f.createDimension('lon', len(lon0))
        f.createDimension('Gen', )

        hour = f.createVariable('hour', hr0.dtype.char, ('hour',))
        day = f.createVariable('day', day0.dtype.char, ('day',))
        lat = f.createVariable('lat', lat0.dtype.char, ('lat',))
        lon = f.createVariable('lon', lon0.dtype.char, ('lon',))
        f.createVariable('Gen', P.dtype.char, ('hour','day','lat', 'lon'))

        hour[:] = hr0
        day[:] = day0
        lat[:] = lat0
        lon[:] = lon0
        f.variables['Gen'][:] = P

        f.description = "hourly electricity generation of offWind"
        f.history = "Created " + time.ctime(time.time())
        hour.units = "hours from 00:00 to 23:00"
        day.units = "date of the month"
        lat.units = "degrees_north"
        lon.units = "degrees_east"
        f.units = "MWh"

    return '{0} {1} Samp_{2} {3} {4} complete'.format(scen,nao,year,month,tech_name[1]) #
[hr0,day0,lat0,lon0,P]

def roofPV_month(scen,nao,year,month):
    G_stc = 1000 # W/m2
    PR_stc = 0.9; T_stc = 25 # C
    PT_coeff = panel.PT_coeff[tech_name[2]]
    T_low = panel.low_T[tech_name[2]]
    T_high = panel.high_T[tech_name[2]]

    with Dataset(d_cap+'{0}_{1}_cap_distr.nc'.format(scen,tech_name[2]),'r') as fp:
        cap = fp.variables['CAP'][:]    # (160,220)
    with Dataset(d_weather+'{0}/hr_T2_Samp_{1}_month_{2}.nc'.format(nao,year,month),'r') as fp:
        T2 = fp.variables['T2'][:]  # (31,160,220)
    with Dataset(d_weather+'{0}/hr_TN_Samp_{1}_month_{2}.nc'.format(nao,year,month),'r') as fp:
        TN = fp.variables['Tn'][:]
    with Dataset(d_weather+'{0}/hr_TX_Samp_{1}_month_{2}.nc'.format(nao,year,month),'r') as fp:
        TX = fp.variables['Tx'][:]  # (31,160,220)
    with Dataset(d_weather+'{0}/hr_wind10_Samp_{1}_month_{2}.nc'.format(nao,year,month),'r') as fp:
        V10 = fp.variables['speed'][:]  # (31,160,220)
    with Dataset(d_weather+'{0}/hr_SSRD_Samp_{1}_month_{2}.nc'.format(nao,year,month),'r') as fp:
        G = fp.variables['SSRD'][:]/3600  # (24,31,160,220) convert to W/m2 from J/hr/m2
        hr0 = fp.variables['hour'][:]
        day0 = fp.variables['day'][:]
        lat0 = fp.variables['lat'][:]
```

```
        lon0 = fp.variables['lon'][:]

    T_a = (T2 + TX)/2; T_c = 0.943 * T_a + 0.028 * G + (-1.528 * V10) + 4.3
    eff_T = 1 + PT_coeff * (T_c - T_stc)
    PR = PR_stc * eff_T
    P = (cap * PR * G / G_stc) * (TN>=T_low)*(TX<=T_high)    # MWh per grid

    GWElib.GWE(d_weather + 'Egen/{0}/'.format(scen)).mkdir(parents=True, exist_ok=True)
    with Dataset(d_weather +
'Egen/{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,year,month,tech_name[2]), 'w') as f:
        f.createDimension('hour', len(hr0))
        f.createDimension('day', len(day0))
        f.createDimension('lat', len(lat0))
        f.createDimension('lon', len(lon0))
        f.createDimension('Gen', )

        hour = f.createVariable('hour', hr0.dtype.char, ('hour',))
        day = f.createVariable('day', day0.dtype.char, ('day',))
        lat = f.createVariable('lat', lat0.dtype.char, ('lat',))
        lon = f.createVariable('lon', lon0.dtype.char, ('lon',))
        f.createVariable('Gen', P.dtype.char, ('hour','day','lat', 'lon'))

        hour[:] = hr0
        day[:] = day0
        lat[:] = lat0
        lon[:] = lon0
        f.variables['Gen'][:] = P

        f.description = "hourly electricity generation of roofPV"
        f.history = "Created " + time.ctime(time.time())
        hour.units = "hours from 00:00 to 23:00"
        day.units = "date of the month"
        lat.units = "degrees_north"
        lon.units = "degrees_east"
        f.units = "MWh"

    return '{0} {1} Samp_{2} {3} {4} complete'.format(scen,nao,year,month,tech_name[2]) #
[hr0,day0,lat0,lon0,P]

def utilPV_month(scen,nao,year,month):
    G_stc = 1000 # W/m2
    PR_stc = 0.9; T_stc = 25 # C
    PT_coeff = panel.PT_coeff[tech_name[3]]
    T_low = panel.low_T[tech_name[3]]
    T_high = panel.high_T[tech_name[3]]

    with Dataset(d_cap+'{0}_{1}_cap_distr.nc'.format(scen,tech_name[3]),'r') as fp:
        cap = fp.variables['CAP'][:]    # (160,220)
    with Dataset(d_weather+'{0}/hr_T2_Samp_{1}_month_{2}.nc'.format(nao,year,month),'r') as fp:
        T2 = fp.variables['T2'][:]  # (31,160,220)
    with Dataset(d_weather+'{0}/hr_TN_Samp_{1}_month_{2}.nc'.format(nao,year,month),'r') as fp:
        TN = fp.variables['Tn'][:]
    with Dataset(d_weather+'{0}/hr_TX_Samp_{1}_month_{2}.nc'.format(nao,year,month),'r') as fp:
        TX = fp.variables['Tx'][:]  # (31,160,220)
    with Dataset(d_weather+'{0}/hr_wind10_Samp_{1}_month_{2}.nc'.format(nao,year,month),'r') as fp:
        V10 = fp.variables['speed'][:]  # (31,160,220)
    with Dataset(d_weather+'{0}/hr_SSRD_Samp_{1}_month_{2}.nc'.format(nao,year,month),'r') as fp:
        G = fp.variables['SSRD'][:]/3600  # (24,31,160,220) convert to W/m2 from J/hr/m2
        hr0 = fp.variables['hour'][:]
        day0 = fp.variables['day'][:]
        lat0 = fp.variables['lat'][:]
        lon0 = fp.variables['lon'][:]

