HRensemble Project Progress in applying short-range Ensemble Forecasts for Offshore Wind Power Predictions

Möhrlen, Corinna[1],Jørgensen, J. U.[1], Pinson,P.[2], Madsen,H[2] , Lange, B.[3] ,Cali,Ü. [3] , Bolding,K. [4] Giebel,G. [5] ,Tøfting,J. [6] ,Runge Kristoffersen, J.[7]

[1]WEPROG ApS, Aahaven 5, 5631 Ebberup, Denmark, Tel. +45 64811863 Fax +45 64712094 http://www.weprog.com < com@weprog.com>, [2]DTU-Informatics and Mathem. Modelling, [3] ISET e.V., [4] Bolding & Burchard ApS, [5]Risø DTU, [6] DONG Energy, [7] Vattenfall

Abstract

In this project we are studying the interactions of ocean and atmosphere by combining developments in ocean, ensemble weather and wind power prediction to create an optimised model system for large-scale integration of wind power. The objective of this project is to generate best possible data for training of different wind to power conversion approaches by new ensemble prediction methods, including coupling of an ocean model with an ensemble prediction system. A 3-year simulation with the 75 member Multi-scheme ensemble prediction system (MSEPS) has been carried out to generate data for training of two new power prediction methodologies, orthogonal fitting and a neural network approach targeted to use ensemble predictions, and simulations with an ocean model. Additionally, the data was used to design an algorithm to conduct future scenarios of on- and offshore integration of wind power. Results from these developments are presented and discussed.

Introduction

The wind farm output of large wind farms change between nearly constant output to highly variable power output. A balance responsible would therefore benefit from knowing the variability of a wind farm in advance. Some understanding of the observed variability and the corresponding forecast error on large wind farms has been gathered in the past few years. In fact, it was found that the size of the wind farm and the average generation (load factor) play a stronger role for the predictability than the location of the wind farm, i.e. whether the wind farm is onshore or offshore (e.g. [1], [2]). Nevertheless, there exist a number of challenges that have impact on the predictability of offshore wind power, such as the sea-atmosphere interaction, correlations of generated power, power curve estimation over sea, and not to forget the integration of offshore wind power that requires intense research (e.g.[3]).

In the following, we describe the first part of the HREnsemble project. We discuss results from an experiment, which aimed to investigate the impact of large-scale integration of offshore wind power in the North sea [7]. Additionally, we describe two new power curve estimation methodology making use of the additional information of the ensemble predictions [4,8] and the challenges associated with the ocean-atmosphere coupling.

Ensemble Simulations covering North Sea, Baltic Sea and Irish Sea

In a first attempt to estimate the impact of the large-scale integration of wind power offshore, we registered all wind farms in the North sea, the Baltic Sea and the Irish Sea that are operational or in the planning state with granted planning permission in the ensemble system and extracted data from ensemble simulations that were generated in the first part of this project over a period of 2.5 years (from September 2004 to March 2007) with WEPROG's Multi-Scheme Ensemble Prediction System (MSEPS).

The simulation contained 75 Ensemble members that were computed over the 2.5 years four times per day with a forecast length of 48h ahead and 30 weather variables, which were stored in hourly resolution from all 75 ensemble members. This simulation was equivalent to 1500 model years: 75fc x 4perday x 2days x 2.5years = 1500 model years.

Point data was generated for 63 partially planned and partially operational wind farm locations in the North sea, Baltic sea and the Irish sea. Among these, 29 locations were in the Danish-German-Dutch part of the Northsea, of which two are operational. In the Irish sea and the UK part of the Northsea there were 19 wind farm locations and 15 wind farm locations were modelled in the Baltic sea.

The Measurements

Measurements for the Horns Rev wind farm were provided by Vattenfall. The Horns Rev wind farm was constructed in 2002. The wind farm is sited in Denmark, 14-20 km into the North Sea, west of Blåvands Huk and consists of 80 2MW wind turbines. The measurements used in this study were from the north-westerly mast. Meteorological data from the FINO1 research platform (http://www.fino1.de) has been used in this study. Access to the FINO1 database has been granted by the German federal maritime and hydrographic agency (BSH),

A future North Sea scenario with 14GW Offshore Wind Power

In order to verify the quality and identify the weaknesses of the ensemble prediction system not only on a single site, but also in a future scenario, we designed a future scenario of 29 wind farm locations in the Danish-German-Dutch part of the Northsea and included the operational Horns Rev wind farm (HRV) and all of those Danish, German and Dutch wind farms that have received planning permission in the second stage. This amounted in a total capacity of 14GW.

