SafeWind

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Abstract: This deliverable summarizes the highlights of Safewind/WP7, which explores the benefits of considering predictability aspects during the planning phase of wind energy development. Two predictability levels are considered: in the context of wind power forecasting during the operational phase and in the context of site assessment considering the predictability of the extreme wind speed over 50-years. The topic is especially relevant to be considered in upcoming EU27 Wind Atlas, where the developed tools can contribute to a better integration of the planning and operational phases of wind energy.

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Contents

1. Introduction

The use of wind power forecasting is linked to the operational phase of a wind farm in connection with different end uses and scales of the prediction. In the very short term, from seconds to a few minutes, forecasts are used for turbine and wind farm control. In the range of some hours to some days, short term forecasting is used by transmission system operators (TSO) for power system management (scheduling, reserves planning, congestion management, etc). Wind farm operators use day-ahead and intraday forecasts for trading in the energy market. Long-term forecasting (5-7 days ahead) is also used for operation and maintenance planning of wind farms, conventional power plants or transmission lines. Optimal use of long-term forecasting is particularly important for offshore wind farms, wherein important logistics are mobilized when good weather windows are predicted. Even, seasonal and decadal wind forecasting can be approached by linking wind power generation with teleconnection weather patterns (Brayshaw et al., 2011).

Wind power forecasting is a matter of temporal scales as an inherent characteristic of the wind speed variability of the weather (Lange and Focken, 2005). From seasonal scales driven by global circulation weather patterns to daily cycles due to temperature changes and to sub-minute turbulence variations generated by local topography, wind power integration requires spectral consideration. Managing the variability of wind generation is a key aspect for an optimal integration of wind power in the electrical grid, especially when large penetration is sought as it is the case for European targets of 20% share of renewables by 2020 According to the European Wind Energy Association (EWEA) wind energy is expected to contribute with 15.7 to 18.4% of EU's energy demand (EWEA, 2011) in 2020.

Large wind power penetration and efficient wind farm operation require early consideration of the impact of wind power deployment from site to regional/country and continental levels. Spatial planning aspects are typically considered during the resource assessment phase, when wind energy prospecting meets the geo-political and environmental constraints of the area of interest. This activity is aided by the use of a wind atlas embedded in a geographical information system (GIS, see for instance: Dutra and Szklo, 2008, Dvorak et al, 2010) that, in a layered format, accounts for all the geographical information relevant for wind energy deployment: wind resource, terrain elevation, land use, political boundaries, transmission lines, environmentally restricted areas, etc. The wind resource layer is traditionally reduced to two variables: the wind speed and the wind power density, both averaged over the expected lifetime of the wind farm which is set to 20 years. This very limited information is useful to classify a site in terms of energy potential but does not include any information about the quality of this energy in terms of grid integration, turbine safety or operational costs. Only by introducing wind power variability and predictability aspects in spatial planning tools it is possible to obtain an integrated vision of the value of wind energy throughout the live cycle of the development. This enriched wind atlas allows a more comprehensive planning of wind energy deployment considering all the stakeholders interests in a seamless framework.

The aim of this paper is to explore the added value of introducing wind power variability and predictability in the wind resource assessment phase for spatial planning purposes. A summary of the results obtained in the framework of the EU project Safewind is presented. Case studies are described with different end-user perspectives at different scales, from the large European scale to the site level in connection to wind turbine safety.

1.1 Motivation: The EU-27 Wind Atlas

In 2010 the European Wind Energy Technology Platform (TPWind) coordinated the launch of the European Wind Initiative (EWI), as part of the EU Strategic Energy Technology Plan (SET-Plan) and one of the most important instruments to support the development of wind power in Europe. The objective of EWI is to focus available R&D funds on a strategic research agenda in order to increase the efficiency of public funding. One of the top priorities of this initiative, also shared by the European Energy Research Alliance (EERA), is the development of a new EU-27 wind atlas that replaces the only existing public atlas of European coverage (12 countries) published by Risoe National Laboratory in 1989 (Troen and Petersen, 1989).

The aim of this new EU-27 wind atlas is to extend the traditional capabilities of a wind atlas to cover not only the planning phase but all the stages of the life-cycle of a wind farm project (prospecting,

design, development and operation). As such it shall include comprehensive information relevant to all the stakeholders (wind farm developers, turbine manufacturers, investors, system operators, decision makers, etc). This integrated approach will contribute to more detailed and comprehensive spatial planning with less uncertainties resulting in significant reductions of the cost of wind energy.

The enriched wind atlas includes the following relevant aspects: wind resources, extreme winds, turbulence characteristics, probabilities of adverse weather conditions (icing, electrical storms) and the level of predictability for short term forecasting. This paper addresses two of these aspects: extreme winds and predictability putting a value on the various uses of these parameters during the planning phase and providing some indication about the associated accuracy expected from state-of-the-art models.

1.2 The Model Chain in Wind Resource Assessment and Forecasting

All the application-scales are meteorologically interrelated in space and time. Hence, a chain of meteorological models constitute the core of a wind atlas. Numerical weather prediction (NWP) models are driven by Global Circulation Models (GCM) outputs produced by met-offices like NCEP/NCAR in the United States or ECMWF in Europe. GCMs are used, with data assimilation systems, to resolve the large scale fields of the weather, at resolutions of several hundreds of kilometres, in order to define the state of the atmosphere at typically 6-hourly intervals (so called analyses). NWPs operating at regional scale further refine the weather patterns to produce forecasts at mesoscale level, at resolutions of several kilometers and hourly time steps. Even though there are mesoscale models that can proceed with physical downscaling to microscale levels, due to the computational cost, all the sub-grid scales are not resolved but rather parameterized, i.e. semi-empirical formulation is used to fill the sub-grid gap which is not simulated by the meteorological models.

NWP outputs are used to feed forecasting models that make the translation of the meteorological variables to wind power. This translation can be done by physical or statistical downscaling although typically a combination of both is normally adopted for sake of efficiency. Physical downscaling requires resolving the dynamics of the physical processes that are relevant for the scale of the application. At sub-kilometre (microscale) resolution this type of modelling becomes very costly and statistical methods are adopted.

Microscale models are used to correct the errors of mesoscale models especially in areas of complex terrain. These models introduce speed-up factors to account for the sub-grid terrain elevation and roughness differences and derive wind speed predictions at site level with a spatial resolution of the order of 100 m. Computational fluid dynamic (CFD) models can be used at microscale level but at much higher computational cost that their linearized counterparts. Linear models like WAsP can translate local wind speed predictions at hub height to wind farm power output making use of the theoretical power curve of the turbine and estimating the wake losses within the array of turbines. This methodology produces wind power forecasts making use of global inputs and static data of the wind farm, i.e. the layout positions and the turbine specifications. Hence, it is suitable for mapping purposes at high resolution.

When dynamic data from the wind farm is available in almost-real time it can be used to build statistical models, so called Model Output Statistics (MOS), which act as a transfer function between the NWP outputs and the wind power predictions. These tools are more efficient than full-physical models and have proven very effective at removing systematic errors coming from both the NWP and the wind farm power curve. This is the standard approach for operational short-term deterministic wind power forecasting. Probabilistic forecasting constitutes an important field of research as it allows the introduction of uncertainty in the prediction. An up-to-date review of wind power forecasting models can be found in Giebel et al. (2011) and Foley et al. (2012).

In the context of spatial planning, real-time (operational) forecasting is not at stake since the aim is to produce lifetime integrated values. Instead, forecasting models are used like wind resource assessment models in hindcast mode, where a long-term integration of historical data is used to produce the most likely wind statistics of the area of interest.