    T_a = (T2 + TX)/2; T_c = 0.943 * T_a + 0.028 * G + (-1.528 * V10) + 4.3
    eff_T = 1 + PT_coeff * (T_c - T_stc)
    PR = PR_stc * eff_T
    P = (cap * PR * G / G_stc) * (TN>=T_low)*(TX<=T_high)    # MWh per grid

    GWElib.GWE(d_weather + 'Egen/{0}/'.format(scen)).mkdir(parents=True, exist_ok=True)
    with Dataset(d_weather +
```

```
'Egen/{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,year,month,tech_name[3]), 'w') as f:
        f.createDimension('hour', len(hr0))
        f.createDimension('day', len(day0))
        f.createDimension('lat', len(lat0))
        f.createDimension('lon', len(lon0))
        f.createDimension('Gen', )

        hour = f.createVariable('hour', hr0.dtype.char, ('hour',))
        day = f.createVariable('day', day0.dtype.char, ('day',))
        lat = f.createVariable('lat', lat0.dtype.char, ('lat',))
        lon = f.createVariable('lon', lon0.dtype.char, ('lon',))
        f.createVariable('Gen', P.dtype.char, ('hour','day','lat', 'lon'))

        hour[:] = hr0
        day[:] = day0
        lat[:] = lat0
        lon[:] = lon0
        f.variables['Gen'][:] = P

        f.description = "hourly electricity generation of roofPV"
        f.history = "Created " + time.ctime(time.time())
        hour.units = "hours from 00:00 to 23:00"
        day.units = "date of the month"
        lat.units = "degrees_north"
        lon.units = "degrees_east"
        f.units = "MWh"

    return '{0} {1} Samp_{2} {3} {4} complete'.format(scen,nao,year,month,tech_name[3]) #
[hr0,day0,lat0,lon0,P]

# calculate power generation
start_time = time.time()   # record time consumption
for scen in scen_name:
    for nao in NAO:
        for yr in [selection.loc[nao].Min,selection.loc[nao].Max]:
            ## onshore turbine
            print(onWind_month(scen,nao,yr,'01')); print(onWind_month(scen,nao,yr,'02'));
print(onWind_month(scen,nao,yr,'12'))
            ## offshore turbine
            print(offWind_month(scen,nao,yr,'01')); print(offWind_month(scen,nao,yr,'02'));
print(offWind_month(scen,nao,yr,'12'))
            ## roofPV
            print(roofPV_month(scen,nao,yr,'01')); print(roofPV_month(scen,nao,yr,'02'));
print(roofPV_month(scen,nao,yr,'12'))
            ## utilPV
            print(utilPV_month(scen,nao,yr,'01')); print(utilPV_month(scen,nao,yr,'02'));
print(utilPV_month(scen,nao,yr,'12'))

    print("--- %s seconds ---" % (time.time() - start_time))

# construct csv file per region

def readcdf(d):
    with Dataset(d, 'r') as fr:
        gen = fr.variables['Gen'][:]    # (24,31,160,220)
        day0 = fr.variables['day'][:]
    return [gen, day0]

lat0 = np.arange(35.125,75.0,0.25); lon0 = np.arange(-14.875,40.0,0.25); hour0 = np.arange(1,25)
grids = pd.read_csv('/nobackup/users/huang/Data/Cap_distribution/cap_distr.csv',index_col=0,
usecols=[x for x in range(0,4)]+[x for x in range(23,35)])

def region_sum(cdf, ISO, tech, month):  # cdf: outputof readcdf(); region: ISO; tech:
e.g.RES40_onWind
    Egen = cdf[0]; day = cdf[1]
    grids_region = grids[grids.ISO==ISO]
    Egen_region = np.zeros((len(hour0),len(day)),dtype=np.float32)
    for i in grids_region.index:
        if getattr(grids_region,tech)[i]>0:
            for y in range(len(lat0)):
```

```
                for x in range(len(lon0)):
                    if (lat0[y]==grids_region.lat[i] and lon0[x]==grids_region.lon[i]):
                        Egen_region += Egen[:,:,y,x]
    return [np.transpose(Egen_region,(1,0)), month]   # return array shape = (31,24)

def buildDataFrame(*cdf_ISO):   # input form region_sum()
    frames = []
    new_col = ['Year','Month','Day']+[str(x) for x in range(1,len(hour0)+1)]
    for f in cdf_ISO:
        E = f[0]; m = f[1]  # E.shape = (31,24)
        Day = np.arange(1,len(E)+1)
        Month = np.full((len(E),),int(m),dtype=int)
        Year = np.full((len(E),),2050,dtype=int)
        df = pd.DataFrame(np.c_[Year,Month,Day,E])
        df.columns = new_col
        frames.append(df)
    frames = pd.concat(frames, ignore_index=True)
    for s in ['Year','Month','Day']:
        frames[s] = frames[s].astype(int)
    return frames