The following is a summary of the estimation method, which is described in detail in [6],and [7].

- Long-term simulations covering the North Sea
- Extraction of individual wind farms from the simulation data
- Conversion of wind speed observations to wind power at FINO1 to a 500MW wind farm
- Conversion of wind speed observations to wind power at Horns rev wind farm
- Verification of fitness of generated wind power and measured wind power at Horns Rev
- Computation of forecast correlations between each future wind farm and the FINO1
- Computation of forecast correlations between each future wind farm and HRV
- Computation of the forecast error at FINO1 and HRV
- Computation of the error at each wind farm as a function of FINO and HRV error
- Computation of the produced wind power as the sum of the differences between forecast and computed error at each wind farm

In this computation we do not assume that the weather is correlated, but we assume that the forecast error is spatially correlated. This is a lower approximation level and this means that we do not assume that the wind speed varies linearly in space between the two reference sites. More over we exploit that the uncertainty is dependent on the weather at each location. The error is automatically scaled up if there is a front located in the region also if the front is not visible at neither FINO1 nor Horns Rev. Similar if one of the two reference points have a high instant error due to a front, which is only present at a few wind farms including the reference, then this will be accounted for consistently via the ensemble spread. The estimation method is therefore physically consistent, if the ensemble spread is representative for the uncertainty in the weather forecast. It is important to use time averaged measurements to prevent that the highest frequencies are assumed to be concurrent at all sites. The time scale of typical Planetary Boundary Layer eddies must be filtered out on the reference sites. This was done by time integration of the power computation over one hour.

Results of the Monthly Verification for 14GW wind power in the North Sea

Figure 1 and Figure 2 show the mean absolute error in each month relative to the produced power and the installed capacity, respectively (blue boxes), for the FINO1 wind farm (Figure 1) and the aggregated wind power over the North Sea (Figure 2). The red boxes indicate the average load factor in the respective months. The minimum forecast horizon is 12 hours and the average 15 hours.

There is marginal differences of the error patterns between the single farm and the aggregated wind power. Both show relatively higher error in the low wind speed months (summer), where there is less full load hours and more hours where the wind speed is at the steep part of the power curve.

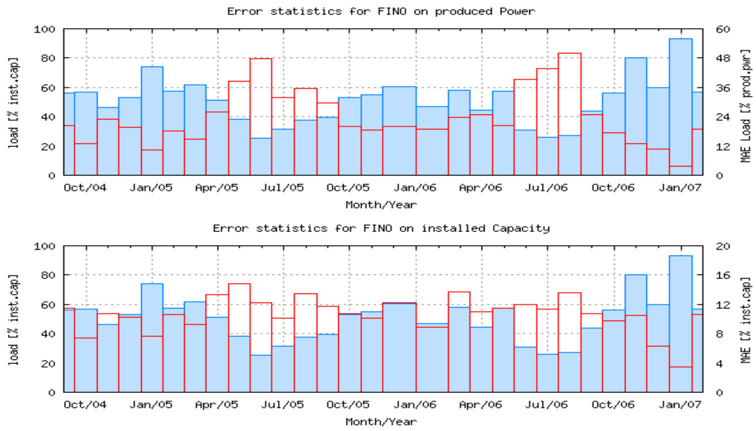

Figure 1: Monthly error statistics for the FINO1 wind farm for the period Sep. 2004 until Feb. 2007. The blue boxes show the mean load, the red filled boxes are the mean absolute error in percent of produced power (upper graph) and in percent of installed cap. (lower graph).

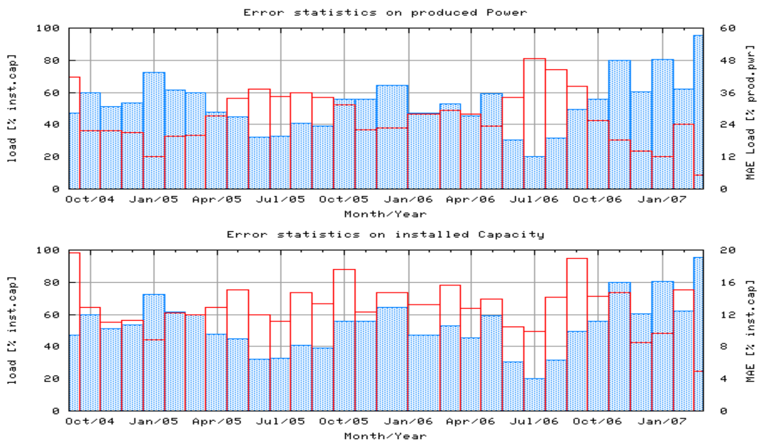

Figure 2: Monthly error statistics for the 14GW North Sea wind power for the period Sep. 2004 until Feb. 2007. The boxes have the same meaning as in Figure 1.