When a GCM is used with a data assimilation system in hindcast mode a reanalysis is produced, such as ERA-40 (Uppala et al., 2005) or ERA-Interim (Dee et al., 2011) from ECMWF or the NCEP/NCAR

reanalysis (Kalnay et al., 1996). The integration period extends back in time for several decades at resolutions of the order of 100 km. Since reanalyses are produced using fixed, modern versions of data assimilation systems developed for numerical weather prediction, the databases are more consistent in time than analyses and are more appropriate products for long-term climatological studies such as wind atlases. Consistent with this philosophy, an enriched wind atlas model chain is driven by a global reanalysis and stores time series of the most relevant parameters for wind energy planning at the highest resolution of practical use, say 1 km. Such database shall be updated regularly in order to improve its long-term representativeness and run concurrent with new wind energy developments.

Wind atlas outputs can be used by microscale models to further downscale the wind resource and produce parameters relevant to site assessment like turbulence intensity, wind shear and extreme wind speed (Vref). Vref is directly related to the design conditions of a given turbine class according to the IEC 61400-1 standard (IEC, 2005). It is defined as the value of the highest wind speed, averaged over 10 minutes, with an annual exceeding probability of 2%, i.e. a recurrence period of 50 years. Hence, Vref assessment is also a predictability issue, related to both the log-term climatology and the local turbulence characteristics of the site.

2. The value of Predictability in Spatial Planning

The spatio-temporal characteristics of wind predictability can be exploited to contribute to a more efficient and secure integration of wind energy in the power grid. Hence, smart consideration of meteorological aspects can not only promote optimum use of the wind energy potential but can also contribute to important savings in operational costs. For instance, at site level, It is possible that the market value of wind power of a certain wind farm decreases if the wind power day-ahead wind power predictions are very inaccurate although the wind resource is very good.

At larger scales, temporal variability decreases and predictability increases due to spatial error smoothing, i.e. the correlation between forecast errors becomes weaker with distance and the predictability of a region is always better than that of a single wind farm (Focken et al., 2002). Hence, a large wind power operator finds market benefits in distributing the wind farm portfolio along large areas whose wind patters are maximally uncorrelated. This way, a compensation of forecasting errors takes place and leads to significant improvements in the aggregated predictability and market revenues. This portfolio effect is also beneficial for the TSOs in reducing the balancing costs associated with reserves and congestion management. This can be especially advantageous in the development of a European grid with a unified energy market, where strong cross-border interconnections allow an efficient exchange of energy across the EU. Hence, higher penetration of renewable energy generation is possible, reducing energy supply risks and lowering the electricity prices (EWEA, 2009; Rombauts et al., 2011).

Improvements in day-ahead wind power forecasting were very significant in the first decade of 2000. Lange et al. (2006) report wind power forecasting errors (RMSE in % of installed capacity) in the E.ON Netz area of the German grid improving from 10% in 2001 to 6.5% in 2006. For Germany this error is of the order of 5% while for an individual wind farm in complex terrain the error can be as high as 20% (Giebel et al., 2011).

2.1 Wind Power Predictability Mapping

While the wind resource for Europe is already known to a great extend, mesoscale modelling and forecasting gives us an opportunity to consider forecast skills as well. In this context the COSMO-EU mesoscale model (COSMO, 2011) wind speed data was utilized to create a spatial dataset of different forecast skills and visualize those in form of European predictability maps. To demonstrate spatial smoothing effects (Focken et al., 2002), a smoothing of the data was performed, to reduce forecast errors.

The COSMO-EU model resolution is 7 by 4.1 km. The wind speed data was converted to wind power, using a typical power curve, which is the mean of two turbine types: Vestas V90/2 and Enercon E82 . This virtual wind power data then serves as input to calculate the mean absolute error (MAE) and the root-mean-squared error (RMSE). The wind power data has been normalised with the load factor (yearly averaged capacity factor).

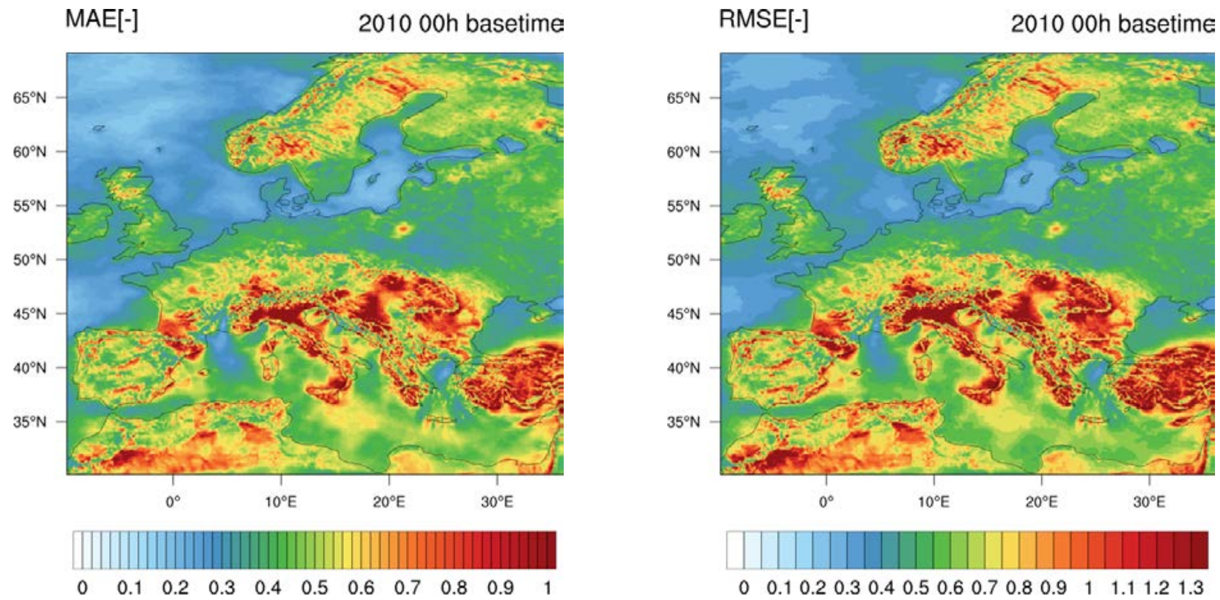

Figure 1: MAE (left) and RMSE (right), both normalised with the capacity factor for forecast day 2 for 2010.

The MAE (Figure 1) shows significantly smaller values offshore than onshore, especially in Northern Europe. The more complex the terrain is, the larger the MAE. The same is valid for the RMSE which is more sensitive to more extreme values. MAE and RMSE are influenced not only by the orography but also by local meteorological phenomena. One example is the Mistral wind in the Rhone Valley in southern France. The Mistral occurs rather frequently, provided that there is a high pressure system in the Biscayan Region and a low pressure system in Central Europe. The tunnelling effect of the Rhone Valley increases wind speeds in these regions and wind is blowing out far into the Mediterranean Sea. As a result, forecast errors are small in the Mistral regions. Another meteorological phenomenon in the Mediterranean is the Cut-off low, also named cold air pool. Cold air pools develop when a trough from the polar belt is cut off from the main flow. If this upper low pressure zone reaches warm water, as it is the case in the South of Italy, it develops downwards to the ground. This ground low is difficult to forecast, resulting in high forecast errors.