start_time_0 = time.time()   # record time consumption
d0 = '/nobackup/users/huang/Data/Selection_1/hr_Egen/'
ISO = ['BR','FR','GE','IB','IT','SC']
month = ['01','02','12']
for scen in scen_name:
    GWElib.GWE(d_weather + 'Egen/{0}_csv/'.format(scen)).mkdir(parents=True, exist_ok=True)
    for nao in NAO:
        for yr in [selection.loc[nao].Min,selection.loc[nao].Max]:
            ## onshore wind
            start_time = time.time()   # record time consumption
            E01 = readcdf(d0 +
'{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,yr,month[0],tech_name[0]))
            E02 = readcdf(d0 +
'{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,yr,month[1],tech_name[0]))
            E12 = readcdf(d0 +
'{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,yr,month[2],tech_name[0]))

            for regn in ISO:
                df = buildDataFrame(region_sum(E01, regn, scen+'_'+tech_name[0], '01'),
                                    region_sum(E02, regn, scen+'_'+tech_name[0], '02'),
                                    region_sum(E12, regn, scen+'_'+tech_name[0], '12'))
                df.to_csv(d_weather +
'Egen/{0}_csv/{0}_{1}_Samp_{2}_{3}_{4}.csv'.format(scen,nao,yr,regn,tech_name[0]), index = False)
                print('{0} {1} {2} {3} {4} complete'.format(scen,nao,yr,regn,tech_name[0]))
            print("--- %s seconds ---" % (time.time() - start_time))

            ## offshore wind
            start_time = time.time()   # record time consumption
            E01 = readcdf(d0 +
'{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,yr,month[0],tech_name[1]))
            E02 = readcdf(d0 +
'{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,yr,month[1],tech_name[1]))
            E12 = readcdf(d0 +
'{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,yr,month[2],tech_name[1]))

            for regn in ISO:
                df = buildDataFrame(region_sum(E01, regn, scen+'_'+tech_name[1], '01'),
                                    region_sum(E02, regn, scen+'_'+tech_name[1], '02'),
                                    region_sum(E12, regn, scen+'_'+tech_name[1], '12'))
                df.to_csv(d_weather +
'Egen/{0}_csv/{0}_{1}_Samp_{2}_{3}_{4}.csv'.format(scen,nao,yr,regn,tech_name[1]), index = False)
                print('{0} {1} {2} {3} {4} complete'.format(scen,nao,yr,regn,tech_name[1]))
            print("--- %s seconds ---" % (time.time() - start_time))

            ## roofPV
            start_time = time.time()   # record time consumption
            E01 = readcdf(d0 +
'{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,yr,month[0],tech_name[2]))
            E02 = readcdf(d0 +
```

```
'{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,yr,month[1],tech_name[2]))
            E12 = readcdf(d0 +
'{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,yr,month[2],tech_name[2]))

            for regn in ISO:
                df = buildDataFrame(region_sum(E01, regn, scen+'_'+tech_name[2], '01'),
                                    region_sum(E02, regn, scen+'_'+tech_name[2], '02'),
                                    region_sum(E12, regn, scen+'_'+tech_name[2], '12'))
                df.to_csv(d_weather +
'Egen/{0}_csv/{0}_{1}_Samp_{2}_{3}_{4}.csv'.format(scen,nao,yr,regn,tech_name[2]), index = False)
                print('{0} {1} {2} {3} {4} complete'.format(scen,nao,yr,regn,tech_name[2]))
            print("--- %s seconds ---" % (time.time() - start_time))

            ## utilPV
            start_time = time.time()    # record time consumption
            E01 = readcdf(d0 +
'{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,yr,month[0],tech_name[3]))
            E02 = readcdf(d0 +
'{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,yr,month[1],tech_name[3]))
            E12 = readcdf(d0 +
'{0}/{0}_{1}_Samp_{2}_{3}_{4}'.format(scen,nao,yr,month[2],tech_name[3]))

            for regn in ISO:
                df = buildDataFrame(region_sum(E01, regn, scen+'_'+tech_name[3], '01'),
                                    region_sum(E02, regn, scen+'_'+tech_name[3], '02'),
                                    region_sum(E12, regn, scen+'_'+tech_name[3], '12'))
                df.to_csv(d_weather +
'Egen/{0}_csv/{0}_{1}_Samp_{2}_{3}_{4}.csv'.format(scen,nao,yr,regn,tech_name[3]), index = False)
                print('{0} {1} {2} {3} {4} complete'.format(scen,nao,yr,regn,tech_name[3]))
            print("--- %s seconds ---" % (time.time() - start_time))

print("--- %s seconds ---" % (time.time() - start_time_0))

'''Test area'''
start_time = time.time()    # record time consumption
lat0 = np.arange(35.125,75.0,0.25); lon0 = np.arange(-14.875,40.0,0.25); hour0 = np.arange(1,25)
grids = pd.read_csv('/nobackup/users/huang/Data/Cap_distribution/cap_distr.csv',index_col=0,
usecols=[x for x in range(0,4)]+[x for x in range(23,35)])

cdf=readcdf(d0+'RES40/RES40_Neg_cold_Samp_029_01_onWind')
Egen = cdf[0]; day = cdf[1]
grids_region = grids[grids.ISO=='GE']
Egen_region = np.zeros((len(hour0),len(day)),dtype=np.float32)
for i in grids_region.index:
    if grids_region.RES40_onWind[i]>0:
        for y in range(len(lat0)):
            for x in range(len(lon0)):
                if (lat0[y]==grids_region.lat[i] and lon0[x]==grids_region.lon[i]):
                    Egen_region += Egen[:,:,y,x]
print("--- %s seconds ---" % (time.time() - start_time))