Frequency Analysis

The frequency distribution of the actual generation is computed by counting the number of hours with generation within a certain interval. The possible output values lie between 0 and 100% of the full capacity. This interval is divided into 20 equally sized sub intervals/bins. The number of hours in each bin is then counted for the measurements and the forecasts. Both frequency distributions are normalized to 100.

Figure 3 show the frequency distribution over the verified 30 months for the FINO1 500MW wind farm and the 14GW aggregated North Sea wind power. Ideally the two should be identical, but differences indicate systematic prediction bias errors. It can be seen in Figure 3 (left side) that for a single wind farm the measured distribution follows almost a on/off pattern, indicating that the bulk of the generation is happening at full load. The forecast is more conservative at times with full generation and hence gives zero.
For the aggregated North Sea wind power, shown in Figure 3 (right side), this pattern is changed and the smoothing effect can be seen in a more constant distribution over the range of generation, which indicates that increased offshore wind power integration has a positive effect on the predictability of the generation.

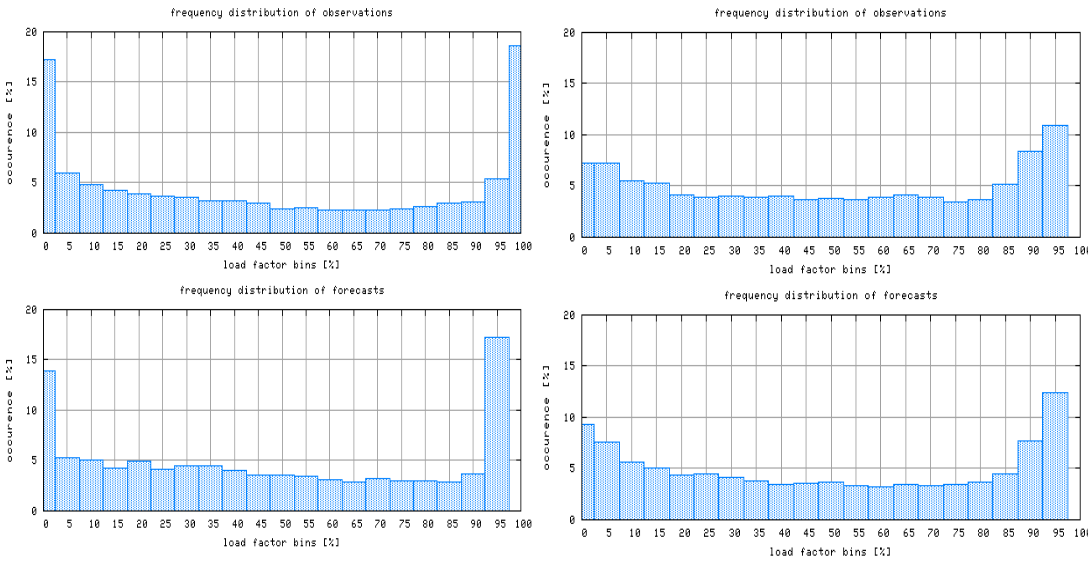

Figure 3: Frequency distribution of the 500MW FINO1 wind farm generation (left upper) and of forecasts (left lower), the 14GW North Sea generation (right upper) and of 14GW forecasts (right lower) in intervals of 5% (0-100%) of inst. cap. (x-axis) and intervals of 5% of freq. (0-20%, y-axis).

Discussion of the North Sea Future Scenario Verification

One of the major drawbacks of large amounts of wind power installed in the North Sea is the high correlation level within. In order to estimate the consequences of the high correlation from a grid security perspective, it is necessary to study the development of the forecasting error over the forecast horizon and the smoothing effect from larger amounts of installed capacity. Since there exists a smoothing effect, and it has been shown that the generation is more constant distributed over the generation range (see and), the installation of larger amounts of wind power is beneficial, also from a forecasting point of view. Nevertheless, there are a number of challenges, such as the stron error growth, that It has been found in the verification of the future North Sea scenario with 14GW that the error growth over the forecast length was stroner than expected. In order get a better understanding a comparison between single and aggrgated wind power at FINO1, the North Sea and other areas has been carried out. Figure 4 shows the error growth at the FINO1 wind farm and the 14GW aggregated North Sea wind power. As expected the FINO1 wind farm has a higher error than the aggregated wind power. However, it should be noted that the error growth of the single farm is nearly parallel to the aggregated wind power, i.e. the error grows with almost the same bias. This confirms our previous findings of the high correlation of the generation offshore, and especially in the North Sea.