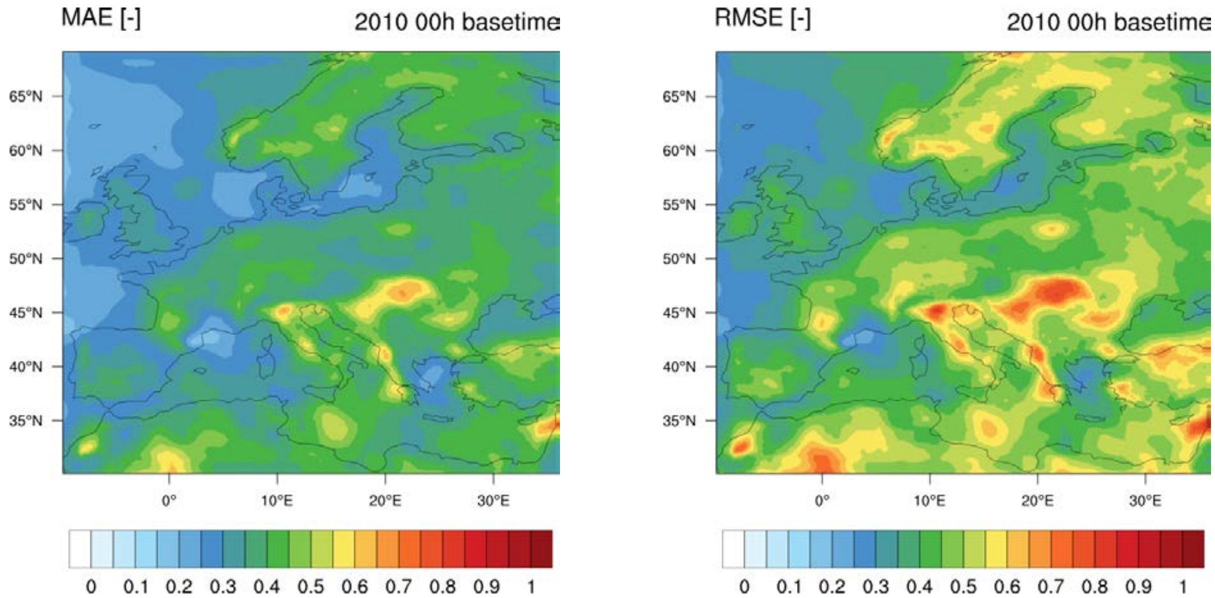

Figure 2: 100 km radius smoothed MAE (left) and RMSE (right), both normalised with the capacity factor for forecast day 2 for 2010.

To analyse the effect of spatial smoothing an averaging algorithm was applied on the grid point wind power forecast and analysis data for every time step. Afterwards the forecast skills were calculated again out of the smoothed data (Figure 2). The error smoothing was performed over a radius of 100

km centred at each grid point, which is approximately the size of a small TSO zone. To quantify the effect of smoothing, the so-called smoothing factor was calculated. This is the ratio between the smoothed forecast error and the grid point based forecast error. Both, the smoothed MAE and the smoothed RMSE show a decrease of up to 60 % in some regions compared to the gridded data (see smoothing factor of the RMSE in Figure 4). Especially for the coastal waters of the North Sea and Baltic Sea the smoothing effect results in 60 % forecast error reduction, which is of great interest for offshore planning. This result is very promising when the aim is not to forecast the wind power for a single wind farm but rather for a portfolio of wind farms spread over larger regions. This reduces not only the variability and the forecast error, but also the need of adding other forms of energy to the grid to compensate for the fluctuations in wind power generation. In the future the demand of storage capacity may also be decreased by pooling wind farms together.

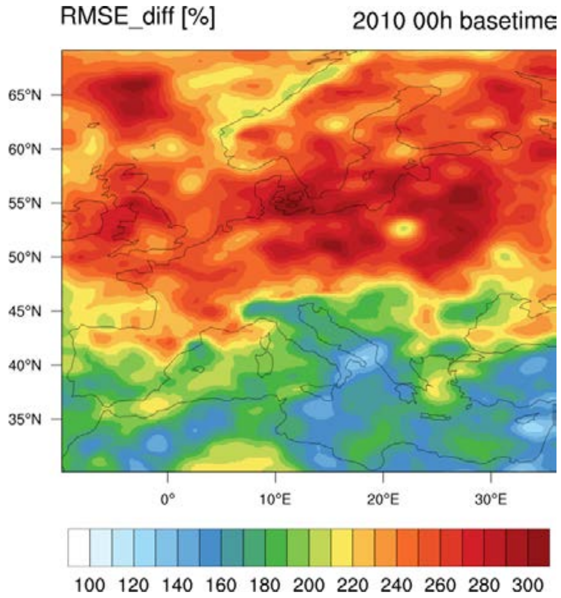

Figure 3: Difference between the 100 km radius smoothed RMSE of forecast day 3 and forecast day 2 in percent for 2010.

In some regions the error growth from forecast day 1 to forecast day 3 is larger than in other regions (Figure 3). Especially the Baltic Sea is characterized by an error growth of up to 300 %. The error growth is largest in regions where the initial forecast error is small due to local conditions like small roughness or flat terrain. In these regions the error grows rapidly beyond day 2 due to amplification of initial condition errors in the forecast model.

2.2 Planning Based on Predictability

In terms of resource assessment the knowledge of the capacity factor is of major interest. But small variability and forecast errors as well as a decorrelation to the surrounding area and the smoothing factor will also help reducing the costs of wind integration. Therefore these forecast skills can be combined to form a metric that can be used to find places of interest for wind farm deployment. To demonstrate this approach, forecasts for a real TSO zone are performed with the original distribution of wind farms and a redistribution according to a predictability-based metric.

As in the previous chapter, the COSMO-EU model is utilized to compute the metric. The 100 km radius smoothed RMSE (Figure 2) and the correlation of the analysis are given a weight of 10 % while the focus of the metric lies on the smoothing factor with 80 %. The resulting metric can be seen in Figure 4, where the best areas for wind energy deployment would be found where the metric has the lowest values.

To quantify the results of the metric, forecasts for the German Tennet TSO zone are performed. The real distribution of the installed power in the zone is compared to a new optimised redistribution based on the new predictability metric (Figure 5). The redistribution shows that if the wind farms had been arranged differently during the resource assessment phase, the forecast error would have been reduced.

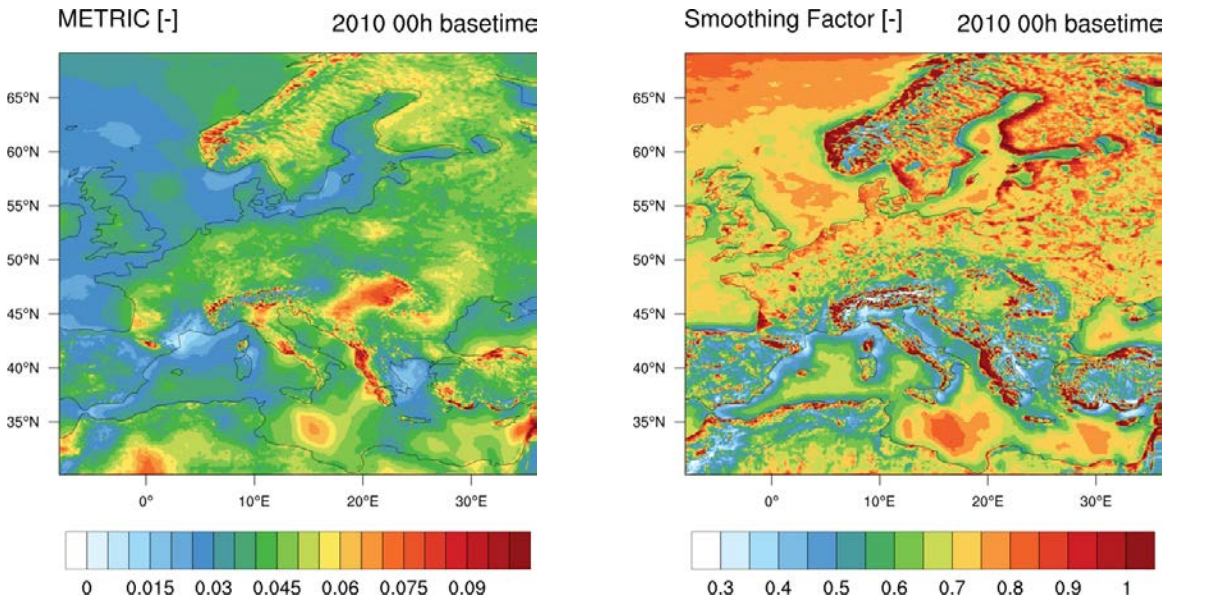

Figure 4: Metric (left) of the 100 km radius smoothed RMSE for forecast day 2 normalised with the load factor (10%), the 100 km correlation (10%) and the smoothing factor of the RMSE (80%). Smoothing factor of the RMSE (right).