start_time = time.time()    # record time consumption
E = np.transpose(Egen_region,(1,0)); m = '01'  # E.shape = (31,24)
Day = np.arange(1,len(E)+1)
Month = np.full((len(E),),int(m),dtype=int)
Year = np.full((len(E),),2050,dtype=int)
df = np.c_[Year,Month,Day,E]
df = pd.DataFrame(df)
new_col = ['Year','Month','Day']+[str(x) for x in range(1,len(hour0)+1)]
df.columns = new_col
df1 = df.drop(df.index[[30]])
csv = pd.concat([df,df1], ignore_index=True)
for s in ['Year','Month','Day']:
        csv[s] = csv[s].astype(int)
csv.to_csv(d_weather + 'Egen/test.csv', index = False)
print("--- %s seconds ---" % (time.time() - start_time))

start_time = time.time()    # record time consumption
# wind turbine production
## onshore turbine
```

```
u_ci = turbine.Cut_in[tech_name[0]]
u_co = turbine.Cut_out[tech_name[0]]
u_r = turbine.Rated[tech_name[0]]
T_low = turbine.low_T[tech_name[0]]
T_high = turbine.high_T[tech_name[0]]
P_r = turbine.Capacity_MW[tech_name[0]]
H = turbine.Hub_height[tech_name[0]]

with Dataset(d_weather+NAO[0]+'/hr_wind_{0}_Samp_029_month_01_HH.nc'.format(H),'r') as fp:
    u = fp.variables['speed'][:]
    hr = fp.variables['hour'][:]
    day = fp.variables['day'][:]
    lat = fp.variables['lat'][:]
    lon = fp.variables['lon'][:]
with Dataset(d_weather+NAO[0]+'/hr_TN_Samp_029_month_01.nc','r') as fp:
   TN = fp.variables['Tn'][:]
with Dataset(d_weather+NAO[0]+'/hr_TX_Samp_029_month_01.nc','r') as fp:
   TX = fp.variables['Tx'][:]
with Dataset(d_cap+'{0}_{1}_cap_distr.nc'.format(scen_name[0],tech_name[0]),'r') as fp:
   cap = fp.variables['CAP'][:]
eff = (TN>=T_low)*(TX<=T_high)*((u>=u_r)*(u<u_co)*1 + \
   (u>=u_ci)*(u<u_r)*((np.power(u,3)-np.power(u_ci,3))/(np.power(u_r,3)-np.power(u_ci,3))))
P = cap * eff # MWh per grid
print("--- %s seconds ---" % (time.time() - start_time))


# roofPV
start_time = time.time()   # record time consumption
G_stc = 1000 # W/m2
PR_stc = 0.9; T_stc = 25 # C
PT_coeff = panel.PT_coeff[tech_name[2]]
T_low = panel.low_T[tech_name[2]]
T_high = panel.high_T[tech_name[2]]

with Dataset(d_cap+'{0}_{1}_cap_distr.nc'.format(scen_name[0],tech_name[2]),'r') as fp:
    cap = fp.variables['CAP'][:]    # (160,220)
with
Dataset(d_weather+'{0}/hr_T2_Samp_{1}_month_01.nc'.format(NAO[0],selection.loc[NAO[0]].Min),'r') as
fp:
    T2 = fp.variables['T2'][:]  # (31,160,220)
with
Dataset(d_weather+'{0}/hr_TN_Samp_{1}_month_01.nc'.format(NAO[0],selection.loc[NAO[0]].Min),'r') as
fp:
    TN = fp.variables['Tn'][:]
with
Dataset(d_weather+'{0}/hr_TX_Samp_{1}_month_01.nc'.format(NAO[0],selection.loc[NAO[0]].Min),'r') as
fp:
    TX = fp.variables['Tx'][:]  # (31,160,220)
with
Dataset(d_weather+'{0}/hr_wind10_Samp_{1}_month_01.nc'.format(NAO[0],selection.loc[NAO[0]].Min),'r')
as fp:
    V10 = fp.variables['speed'][:]  # (31,160,220)
with
Dataset(d_weather+'{0}/hr_SSRD_Samp_{1}_month_01.nc'.format(NAO[0],selection.loc[NAO[0]].Min),'r')
as fp:
    G = fp.variables['SSRD'][:]/3600  # (24,31,160,220) convert to W/m2 from J/hr/m2
    hr0 = fp.variables['hour'][:]
    day0 = fp.variables['day'][:]
    lat0 = fp.variables['lat'][:]
    lon0 = fp.variables['lon'][:]

T_a = (T2 + TX)/2; T_c = 0.943 * T_a + 0.028 * G + (-1.528 * V10) + 4.3
eff_T = 1 + PT_coeff * (T_c - T_stc)
PR = PR_stc * eff_T
P = (cap * PR * G / G_stc) * (TN>=T_low)*(TX<=T_high)   # MWh per grid
print("--- %s seconds ---" % (time.time() - start_time))
```

F.4.2 Calculate capacity factors which the PLEXOS requires

```
#!/usr/bin/env python3
# -*- coding: utf-8 -*-
```

```
' this file functions to convert production profiles of '
'solar panel and wind turbine into proper PLEXOS input .csv file '

"""
__author__ ='Huang, Jiangyi'

Created on 2017/09/19
"""

import numpy as np
import pandas as pd
import time, GWElib, os
from datetime import date, timedelta
import matplotlib.pyplot as plt

ISO = ['BR','FR','GE','IB','IT','SC']
map_name = dict(zip(ISO,['Bri','Gal','Ger','His','Ita','Sca']))
d_distr = 'D:\Workspace\Develop\Data\distr_netCDF'
d_gen = 'D:\Workspace\Develop\Data\Generation_profile'