Next, we compared the FINO1 wind farm with a coastal wind farm (SA1) of similar size in the South of Australia. Figure 5 shows the error statistic of the two wind farms. While the mean load (gray lines) is slightly higher for the offshore farm, there exists a significant difference in the error growth over sea. Looking at the MAE relative to installed capacity, the SA1 wind farm starts with a significant higher error of almost 2%, the FINO1 farm's error growth is so much higher that is crosses the SA1 farm after 30h and ends with an approximately 1% higher MAE. When looking at the MAE relative to produced wind power, the North sea offshore farm has a constantly lower error than the coastal wind farm. This suggests that the generation efficiency over sea is higher than on land. The nearly constant low bias over sea also confirms this, while the coastal wind farm has an increasingly negative bias over the forecast horizon. Next, we compared the FINO1 wind farm with a coastal wind farm (SA1) of similar size in the South of Australia. Figure 5 shows the error statistic of the two wind farms. While the mean load (gray lines) is slightly higher for the offshore farm, there exists a significant difference in the error growth over sea.

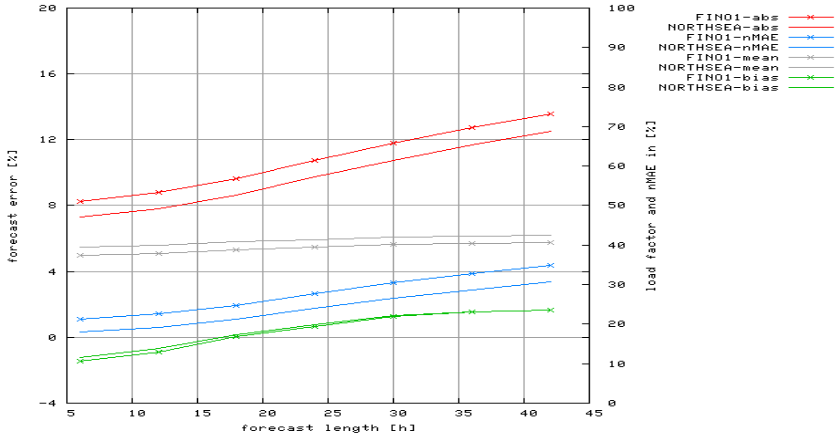

Figure 4: Comparison between 1 Offsore wind farm (FINO1, 500MW) and aggregated offshore wind power at the North Sea (14GW)

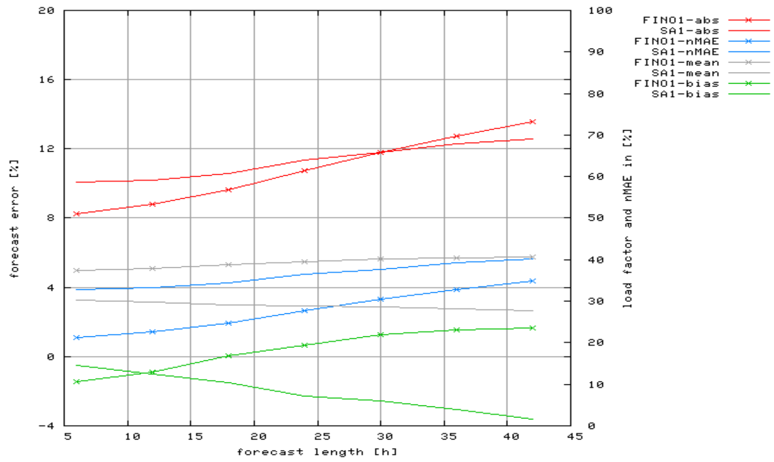

Figure 5: Error statistics for FINO1 wind farm and a coastal wind farm in South Australia (SA1).