The results with the new distribution for the Tennet TSO zone can be seen in Figure 5. The Tennet zone is a very wide spread zone reaching from the windy North Sea coast to the South of Germany, which is characterized by complex terrain and lower wind resource. In the original distribution, the largest amounts of installed capacity are concentrated along the North Sea Coast. This leads to a high output of wind power over the year but also results in high forecast errors due to the large coastal wind variability. After the redistribution, the highest capacities are still concentrated in the northern part of the zone, but are more separated from the coastline.

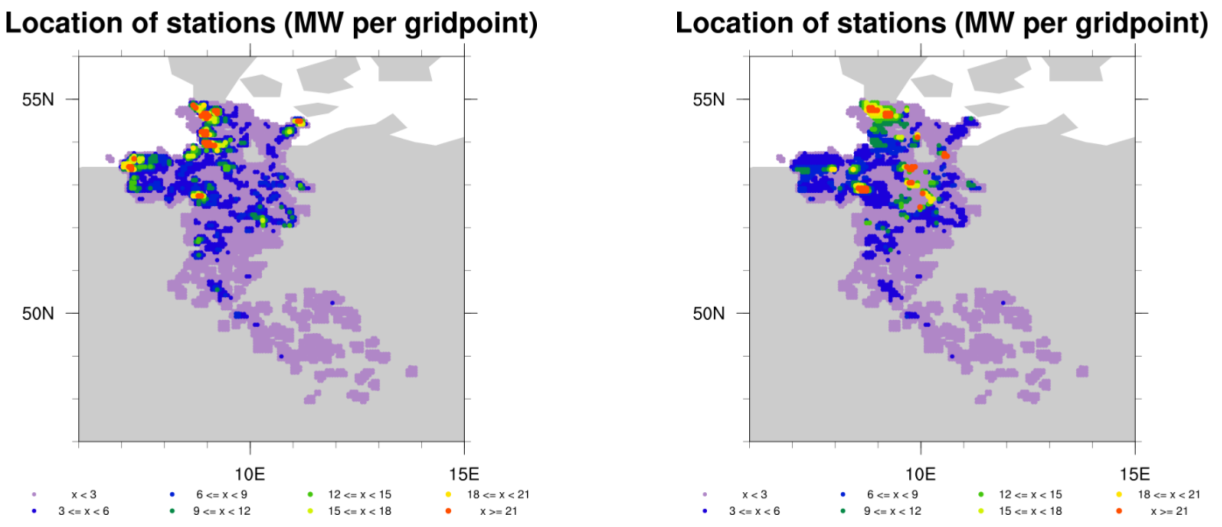

Figure 5: Original distribution of MW per grid point for the Tennet zone (left) and redistribution according to the predictability-based metric (right).

Finally, the COSMO-EU forecast and analysis data is utilized, in order to calculate the wind power error for the TSO zone. The largest forecast errors occur for high wind speeds and hence large wind power outputs. Therefore, only wind power values larger than 6000 MWh are considered for calculating the forecast step depending RMSE. The results are shown in Figure 6. While the RMSE values for the original distribution and the new distribution are almost the same for forecast day 3, the RMSE of the new distribution is slightly smaller for the first two forecast days. The average RMSE of all three days is 0.0827 for the original distribution and 0.0821 for the new distribution. This leads to a reduction of the RMSE of 0.73 %.

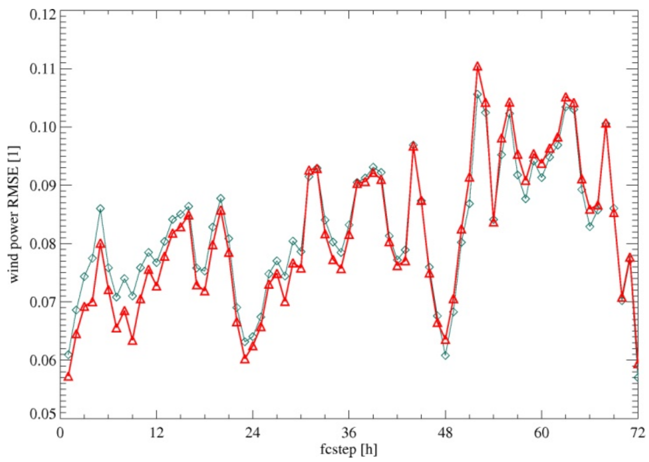

Figure 6: Forecast step depending RMSE normalised with the load factor for the Tennet zone for the original distribution (green) and the redistribution according to the metric (red).

While the forecast error was reduced, the overall wind power production was reduced as well by 1.29 % for values larger than 6000 MWh. This is a logical consequence, regarding the fact that wind power generation and forecast error are strongly correlated and the metric prioritizes sites with low wind power forecast error. More elaborated metrics would integrate wind resource and predictability information among other planning factors to compute the cost of wind energy and produce integrated feasibility maps.

2.3 Predictability in the Decision Making Process of a Wind Energy Developer

Girard et al. (2012) analyzed the financial benefit of increasing predictability from a producer's point of view. The analysis was based on a simplified market model with real-world wind power production and day-ahead market data from the Elspot market. The considered study builds upon a case study in Western Denmark. This area is characterized by high wind potential and rather flat landscapes. It was chosen due to the high number of wind farms located there and the existence of sufficiently long tracks of data (4 years) to permit us to produce results with a statistical meaning. The considered wind farms are represented in Figure 7.

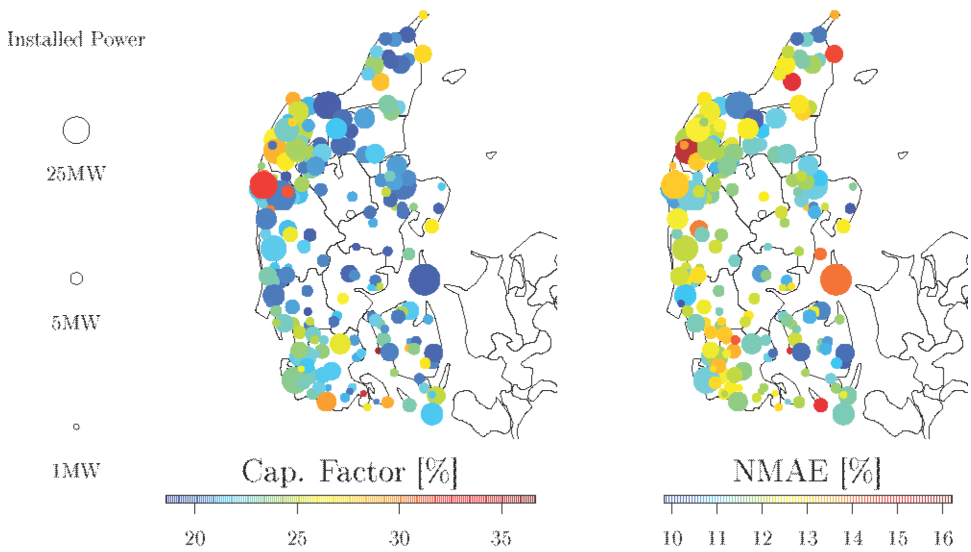

Figure 7: Location of the wind farms in the case study of Western Denmark. Circle size represents installed wind farm capacity. The colour code gives the capacity factor (left), as well as the day-ahead NMAE (right), both in [% Nominal Power]

It is shown that the financial loss due to imbalance costs, induced by imperfect predictions, represents a low share of revenue in the day-ahead market. Only an increase in predictability resulting from aggregation could lead to a substantial increase in benefits. In this paper, the potential gains have

been quantified through the modeling of the relationship that exists between total revenue, the capacity factor and predictability. The results are shown in Figure 8.