NAO = ['Neg_cold','Neg_warm','Pos_cold','Pos_warm']
tech_name = ['onWind','offWind','roofPV','utilPV']
scen_name = ['RES40','RES60','RES80']
lat0 = np.arange(35.125,75.0,0.25); lon0 = np.arange(-14.875,40.0,0.25); hour0 = np.arange(1,25)

start_time0 = time.time()   # record time consumption

# count maximum capacity per region
cap_distr = pd.read_csv('D:\Workspace\Develop\Data\cap_distr.csv',index_col=0, usecols=[x for x in
range(0,2)]+[x for x in range(23,35)])
cap_distr = cap_distr.groupby('ISO').sum()

indx_list = cap_distr.index.tolist()
for i in range(len(indx_list)):
   indx_list[i] = map_name[cap_distr.index[i]]
cap_distr.index = indx_list

GWElib.GWE('D:\Workspace\Develop\Data\PLEXOS').mkdir(parents=True, exist_ok=True)
cap_distr.to_csv('D:\Workspace\Develop\Data\PLEXOS\Distr_region.csv')

def timespan(start, end, delta):   # generate time dateset
    curr = start
    while curr <= end:
        yield curr
        curr += delta

def standard_df():
   yyyy = []; mm = []; dd = []
   for result in timespan(date(2050, 1, 1), date(2050, 12, 31), timedelta(days=1)):
      yyyy.append(result.strftime('%Y'))
      mm.append(result.strftime('%m'))
      dd.append(result.strftime('%d'))  # without 2050-02-29
   E0 = np.zeros([len(dd), len(hour0)])  # E0.shape = (31,24)
   day = np.full((len(dd),), dd, dtype=int)
   month = np.full((len(mm),), mm, dtype=int)
   year = np.full((len(yyyy),), yyyy, dtype=int)
   new_col = ['Year', 'Month', 'Day'] + [str(x) for x in range(1, len(hour0) + 1)]
   df0 = pd.DataFrame(np.c_[year, month, day, E0])
   df0.columns = new_col
   for col in ['Year', 'Month', 'Day']:
      df0[col] = df0[col].astype(int)
   return df0

def yr_gen(gen_csv):   # directory of generation profile (.csv)
   df0 = standard_df()
   month = np.unique(df0.Month)
   # allocate into the standard df
   gen = pd.read_csv(gen_csv)
   gen = gen[-((gen.Month == 2) & (gen.Day == 29))]   # delete data of 2050-02-29
```

```
    for m in month:
        if len(gen[gen.Month == m].index) != 0:
            new_index = df0[df0.Month == m].index
            gen_month = gen[gen.Month == m].set_index(new_index)
            df0[df0.Month == m] = gen_month    # copy between dataframe can only success with the same
index
    return df0

#df =
yr_gen('D:\Workspace\Develop\Data\Generation_profile\RES40_csv\RES40_Neg_cold_Samp_029_BR_offWind.c
sv')
#cap_distr = pd.read_csv('D:\Workspace\Develop\Data\PLEXOS\Distr_region.csv', index_col = 0)
#cap = cap_distr.RES40_offWind[map_name['BR']]

def cal_CF(yrgen, capmax, tech = 'solar'):     # tech - 'solar' or 'wind'
    r_opt = 1
    if tech == 'wind':
        r_opt = 0.88     # operational loss in wind turbine
    df0 = standard_df()
    df0.iloc[:,3:] = yrgen / capmax * r_opt * 100
    return df0

def replace(CF_0,CF_1,*month):     # substitute values of CF_0 with values of CF_1, in specific
month
    df_0 = pd.read_csv(CF_0, index_col=False)
    df_1 = pd.read_csv(CF_1, index_col=False)
    for m in month:
        df_0.iloc[df_0[df_0.Month == m].index, 3:] \
            = df_1.iloc[df_1[(df_1.MONTH == m) & (df_1.YEAR == 2050)].index, 3:]
    df_0.to_csv(CF_0,index=False)
    return None

neg_cold = ['071','029']
neg_warm = ['055','010']
pos_cold = ['082','019']
pos_warm = ['034','036']

selection = pd.DataFrame(np.c_[neg_cold, neg_warm, pos_cold, pos_warm])
selection.columns = NAO
selection.index = ['Max', 'Min']

print("--- %s seconds ---" % (time.time() - start_time0))

print('processing for capacity factor...')
start_time1 = time.time()
month_NAO = [1,2,12]; month_yr = [x for x in range(1,13)]
month_replace = list(set(month_yr)-set(month_NAO))
for scen in scen_name:
    for nao in NAO:
        for yr in [getattr(selection,nao).Min, getattr(selection,nao).Max]:
            GWElib.GWE('D:\Workspace\Develop\Data\PLEXOS\Samp_{0}'.format(yr)).mkdir(parents=True,
exist_ok=True)
            for region in ISO:
                ## roofPV, name as RegPV_rf.csv
                cap_max = getattr(cap_distr, '{0}_{1}'.format(scen, tech_name[2]))[map_name[region]]
                CF_PV_rf = cal_CF(yr_gen('D:\Workspace\Develop\Data\Generation_profile'
                                   '\{0}_csv\{0}_{1}_Samp_{2}_{3}_{4}.csv'
                                   .format(scen, nao, yr, region, tech_name[2])),
                              cap_max, tech = 'solar')
                CF_PV_rf.to_csv('D:\Workspace\Develop\Data\PLEXOS\Samp_{1}\{0}_{2}_rfPV.csv'
                            .format(scen, yr, map_name[region]), index=False)
                replace('D:\Workspace\Develop\Data\PLEXOS\Samp_{1}\{0}_{2}_rfPV.csv'
                        .format(scen, yr, map_name[region]),
                        'D:\Workspace\Develop\Data\control_CF\{0}PV.csv'
                        .format(map_name[region]),*month_replace)