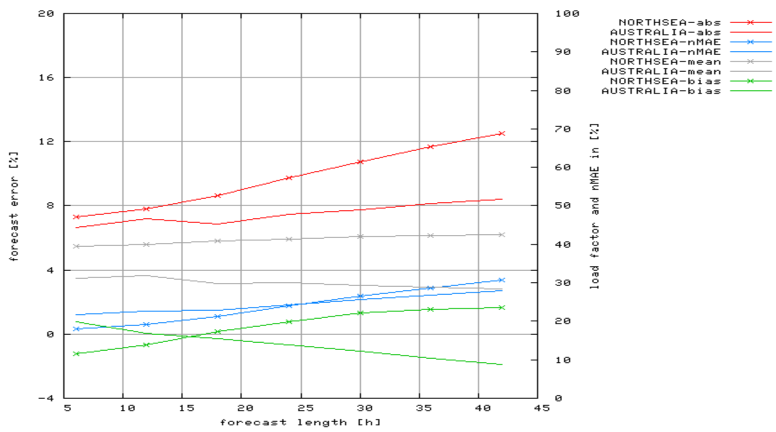

Figure 6: Error statisitcs for the aggregated North Sea wind farms FINO1 and Horns Rev (660MW) and South Australias wind farms (680MW)

Looking at the MAE relative to installed capacity, the SA1 wind farm starts with a significant higher error of almost 2%, the FINO1 farm's error growth is so much higher that is crosses the SA1 farm after 30h and ends with an approximately 1% higher MAE. When looking at the MAE relative to produced wind power, the North sea offshore farm has a constantly lower error than the coastal wind farm. This suggests that the generation efficiency over sea is higher than on land. The nearly constant low bias over sea also confirms this, while the coastal wind farm has an increasingly negative bias over the forecast horizon.

Figure 6 shows the statistics for the sum of FINO1 and Horns Rev with a capacity of (660MW) and the South Australian aggregated wind power with 680MW installed capacity. Although the installed capacity differs by a factor of 2, the comparison was conducted to get an idea of the impact of spacial dispersion. While the offshore wind farms are highly correlated and influenced by the same weather pattern, the Australian wind farms are more dispersed with less correlation and are located in quite different terrain types. In comparison to the single wind farms, it can now be seen that even the MAE (abs) of installed capacity is lower when aggregating the wind power in Australia (compare Figure 4). This also holds now for the MAE related to the produced power. Although the difference is not significant, the onshore wind power generation has a more constant and lower error growth than the offshore wind power and hence ends with a slightly smaller error at the end of the forecast horizon. The significant higher load factor offshore while the forecast error on produced power is almost similar however indicates that the offshore wind power has a higher efficiency.
To conclude, this study has shows that there exists a requirement to study the error growth offshore and to find ways to parametrise the forecasting models with focus on lowering the error growth. If this can be achieved, the higher efficiency of offshore wind power will also be capable of generating the necessary payback for the increased construction, connection and maintenance costs.

New Methodologies of ensemble conversion for power curve estimation
At present two different methodologies are investigated for the conversion from wind to power in this project. The two methodologies are briefly described hereafter. More details can be found in [4,6,7].

1. Orthogonal Power Curve Fitting
Local polynomial regression is an appealing non-parametric approach to modelling a wind farm power curve, for which the model coefficients can be adaptively estimated with recursive Least Squares (LS) methods. An assumption when applying LS estimation methods is that a noise component is present in the response variable only, i.e. the power output in our case. However, it appears unlikely that the forecasts of meteorological variables used as input do not have an error component.

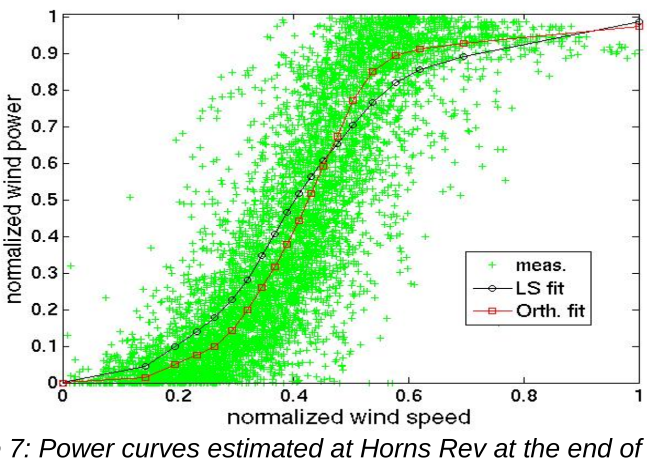

Figure 7: Power curves estimated at Horns Rev at the end of January 2006, for both Least-Squares (LS) and orthogonal fitting of the power curve mode.