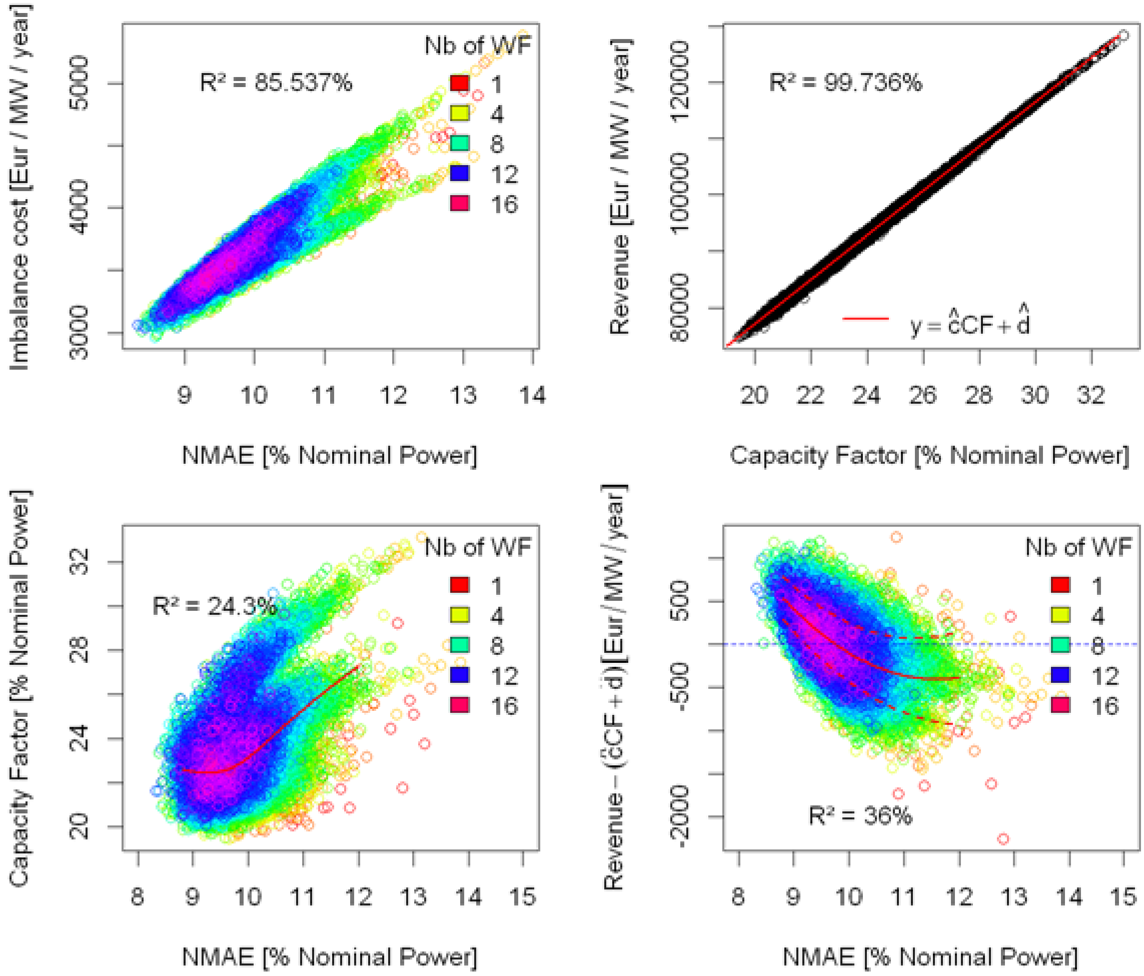

Figure 8 Relations between capacity factor, imbalance cost, revenue, predictability, and the number of wind farms in the portfolio. The solid red lines in the two upper graphs are obtained through linear regression (the corresponding determination coefficients are given). For the bottom-left plot, it is obtained using local polynomial fitting, while for the bottom-right plot it is obtained through second-order polynomial estimation (associated R^2 is given). The red dashed lines on the right give the conditional quantiles (90% upper and 10% lower) obtained with second order polynomial models. The color code gives the number of wind farms within a given cluster.

The associated sensitivity analysis showed that in a case when aggregation is not considered, only 0.02% of the revenue's variance can be explained by predictability, while in a case where aggregation is considered, this proportion reaches 0.15%. This low benefit from predictability is explained partly by the level of imbalance costs and partly by the strong positive correlation that exists between prediction errors and the capacity factor. Ultimately, this implies that in the resource assessment phase, lower predictability will typically go hand in hand with a high associated capacity factor. This makes predictability less relevant than capacity factor in the resource assessment phase, at least from a wind power producer's point of view. Note that there is a difference between considering predictability in the resource assessment phase and considering predictability for an operational wind farm. In the second case, not treated in this paper, the capacity factor is fixed and the role of predictability is different.

Market imbalance cost reduction is not the only benefit a wind power producer can obtain from predictability. Within the operation and maintenance cost breakdown, predictability can play a more important role, especially for offshore wind farms, where the lack of predictability leads not only to market imbalance costs but also to loss of availability due to downtime periods (turbines not accessible due to bad weather that was not well predicted in the maintenance strategy). Still, apart

from specific rules in tenders for wind power installation projects, market imbalance costs constitute the only incentive for producers toward achieving more predictability.

While the results of this paper show the market's incentive action on wind power producers towards achieving greater predictability, it does not quantify the benefit of predictability from the system's point of view. Indeed, the effectiveness of the market measure does not necessarily coincide with the value of predictability with respect to the electric system, and might miss the benefits and costs brought about by longer-term investment. Further work should contain a systemic analysis in the spirit of the capacity value (Keane et al., 2011), in order to reveal the intrinsic value of increasing predictability for a given system at a given level of predictability.

Girard et al. (2012) also provided a prospective analysis, based mainly on the relationship that exists between imbalance prices, spot prices and aggregation of prediction errors in the system. Under the assumption that the market mechanism will remain the same in the future, it is shown that the benefit of predictability for an independent producer participating in the electricity market is unlikely to increase.

It is also shown that the obtained results would not be different with a larger spatial smoothing effect that could result from the consideration of a larger area. However, this result depends on the analyzed Nordpool market. Alternative market mechanisms, e.g. based on nodal pricing, would most likely give fundamentally different results. The analysis of such cases w.r.t. predictability makes part of the perspectives of this work.

2.4 Portfolio Effect in Wind Energy Trading

It is well known by wind farm operators that higher revenues are obtained by participating in the energy market with a cluster rather than with the individual wind farms, a process sometimes called upscaling. Due to error compensation from uncorrelated predictabilities, the aggregated is almost always lower than the individual predictability. For an optimum portfolio effect, the operator must know how to combine the wind farms in terms of the economical impact in the market.

Focken et al., 2002 analyzed the effect of spatial smoothing on wind power predictability over German regions. The analysis showed that the magnitude of the error reduction depends more on the regional size than on the number of wind farms. For a region of a diameter of 370 km an error reduction of 63% was found by aggregating predictions from 50 sites. Above this number a saturation level is reached where the error cannot be further decreased by aggregation. Extending the influence area beyond national borders is definitively an appealing perspective in order to further decrease the error reduction.

In support of the findings of Focken et al. (2002), a case study is presented next in order to illustrate how this portfolio effect works in practice and put in value the extra benefits found when participating in a hypothetic European market instead of a national market. Let's assume that the Iberian electricity daily market rules are adopted, wherein the market operator sets an hourly electricity price as well as imbalance tariffs for down and up-regulation. If the system in a specific situation requires up/down-regulation and the electricity producer is below/above the forecasted (traded) production, a penalization will be issued which is proportional to the deviation and the cost of regulating up/down. Likewise, the operator can obtain profit from deviations that go in favor of the system regulation.