                ## utilPV, name as RegPV_ut.csv
                cap_max = getattr(cap_distr, '{0}_{1}'.format(scen, tech_name[3]))[map_name[region]]
                CF_PV_ut = cal_CF(yr_gen('D:\Workspace\Develop\Data\Generation_profile'
                                   '\{0}_csv\{0}_{1}_Samp_{2}_{3}_{4}.csv'
```

```
                                .format(scen, nao, yr, region, tech_name[3])),
                           cap_max, tech = 'solar')
            CF_PV_ut.to_csv('D:\Workspace\Develop\Data\PLEXOS\Samp_{1}\{0}_{2}_utlPV.csv'
                          .format(scen, yr, map_name[region]), index=False)
            replace('D:\Workspace\Develop\Data\PLEXOS\Samp_{1}\{0}_{2}_utlPV.csv'
                  .format(scen, yr, map_name[region]),
                  'D:\Workspace\Develop\Data\control_CF\{0}PV.csv'
                  .format(map_name[region]), *month_replace)

            ## PV in total, name as RegPV.csv, PV = PV_rf + PV_ut, this file is used to fit the
original PLEXOS model
            CF_PV = CF_PV_rf + CF_PV_ut
            for s in ['Year', 'Month', 'Day']:
               CF_PV[s] = CF_PV_ut[s].astype(int)
            CF_PV.to_csv('D:\Workspace\Develop\Data\PLEXOS\Samp_{1}\{0}_{2}_PVtot.csv'
                        .format(scen, yr, map_name[region]), index=False)
            replace('D:\Workspace\Develop\Data\PLEXOS\Samp_{1}\{0}_{2}_PVtot.csv'
                  .format(scen, yr, map_name[region]),
                  'D:\Workspace\Develop\Data\control_CF\{0}PV.csv'
                  .format(map_name[region]), *month_replace)

            ## onshore wind, name as RegOnW.csv
            cap_max = getattr(cap_distr,'{0}_{1}'.format(scen,tech_name[0]))[map_name[region]]
            CF_onW = cal_CF(yr_gen('D:\Workspace\Develop\Data\Generation_profile'
                               '\{0}_csv\{0}_{1}_Samp_{2}_{3}_{4}.csv'
                               .format(scen,nao,yr,region,tech_name[0])),
                          cap_max, tech = 'wind')
            CF_onW.to_csv('D:\Workspace\Develop\Data\PLEXOS\Samp_{1}\{0}_{2}_OnW.csv'
                         .format(scen,yr, map_name[region]), index = False)
            replace('D:\Workspace\Develop\Data\PLEXOS\Samp_{1}\{0}_{2}_OnW.csv'
               .format(scen,yr, map_name[region]),
               'D:\Workspace\Develop\Data\control_CF\{0}OnW.csv'
               .format(map_name[region]),*month_replace)

            ## offshore wind, name as RegOffW.csv
            cap_max = getattr(cap_distr, '{0}_{1}'.format(scen, tech_name[1]))[map_name[region]]
            CF_offW = cal_CF(yr_gen('D:\Workspace\Develop\Data\Generation_profile'
                               '\{0}_csv\{0}_{1}_Samp_{2}_{3}_{4}.csv'
                               .format(scen, nao, yr, region, tech_name[1])),
                           cap_max, tech = 'wind')
            CF_offW.to_csv('D:\Workspace\Develop\Data\PLEXOS\Samp_{1}\{0}_{2}_OffW.csv'
                          .format(scen, yr, map_name[region]), index = False)
            try:    # not all region install offWind in the base model
               replace('D:\Workspace\Develop\Data\PLEXOS\Samp_{1}\{0}_{2}_OffW.csv'
                  .format(scen,yr, map_name[region]),
                  'D:\Workspace\Develop\Data\control_CF\{0}OffW.csv'
                  .format(map_name[region]),*month_replace)
            except FileNotFoundError:
               print('csv file for {0} offshore wind not found'.format(region))

            print('{0} {1} {2} {3} completed'.format(scen, nao, yr, region))
print("--- %s seconds ---" % (time.time() - start_time1))

# Extract filename list
print('building file name list for substitution in PLEXOS...')
GWElib.GWE('D:\Workspace\Develop\Data\PLEXOS\File_list').mkdir(parents=True, exist_ok=True)
dir0 = 'D:\Workspace\Develop\Data\PLEXOS'
samp_year = ['071','029','055','010','082','019','034','036']

for sc in scen_name:
   for yr in samp_year:
      os.system('dir {0}\Samp_{1}\*W.csv > {0}\File_list\samp_{1}_wind.csv'.format(dir0, yr))
      os.system('dir {0}\Samp_{1}\*PV.csv > {0}\File_list\samp_{1}_PV.csv'.format(dir0, yr))
```

F.5 Calculate other parameters

F.5.1 Capacity credits

```
#!/usr/bin/env python3
# -*- coding: utf-8 -*-
```

```
' a test module '  #文档注释

"""
__author__ ='Huang, Jiangyi'

Created on 2018/01/10
"""

import numpy as np
import pandas as pd


# File directory
dir_CC = 'D:\Workspace\Develop\Data\Capacity_credits'
dir0 = 'D:\Workspace\Develop\Data\PLEXOS'

# constants
region = ['Bri', 'Gal', 'Ger', 'His', 'Ita', 'Sca']
ISO = ['BR', 'FR', 'GE', 'IB', 'IT', 'SC', 'TOT']
tech_name = ['onWind','offWind','roofPV','utilPV']
tech_short = ['OnW','OffW','rfPV','utlPV']
scen_name = ['RES40','RES60','RES80']
tech_category = ['Onshore wind','Offshore wind','rooftop PV','Utility PV','PV total','iRES']
year = ['010', '019', '029', '034', '036', '055', '071', '082']