Our aim when using a power curve model for the conversion of ensemble forecasts of meteorological variables to ensemble forecasts of wind power is for it to be a faithful description of the true wind-to-power conversion process [8]. Therefore, instead of adaptively estimating the Horns Rev power curve by minimizing a LS criterion, this power curve is adaptively fitted by minimizing a Total Least Squares (TLS) criterion, as described in [9]. This latter method can be referred to as orthogonal fitting of the power curve model.
In a first investigation, described in more detail in [6,7] the ensemble mean wind speed forecasts at 105m have been used in a transfer function to convert wind to power in order to be able to use one common power curve for all 75 ensemble forecasts. Including wind direction did not result in significant improvements and was therefore ignored in the first experiments. For the estimation method, the optimal forgetting factor allowing for adaptive estimation was found by using one-fold cross validation to be 0.995.

The main result of this experiment was that the traditionally LS-fitted power curve is a too flat and averaged description of the true power curve of the wind farm as shown in Figure 7. Using such power curves for the conversion of ensembles of meteorological variables to ensembles of wind power would yield under-dispersive ensembles.
This was confirmed by generating a reliability diagram of the two methods to verify the correctness of the ensemble [see 7]. Although the orthogonal fitted power curve is steeper and faster reaching the top and bottom of the production, it is still not optimal. To improve the reliability further, the next step is to generate a power curve for each ensemble member and include other weather parameters, such as wind direction into the fitting.

<u>2. Training of 75 ensemble models using neural Networks</u>
In order to train a neural network to specific input data, its structure and functions have to be determined. They depend on the available input parameters and the time series available for training. The longer the time series, the more complex the network structure can be designed. From initial tests the structure of the ANN to be trained for the MSEPS ensemble has been found optimal, when using the the following properties: 16 input parameters, 30 hidden layers and 1 output parameter.

In a first test setup, ISET's wind power forecasting system WPMS has been set up to use WEPROG's MSEPS ensemble data and trained with measured data from one archived wind farm. The setup has been conducted in two steps:

1. Wind power forecasts were calculated for each ensemble member individually. It has been found that it is an advantage to combine the wind power forecast of the members instead of combining the weather forecast data of the different members and calculate one wind power forecast from this.
2. The optimal number of members of the MSEPS was investigated to minimize unnecessary computational effort.

Recent studies with this methodology at onshore wind farms showed that multi-scheme ensemble prediction systems in combination with statistical and artificial neural network models have a great potential for the reduction of the error in wind power forecasts [4], At present, the adaptation of this setup to offshore usage and training with data from Horns Rev is in progress in order to verify the difference onshore and offshore.

Considerations for the coupling of atmospheric and ocean models

Our objective in this project is to demonstrate the benefits of a direct coupling of ocean and atmospheric model. The ocean model needs upper boundary condition, i.e. 2m temperature, 10m wind components (u,v), humidity, air pressure, cloud cover from the atmospheric model, while the atmospheric model needs the lower boundary condition, i.e. Sea surface temperature (SST) from the ocean model.
The major challenge at this state is to define the weight of the analysed SST. The challenge is that the ocean model GETM is not able to take advantage of measured values but is entirely driven by the atmospheric model's 2m temperature and associated fluxes.
The problem encountered so far is that it is difficult to prevent that the ocean does not develop a

temperature bias. There exists a risk that some ensemble members develop a strong bias that is only becoming visible during a forward integration. We can measure this bias on the surface, but the bulk of the energy lies below the surface and this implies a latent risk of a sudden temperature bias during up-welling. This could be interpreted as a positive signal of using the ocean coupling, because it means that the sensitivity to different SST values in areas with up-welling is simulated. Up-welling will normally cause the SST value to drop, while the amount is dependent on the salinity in the up-welling water. The ”warm” ensemble member would send relatively warmer water up with high salinity, which causes more evaporation. The ”cold” ensemble member will send cold water up that suppresses vertical fluxes and leads to a rather stable atmospheric boundary layer. There is no uncertainty in the processes themselves, but it is going to be a challenge to understand which patterns are a consequence of systematic model errors and which have a physical nature. The primary target is to make sure that the mean temperature in GETM’s ensemble mean is unbiased, because then it is possible to fall back on that for the purpose of making the best possible forecast only. Once the ensemble mean SST of GETM is bias free, we also know that there is a balance between positive and negative biases in the ensemble, which again means that the secondary effects of the ensemble spread can be trusted.
The sea-surface temperature anomalies are desired, if the weather forecast is not accurate, whereas they are not of benefit, if the weather forecast is correct. In the first case the ensemble spread will increase and most likely warn about the forecast error risk in advance. If the weather forecast would be correct, then this would itself be a signal of that the average SST is also correct. However, increased ensemble spread gives also false alarm on the uncertainty level and could cause that extra reserve capacity would be required and the net result would be a economic loss compared to not forecasting SST via an ocean model.