An Irish operator owns 12 wind farms, totalling 202 MW, in Ireland and Northern Ireland and participates in the Irish electricity market. He has the opportunity to buy several wind farms in France (3) and Spain (2) and participate in the European market with 284 MW. He wants to assess the benefits of the portfolio effect when participating in the Irish and the EU markets. To this end, the (Iberian) market tariffs along the year 2008 are used to assess the economical impact of different clustering scenarios. A synchronized database of wind farm productions from these 17 wind farms is used together with their respective wind power forecasts produced with CENER's LocalPred model (Frias et al., 2009). The integrated capacity factor is 0.25 for both the Irish and the EU cases.

The optimization of the clustering process begins by selecting one wind farm as a seed and then aggregating sequentially the wind farm whose combination with the cluster results in the highest predictability. This optimization variable is monitored with the day-ahead mean-absolute-error, normalized by the rated power of the cluster (*NMAE*). The lack of predictability results in system imbalance costs and penalties for the wind energy operator. The cost of predictability is measured as

the difference between the final profit from the market and the profit for perfect prediction. Figure 1 shows the NMAE and the cost of predictability in €/MWh for the Irish and EU test cases.

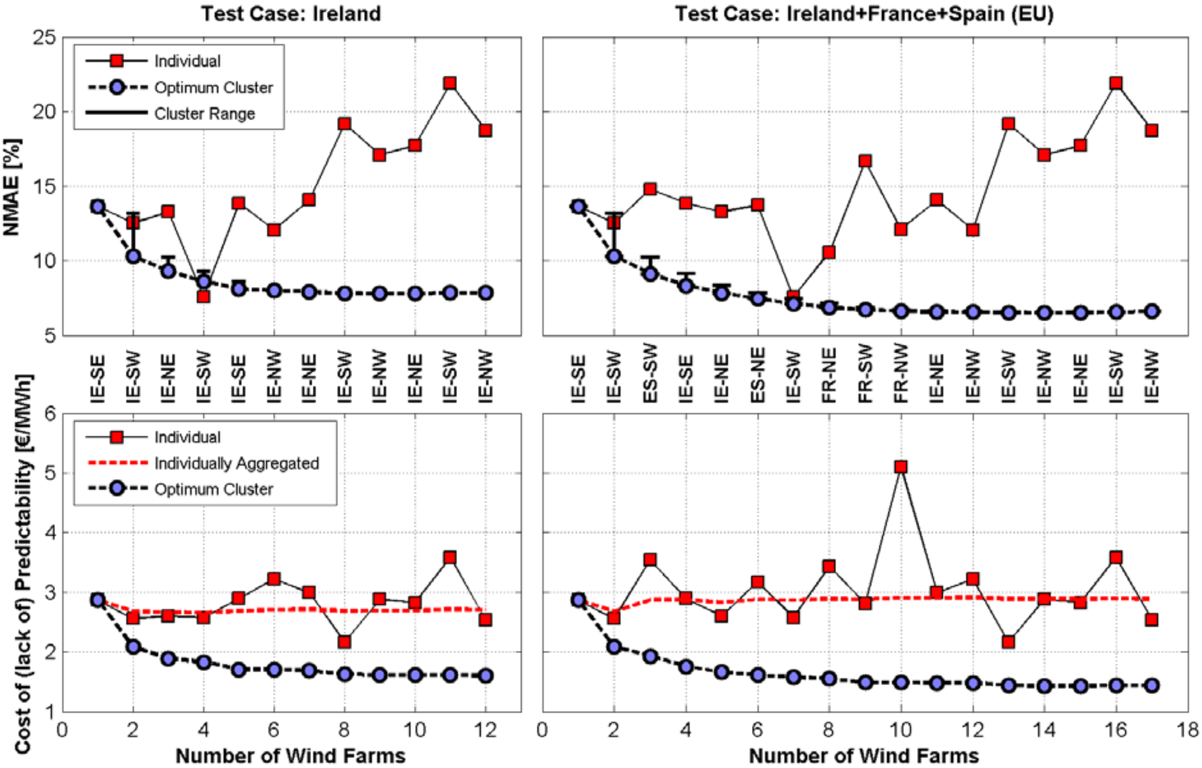

Figure 9: Predictability in NMAE (up) and cost of the lack of predictability (down) for the Irish (left) and EU test cases when participating in the market with individual wind farms and with optimum clusters. The geographical location of each newly aggregated wind farm to the cluster is provided between the upper and lower graphs (IE: Ireland, FR: France, ES: Spain)

The individual wind farms have predictabilities in the range 7.5-22%. A wind farm situated in the SE quadrant of Ireland and having a predictability level close to the mean value of this range is selected as seed for the optimization process. By combination of this wind farm with each one of the other farms of the portfolio reductions in the *NMAE* of 1 to 3.3% are observed. The pair with the lowest *NMAE* is selected and the clustering process continues by adding a third wind farm and so on. In the Irish case, the *NMAE* finds a minimum after adding the ninth wind farm with a cluster predictability of 7.8% (error reduction of 42%). Adding more wind farms results in a slight increase of the error (error saturation due to lack of uncorrelation in the ensemble). It is not surprising that the wind farms with the largest errors are added at the end of the optimization process.

In the EU scenario, the operator includes two wind farms in Spain and 3 in France extending the spatial coverage of his portfolio to a wider range of wind climates. The wind climates of the North and South of Europe are characterized by a mean synoptic weather activity of opposite sign typically resulting in optimally uncorrelated winds. As a result, the cluster predictability can be further reduced to 6.5% (error reduction of 52%), obtained after aggregating the 14th wind farm. The economic impact of the portfolio effect results in penalties of 1.62 and 1.43 €/MWh for the Irish and EU cases respectively, while if the individual wind farms participate in the market the penalties range from 2 to 5 €/MWh. It is worth noticing that the 10th wind farm added to the EU cluster has the maximum individual cost with a moderate predictability level. This is due to a particularly unfavourable combination of forecasting errors and balancing costs in this particular yearly integration. When this wind farm participates in the cluster, this high individual cost in fact produces a slightly positive economic impact.

In terms of the revenues obtained by the operator for year 2008, considering perfect prediction the total profit would be 13.9 and 19.3 M€ for the Irish and EU cases. The lack of predictability respectively results in 0.63 (4.53%) and 0.94 (4.86%) M€ losses if individual wind farms participate in the market and 0.37 (2.69%) and 0.47 (2.42%) M€ losses if participating with the optimized cluster. The savings introduced by the portfolio effect are therefore not negligible: 0.26 and 0.47 M€/year (if

2008 is considered a representative year). The wider the spreading of the wind farm distribution across Europe is, the better performance of the portfolio effect.

3. The value of Extreme Wind Predictability in Site Assessment

The assessment of the 10-min averaged 50-year return wind, so called Vref by the IEC 61400-1 standard, has been traditionally based on extreme-value-analysis (EVA) statistical techniques applied to historical velocity time series (Palutikov, 1999). Regardless of the statistical tool, the classical method is always limited by the short length of the observational time series, the lack of long term homogeneity of the instruments or of the site conditions and, above all, the scarcity of high-quality historical observations. Furthermore, national observational networks are not maintained in the same way which brings consistency problems at trans-national level.

This lack of long-term spatio-temporal consistency of the observational networks shall be remedied by using meteorological models forced by global reanalyses that are precisely built to produce a long-term consistent description of the state of the atmosphere. Larsén and Mann (2009) examined reanalysis data for their applicability in extreme wind assessment. When the wind climate is synoptically dominated like in Denmark, these meteorological products can be directly linked with a microscale model and produce fair estimates of Vref.