# functions
def df_tolist(df):
   list = df['1'].tolist()
   for i in range(2,25):
      list+=df['{0}'.format(i)].tolist()
   return list

def cal_CC(load, gen, capacity):
   # LDC = sorted(load, reverse=True)
   Res = load - gen
   # ResLDC = sorted(Res, reverse=True)

   return (max(load) - max(Res)) / capacity

# inputs: capacity distribution, hourly loads, iRES generation
cap_distr = pd.read_csv(dir0 + '\Distr_region.csv', index_col = 0)
hr = 8760
CC_Samp = []
for yr in year:
   CC_RES = []
   for scen in scen_name:
      CC_table = []
      load_all = np.zeros([hr,]); cap_tot = np.zeros([len(tech_category),]); gen_tot =
np.zeros([len(tech_category),hr])
      for rg in region:
         load = pd.read_csv(dir_CC + '\Loads\{0}LoadAlt.csv'.format(rg), index_col=0)
         load = load[load.index == 2050]
         load = np.asarray(df_tolist(load))
         load_all += load
         # CF in %
         OnW = pd.read_csv(dir0 + '\Samp_{0}\{1}_{2}_OnW.csv'.format(yr, scen, rg), index_col = 0)
         OffW = pd.read_csv(dir0 + '\Samp_{0}\{1}_{2}_OffW.csv'.format(yr, scen, rg), index_col=0)
         rfPV = pd.read_csv(dir0 + '\Samp_{0}\{1}_{2}_rfPV.csv'.format(yr, scen, rg), index_col = 0)
         utlPV = pd.read_csv(dir0 + '\Samp_{0}\{1}_{2}_utlPV.csv'.format(yr, scen, rg), index_col =
0)

         cap_distr_OnW = getattr(cap_distr, '{0}_onWind'.format(scen))['{0}'.format(rg)]
         cap_distr_OffW = getattr(cap_distr, '{0}_offWind'.format(scen))['{0}'.format(rg)]
         if rg == 'Ita':
            cap_distr_OffW = 0
         cap_distr_rfPV = getattr(cap_distr, '{0}_roofPV'.format(scen))['{0}'.format(rg)]
         cap_distr_utlPV = getattr(cap_distr, '{0}_utilPV'.format(scen))['{0}'.format(rg)]

         cap_PV = sum([cap_distr_rfPV, cap_distr_utlPV])
         cap_iRES = sum([cap_distr_OffW, cap_distr_OnW, cap_distr_rfPV, cap_distr_utlPV])
```

```
            gen_OnW = np.asarray(df_tolist(OnW)) / 100 * cap_distr_OnW
            gen_OffW = np.asarray(df_tolist(OffW)) / 100 * cap_distr_OffW
            if rg == 'Ita':
                gen_OffW = np.zeros([hr,])
            gen_rfPV = np.asarray(df_tolist(rfPV))/100 * cap_distr_rfPV
            gen_utlPV = np.asarray(df_tolist(utlPV))/100 * cap_distr_utlPV

            gen_PV = sum([gen_rfPV, gen_utlPV])
            gen_iRES = sum([gen_OffW, gen_OnW, gen_rfPV, gen_utlPV])

            CC_OnW = cal_CC(load, gen_OnW, cap_distr_OnW)
            CC_OffW = cal_CC(load, gen_OffW, cap_distr_OffW)
            if rg == 'Ita':
                CC_OffW = 'N.A.'
            CC_rfPV = cal_CC(load, gen_rfPV, cap_distr_rfPV)
            CC_utlPV = cal_CC(load, gen_utlPV, cap_distr_utlPV)
            CC_PV = cal_CC(load, gen_PV, cap_PV)
            CC_iRES = cal_CC(load, gen_iRES, cap_iRES)

            CC_region = [CC_OnW, CC_OffW, CC_rfPV, CC_utlPV, CC_PV, CC_iRES]
            CC_table.append(CC_region)

            cap_tot += np.asarray([cap_distr_OffW, cap_distr_OnW, cap_distr_rfPV, cap_distr_utlPV,
cap_PV, cap_iRES])
            gen_tot += np.asarray([gen_OffW, gen_OnW, gen_rfPV, gen_utlPV, gen_PV, gen_iRES])

        load_tot = np.ones([len(tech_category),hr]) * load_all
        CC_tot = []
        for x in range(len(tech_category)):
            CC_tot.append(cal_CC(load_tot[x], gen_tot[x], cap_tot[x]))

        CC_table.append(CC_tot)
        CC_table = np.asarray(CC_table)
        df_CC = pd.DataFrame(CC_table, index = ISO, columns = tech_category)
        print('Samp_{0}_{1} completed'.format(yr, scen))

        CC_RES.append(df_CC)

    CC_RES = pd.concat(CC_RES, axis = 1, join_axes = [CC_RES[0].index])
    CC_Samp.append(CC_RES)
CC_Samp = pd.concat(CC_Samp, axis=0)

iter_index = [year, ISO]; multiindex = pd.MultiIndex.from_product(iter_index)
iter_col = [scen_name, tech_category]; multicol = pd.MultiIndex.from_product(iter_col)
CC_Samp.index = multiindex; CC_Samp.columns = multicol
CC_Samp.to_csv(dir_CC+'\capacity_credits.csv', index = True)

writer = pd.ExcelWriter(dir_CC+'\capacity_credits.xlsx')
CC_Samp.to_excel(writer, 'Raw_outputs')
writer.save()
print('Program is completed!')
```

F.5.2 iRES power generation in an average week in winter months