The difficulty with the coupled system's ensemble spread is that the ocean model's SST will often result in two different solutions in the atmosphere, each with a high probability. Probabilistic forecasts that are almost binary are inconvenient, because one knows that the average, which we are likely to choose has an error, while it is still the better alternative to the two more likely but very different solutions. In the case of Horns Rev wind power on a windy day with ensemble spread from the ocean model, one member with a cold ocean may have maximum production and another member with a warm ocean may only show 80% (but variable) of full capacity, because the wind will turn and cause internal turbulence on the wind farm and also change speed very frequent.
Therefore, we need to achieve that the ensemble spread on the SST reflects the physical uncertainty of the ocean. The perturbations should only be a result of latent model bias that is either invisible or strongly visible on wind, depending on the actual flow circumstances. This pattern would rather add mistrust in the forecast. It is the ocean model's turbulence scheme together with the turbulence schemes in the atmospheric models that can generate biased model states. As the atmospheric models use multiple formulations on turbulence, there is a requirement to find a well matching ocean turbulence formulations. Previously GETM had only one turbulence formulation with some tunables, but it is likely that multiple configurations are required. Such an example is described below.

Comparison of two turbulence schemes in GETM/GOTM in the North Sea

Following the principle of the MSEPS ensemble by using different model formulations for uncertain processes a new algorithm for the calculation of the heat- and momentum-fluxes at the air-sea interface has been implemented in the GOTM/GETM modeling system. The original method is based on Kondo [10] and the new method is based on Fairall et. All [11]. Which method to chose is decided at run-time via a namelist variable. The Fairall et.al algorithms are developed for the Toga-COARE community in the early nineties and have since been adopted by other groups. The algorithms include modifications/updates concerned with wind roughness length, low wind gustiness, cool skin physics and true skin temperature. Furthermore, the effect of rainfall on momentum-flux and sensible heat is considered. In our implementation, while the rainfall effect is optional.
A first impression of the influence on the sea surface temperature (SST) of the new implementation of the heat- and momentum-flux has been investigated by running a 1D water-

column model General Ocean Turbulence Model - GOTM - for a site in the Northern North Sea. This site was chosen as it has been investigated in a previous EU-project - see Burchard et. al [12]. The simulation is done for the entire year 1998. Two simulations have been done, where the only difference was the formulation of the heat- and momentum-flux calculations. The simulated SST fields were analysed as daily values. It was found that there were only minor differences between the Kondo and Fairall algorithms for this case with a maximum of 0.5° for a very short period of time.

Coupling strategy og the ocean- and atmospheric model

It has been found that there is a problematic issue regarding the coupling strategy from the fact that GETM has an inherent adaptation to the atmosphere and not to the SST measurements. This means that it takes a while before GETM is better than persistence starting from an analysed SST field. During this period, it is not optimal to use the SST from GETM in the MSEPS system. The MSEPS system must therefore adopt the SST from GETM with a smooth weight function. There is little risk of using a fast increasing weight of GETM's SST for ensemble configurations with low bias. Members with higher bias levels will deterior in quality, if the weight of GETM's SST increases too fast. A slow increase of the weight of GETM's SST will effectively mean that these ensemble members are one-way coupled. The atmospheric variables provided to GETM will not be a response to GETM's SST, but the analysis' analyzed SST (here NCEP's SST) instead.
There are other possible strategies to circumvent that GETM's SST doesn't deviate too much from the analysed SST. It is the primary challenge to achieve this, because there is little information about the vertical temperature profile in the ocean. A bias ocean temperature is therefore a latent risk of sudden poor quality.
Therefore, it was necessary to let GETM run a long simulation with each ensemble member in a one-way coupled setup. Once the simulations are done, they will be verified against the NCEP SST field, which will be regarded as the truth in absence of anything better. It is nevertheless better than single point measurements which may not be representative for areas. For the purpose of producing a reliable forecast the NCEP SST is of good quality. It will nevertheless be interesting to measure the GETM ensemble mean forecast performance once all members are done. We hope that this forecast will be nearly unbiased, so that it is safe to use this forecast as a lower boundary condition for relaxation within all forecasts to ensure a reduced bias.
The coupled modelling system interface has been defined and the necessary tasks to carry out the implementation has been initiated. The coupling consists of providing variables from the atmospheric models (T2, U10, V10, humidity, air pressure and cloud cover) to the ocean-model. Based on these forcing variables an updated SST is provided to the atmospheric models. The schedule for the model simulations have been defined to (see Figure 8):

1. Meteorological model:
   - 18 hours forecast 6 hourly with time-const. SST field from ocean model in last 6 hours
2. Ocean model
   - 12 hours forecast 6 hourly with meteorological forecast started 6 hours ago

The 18 and 12 hour forecasts will be extended to the required length in real forecast mode. The procedure makes sure that the meteorological model's output of the necessary variables is automatically converted into the ocean model's input/output format, which is NetCDF.