When mesoscale and local effects add to the synoptic wind climate, reanalysis cannot be used directly due to the coarse grid of the model. To overcome the lack of resolution of global models, physical and statistical downscaling methods are used. Physical downscaling does not require the use of site measurements and, therefore, it is suitable for producing wind maps and virtual mast data, i.e. long-term time series that can be used by EVA techniques. As onsite measurements become available, statistical downscaling by correlation techniques with the virtual time series can significantly improve the assessment of Vref without the need of long historical observations.

Vref, together with turbulence intensity, are used by wind farm developers and turbine manufacturers to determine the wind turbine class that can be installed on a specific site. Site assessment will always require onsite measurements in order to certify the wind conditions of a wind farm project but, having an early prediction can be very useful for spatial planning. For instance, a wind turbine manufacturer can be interested in regional site assessment in order to evaluate the most frequent design conditions of a country and decide on market deployment strategies.

3.1 Extreme Wind Mapping in Simple Terrain: Denmark

For extreme wind mapping over a relatively large area, Larsén et al. (2012a) developed the so-called “selective dynamical downscaling method” which is briefly described next.

For a chosen area, the annual strongest storms are identified from the global data for each grid point within the area. The identification of the storm episodes is done through the geostrophic wind and the surface winds by selecting the dates where the annual maximum winds occur. The mesoscale Weather Research and Forecasting (WRF) model is then used to simulate the storm episodes using the NCEP Final Analysis (FNL) as forcing mechanism. The FNL data are chosen as the boundary and initial conditions for the WRF modelling because of the good storm structure embedded due to the relatively fine horizontal resolution (1°) in comparison with the NCEP/NCAR reanalysis data (2.5°). Since the FNL data are available from 1999, storms within the period 1999 – 2011 can be simulated. For the chosen area for the Denmark case, during the period 1999 – 2010, there are 59 storms identified and modelled at a horizontal resolution of 5 km and the outputs are saved on 10 min basis. For each mesoscale grid point, 12 annual wind maxima are found and put into a Gumbel fit to obtain the 50-year wind.

The challenge is how to make use of the extreme winds from the mesoscale modelling to particular sites. Within the selective dynamical downscaling method, a post-processing method was developed to correct the mesoscale winds to a “standard condition”, i.e. 10 m above a homogeneous surface with a roughness length of 5 cm - the “standard extreme winds”. This is the standard input to the microscale LINear COMputational model LINCOM, which is used in the software WAsP Engineering. The same computational codes from LINCOM were used to calculate the mesoscale speedup effects from the topography and roughness as used in the mesoscale modelling. Thus we obtain the extreme wind atlas for an area as shown in Figure 2. The extreme wind atlas can be further used in the

microscale model LINCOM to resolve the local effects around the site. The results are satisfactory for the flat terrain of Denmark and the medium complex terrain of the Gulf of Suez with deviations of less than 10% with respect to the values determined directly from observations (Larsén et al. 2012a).

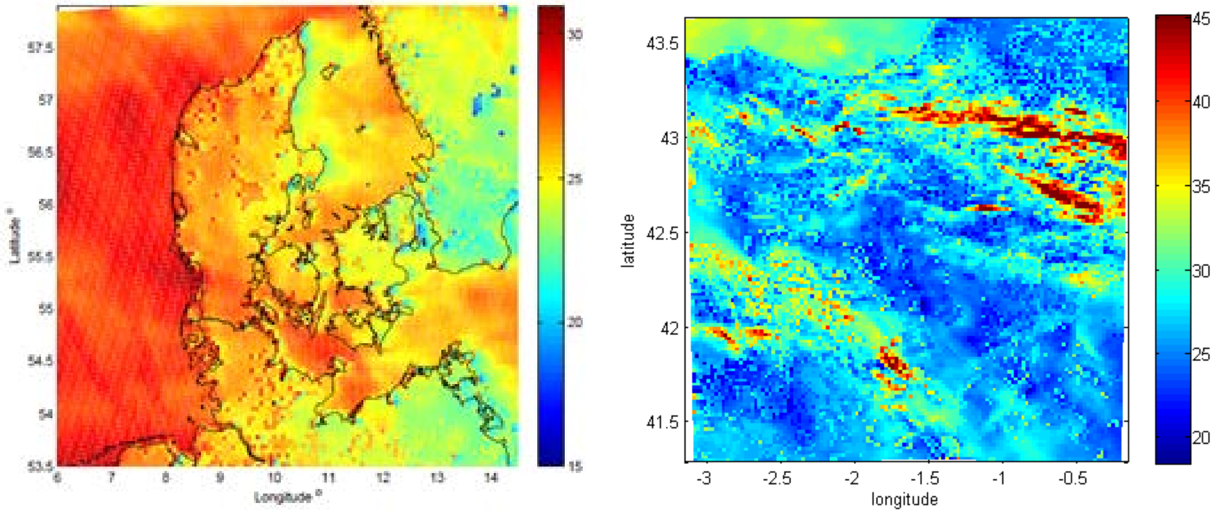

Figure 10: Map of the 50-year wind over Denmark and surroundings (left, from Larsén et al., 2012a) and over Navarre region in the North of Spain (Lársen et al., 2012c)

A second method developed in Safewind for downscaling extreme winds is the so-called "spectral correction approach" (Larsén et al. 2012b). For an area where a mesoscale model has been run to obtain the wind climate for decades, this method can be used to compensate the spectral energy deficit in the high-frequency range, inherent in the smoothing effect of the mesoscale model. If onsite measurements are available, they can be used to better characterize the spectrum from meso to microscale. Otherwise a theoretical decay is imposed.

3.2 Extreme Wind Mapping in Complex Terrain: Navarre (Spain)

The selective dynamical downscaling method has been also applied in the Safewind project to the Navarre region straightforwardly as described in the previous section and reported in Lársen et al. (2012c). The modelling is done with a horizontal spatial resolution of 2 km. The results show better agreement with the measurements in sites characterized by simple to moderate terrain complexity. The crux in the very complex terrain is how to downscale the mesoscale extreme winds to particular sites when the reliability of the linear model is highly questionable. The issues of the linear model in very complex terrain also limit our data validation because we feel reluctant to correct the measurements to the standard conditions using the linear model. Figure 2 shows how Vref varies significantly in space with terrains and roughness, even within a distance of about 20 km.

To overcome the limitations of the linear microscale model, a RIX-based correction is introduced in the downscaling method developed by CENER for the generation of high-resolution virtual time series (Irigoyen et al., 2011). In effect, the RIX index has been effectively used to characterize the complexity of a site at microscale level as a measure of the percentage of surrounding terrain with slopes greater than 30% (Bowen and Mortensen, 1996). Above this limit the flow is likely to detach from the ground, something that linear models cannot handle. The method statistically corrects mesoscale outputs from the Skiron NWP model with local speed-up effects generated with WAsP microscale flow model. The RIX factor is introduced in order to attenuate the speed-up correction in complex terrain, where WAsP is likely to produce over-predictions.

CENER's downscaling technique has proved useful at correcting the large bias of mesoscale models when predicting the mean wind speed in complex terrain sites. It has been shown that the bias is also significantly reduced for the annual maxima and, therefore, reasonably good results are obtained in the assessment of Vref and IEC classification. Figure 3 shows the results of the evaluation of the technique for 11 sites in Navarre region. Together with the Vref values, the RIX index is provided as indicative of the terrain complexity of the sites.