```
#!/usr/bin/env python3
# -*- coding: utf-8 -*-

' a test module '  #文档注释

"""
__author__ ='Huang, Jiangyi'

Created on 2018/01/24
"""

import datetime, calendar, openpyxl
import pandas as pd
import numpy as np
```

```
region = ['Bri', 'Gal', 'Ger', 'His', 'Ita', 'Sca']
ISO = ['BR', 'FR', 'GE', 'IB', 'IT', 'SC']
tech_name = ['onWind','offWind','roofPV','utilPV']
scen_name = ['RES40','RES60','RES80']
year = ['010', '019', '029', '034', '036', '055', '071', '082']
weather = ['Neg_warm', 'Pos_cold', 'Neg_cold', 'Pos_warm', 'Pos_warm', 'Neg_warm', 'Neg_cold',
'Pos_cold']
tech_category = ['Onshore wind','Offshore wind','rooftop PV','Utility PV', 'Loads']
days = ['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday']
dict_yr = dict(zip(year, weather))

# functions
def sum_df(df_list):
   last = list(df_list[0])[len(list(df_list[0]))-1]
   try:
      int(last)
   except ValueError:
      print('No data available.')
      return None
   if int(last) < 1:
      print('No data available.')
      return None
   for i in range(1,len(df_list)):
      df_list[0].loc[:, '1':last] = df_list[0].loc[:, '1':last].add(df_list[i].loc[:, '1':last],
axis='columns')
   return df_list[0]

def df_tolist(df, axis = 0):      # 0: row to list; 1: column to list
   if axis == 1:
      list = df['1'].tolist()
      for i in range(4,28):
         list += df['{0}'.format(i)].tolist()
      return list
   else:
      list = df.loc[days[0], :].tolist()
      for d in days[1:]:
         list += df.loc[d,:].tolist()
      return list

def week_val(df):
   df = df[(df.Month == 1) | (df.Month == 2) | (df.Month == 12)].reset_index(drop=True) # for loads
   df = df[-((df.Month == 2) & (df.Day == 29))].reset_index(drop=True)       # delete data of 2050-
02-29 and update index
   weekdays = []
   for i in range(len(df)):
      date = datetime.datetime(2050, df.Month[i], df.Day[i])
      weekdays.append(calendar.day_name[date.weekday()])
   df.insert(3, 'Weekday', weekdays)
   df = df.loc[:, 'Weekday':'24']
   df = df.groupby('Weekday', as_index=True).mean()
   df = df.reindex(index=days)

   val = df_tolist(df, axis = 0)
   iterables = [df.index.tolist(),[x for x in range(1,25)]]
   multiindex = pd.MultiIndex.from_product(iterables, names=['Day', 'Hour'])
   df = pd.Series(val, index = multiindex)

   return df

# 1. data processing - to average week in winter months
dir_gen = 'D:\Workspace\Develop\Data\Generation_profile'
dir_load = 'D:\Workspace\Develop\Data\Capacity_credits\Loads'
dir_target = 'D:\Workspace\Develop\Data\Avg_week_DJF'

load_tot = []
for rg in region:
   load = pd.read_csv(dir_load+'\{0}LoadAlt.csv'.format(rg))
   load = load[load.Year == 2050]
   load_tot.append(load)
```

```
load_tot = week_val(sum_df(load_tot))
# load_tot.to_csv(dir_target + '\Total_weekly_load.csv', index = True, float_format='%.2f')

results_Samp = []
for yr in year:
   results_RES = []
   for scen in scen_name:
      gen_OnW = []; gen_OffW = []; gen_rfPV = []; gen_utlPV = []
      for rg in ISO:
         gen_OnW.append(pd.read_csv(dir_gen+'\{0}_csv\{0}_{3}_Samp_{1}_{2}_onWind.csv'.format(scen,
yr, rg, dict_yr[yr])))
         gen_OffW.append(pd.read_csv(dir_gen +
'\{0}_csv\{0}_{3}_Samp_{1}_{2}_offWind.csv'.format(scen, yr, rg, dict_yr[yr])))
         gen_rfPV.append(pd.read_csv(dir_gen +
'\{0}_csv\{0}_{3}_Samp_{1}_{2}_roofPV.csv'.format(scen, yr, rg, dict_yr[yr])))
         gen_utlPV.append(pd.read_csv(dir_gen +
'\{0}_csv\{0}_{3}_Samp_{1}_{2}_utilPV.csv'.format(scen, yr, rg, dict_yr[yr])))

      gen_OnW = week_val(sum_df(gen_OnW))
      gen_OffW = week_val(sum_df(gen_OffW))
      gen_rfPV = week_val(sum_df(gen_rfPV))
      gen_utlPV = week_val(sum_df(gen_utlPV))

      result = pd.concat([gen_OnW, gen_OffW, gen_rfPV, gen_utlPV, load_tot], axis=1,
join_axes=[load_tot.index])
      results_RES.append(result)

   result = pd.concat(results_RES, axis = 1, join_axes=[results_RES[0].index])
   results_Samp.append(result)
   print('Samp_{0} completed'.format(yr, scen))

result = pd.concat(results_Samp, axis = 1, join_axes=[results_Samp[0].index])
columns = [year, scen_name , tech_category]
multicol = pd.MultiIndex.from_product(columns)
result.columns = multicol

writer = pd.ExcelWriter(dir_target+'\Weekly_generation.xlsx')
result.to_excel(writer, 'Raw_outputs')
writer.save()

print('Program is completed!')
```

Acknowledgement