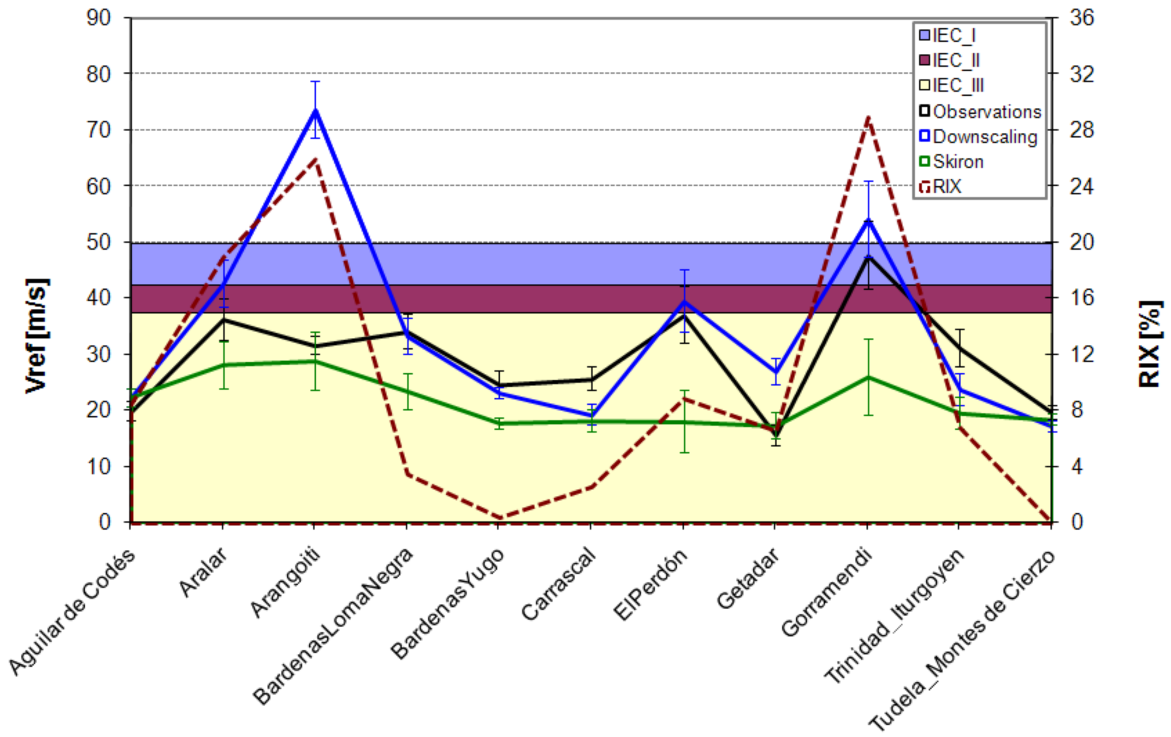

Figure 11: Vref assessment for the Navarre test sites using downscaling from Skiron mesoscale model simulations (from Lársen et al. 2012b). The RIX index on the right vertical axis is indicative of the complexity of the site. The range of each wind turbine IEC class is shown with horizontal bars. Error bars indicate the 95% confidence levels of the Vref value extracted by fitting of the annual maxima to a Gumbel distribution.

Considering mesoscale model outputs alone, without further downscaling, a rather homogeneous value of Vref is obtained which would imply IEC class III for all the sites. In the other hand, the downscaling correction provides a more distinct distribution of the IEC class that takes into account the local site characteristics. Only one of the 11 sites (Arangoiti) missed the right IEC class due to the particularly high sheltered conditions. In well exposed sites, typical of wind energy, the results seem to give consistent results which encourage the development of this technique. Nevertheless, it is necessary to extend the evaluation to a larger number of sites in order to extract more statistically meaningful conclusions.

4. Conclusions

The EU project Safewind represents the state-of-the-art on wind power forecasting in Europe and builds on results from previous EU projects Anemos and Anemos.plus, altogether 10 years worth of research and demonstration activities. An innovative aspect of the project looks into the consideration of forecasting during the planning phase of wind power, the wind resource assessment phase, and how early assessment of the economical and technological impact of wind power forecasting can contribute to better planning decisions.

Spatial planning instruments like wind atlases are progressively integrating more spatio-temporal information in order to build decision-making scenarios that span the lifecycle of wind energy projects. These decision support systems can efficiently promote wind energy based on a comprehensive integration of end-user requirements that considers sometimes conflicting aspects: technological, economic, environmental and social. While the selection of the optimum wind energy locations shall be generally based on reducing the cost of energy, other criteria can be adopted depending on the relative influence of the different aspects at regional level. Nevertheless, regardless of the spatial planning strategy, decisions will be highly influenced by the meteorological fingerprint of wind energy.

Enriched wind atlas products make extensive use of meteorological models that span all the relevant scales of wind energy. The downscaling process implies smart combination of physical and statistical models driven by geographical and meteorological input data. Regardless of the complexity of the models, the background quality of the wind atlas will be always conditioned by the global reanalysis

data, whose quality is progressively improved as larger amounts of data are assimilated at higher resolutions. Nevertheless, data assimilation systems still discard onshore surface wind speed observations due to the influence of local effects that cannot be resolved by the GCM. The input data from GCM is used by NWPs to produce meteorological fields of higher resolution.

At the other end of the model chain, model output statistics have proven very effective at removing errors in wind power prediction by linking NWP outputs and wind farm production measurements. Nevertheless, these corrections cannot go beyond the quality threshold determined by the GCM data feeds, which is typically manifested by an initial step of 5 to 10% error in the first 3 hours of prediction. If higher levels of accuracy are required in this very-short-term range, the forecaster has to progressively decrease the weight of the physical model and rely more on the analysis of the observed time series.

Forecasting models are run on hindcast mode to produce predictability-related information that can be used to anticipate operational costs and produce a better assessment of the cost-benefit of wind energy deployment. Several case studies have been presented to illustrate this approach considering different end-user perspectives.

Meteorological mesoscale models give us the opportunity to evaluate wind power predictability and other forecast skills. In addition to a large capacity factor, small wind variability is also desirable for wind power integration. Hence, the forecast skill maps can provide useful information for spatial planning and to analyse the sources of forecast errors, either by topographical effects or meteorological phenomena.

From the developer's perspective including predictability as a decision factor in the planning phase of a wind farm has a very low weight compared to the capacity factor, which is evidently the main feasibility driver. For the case of Denmark, only when wind farm aggregation is considered, predictability can become more important but only explains 0.15% of the total revenues variance. Nevertheless, predictability can be already assessed during the planning phase to provide an indicator of the quality of wind for grid integration purposes.

A pan-European electricity market offers great advantage for wind energy traders that can benefit from portfolio effects in larger domains. In the case study presented, moving from Ireland to a Western European domain that includes a few wind farms in France and Spain, implies a decrease of around 10% in the aggregated prediction error and in the associated market penalties.

It is necessary to investigate the spatial and temporal variability within the range where mesoscale and microscale modelling should meet, in order to better describe the complexity of the surface conditions and improve flow modelling at high resolution, useful for site assessment. As microscale models are developed for downscaling from NWPs there is increasing interest in using these models also for upscaling, i.e. to link surface observations of wind speed with the NWP fields and correct deviations dynamically. This wind data assimilation capability can be particularly interesting if data from existing operational wind farms is made available to weather services in order to be ingested by the data assimilation stream. Since wind data are precisely located in well exposed sites, representative for wind energy applications, it makes sense to make use of this information in the model chain. As for other meteorological observations, it is necessary that instrumentation, maintenance and data management systems are fit to this purpose in order to ensure minimum levels of quality and homogeneity in the data assimilation process.

Long-term predictability of extreme winds with meteorological databases and downscaling models is also a research area of great potential considering the large improvements observed in global reanalyses. Still large uncertainties are to be expected due to the difficulties of NWPs and microscale models in modelling stormy weather turbulence, especially in complex terrain. Nevertheless, the results obtained in the Denmark and Spain case studies suggest that Vref mapping can be of engineering value during the planning phases of wind energy.

In view of the elaboration of modern wind atlases for spatial planning purposes, it is clearly demonstrated the added value of including predictability of wind power and extreme wind together with the typical wind resource outputs. The result is an enriched wind atlas that can provide a more complete vision of the lifecycle value and cost of wind energy.

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