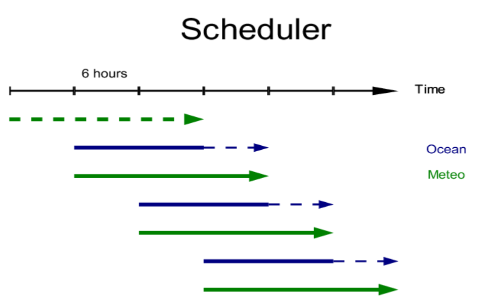

Figure 8: Scheduler of the offline ocean-atmosphere coupling

Conclusion

The currently achieved results indicate progress in the handling of many forecasts to generate optimised wind power prediction based on not only one forecast, but many different forecasts, defining the uncertainty of the underlying weather input. While the power prediction approaches indicate very positive development, there are a number of issues associated with the coupling of ocean- and atmospheric models, especially the different time scales of the two models. These issues and their possible solutions have been identified and are further investigated in this project. The large-scale integration of wind power and the growing capacity per area, especially offshore, require focus on the predictability of aggregated offshore wind power prediction. This question is becoming more important, because of the certainty about the significantly increasing capacity of offshore wind power over the next five years. The first Horns Rev wind farm showed more forecast error than expected. Therefore, it is of vital importance to look at a road map for how the forecast error will develop as the installed capacity offshore increases and also the correlation to the generation on land will have to be part of the larger picture.

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References

1 Möhrlen, C. and Jess U. Jørgensen, *Forecasting wind power in high wind penetration markets, using multi-scheme ensemble prediction methods*, Proc. Deutsche Wind Energie Konferenz, DEWEK, 2007.

2 Möhrlen, C., Presentation at the AESO Wind Power Forecastng Pilot Project CanWEA Pre-Conference Sesson, April 2007.,

3 Ernst, B., Oakleaf, B., Ahlstrom, M.L., Lange, M., Moehrlen, C., Lange, B. Focken, U. Rohrig, K., Predicting the Wind , Models and Methods of Wind Forecasting for Utility Operations Planning, IEEE Power & Energy, *Vol.5 No.6, Nov/Dec. 2007; 5/6:*

4 Cali, Ü.,Jursa, R., Melih K., Lange,B.,Möhrlen,C. Jørgensen, J.,U., Ernst B., "Artificial neural network based wind power forecasting using a multi-scheme ensemble weather prediction model", Proc. European Wind Energy Conference, 2008.

5 Möhrlen,C., Jess U. Jørgensen, HREnsembleHR Public Project Report 1, Aug. 2007.

6 Jess U. Jørgensen, Möhrlen,C., HREnsembleHR Public Project Report 2, Jan. 2008.

7 Möhrlen,C., Jess U. Jørgensen, Pinson P, Madsen H. HRENSEMBLEHR – High Resolution Ensemble for Horns Rev: A project overview, Proc. European Offshore Conference, BT2.4 (0134), Berlin, 2007.

8 Nielsen HAa, Nielsen TS, Madsen H, Badger J, Giebel G, Landberg L, Sattler K, Voulund L, Tøfting J. From wind ensembles to probabilistic information about future wind power production. Proc. PMAPS 2006, IEEE Conference, Stockholm, Sweden, 2006.

9 Pinson P, Nielsen HAa, Madsen H, Nielsen TS. Local linear regression with adaptive orthogonal fitting for the wind power application. Statistics and Computing 2007; in press.

10 Kondo, J., Air-sea bulk transfer coefficients in diabatic conditions, Bound. Layer Meteor., 9, 91-112,1975.

11 Fairall, C. W., E. F. Bradley, D. P. Rogers, J. B. Edson, and G. S. Young, Bulk parameterization of air-sea fluxes for TOGA-COARE, J. Geophys. Res., i101, 3747-3764, 1996.

12 H. Burchard, K. Bolding, T. P. Rippeth, A. Stips, J. H. Simpson, and J.Sündermann, Microstructure of turbulence in the northern north sea: comparative study of observations and model simulations, J. of Sea Research, vol. 47, pp. 223-238, 2002.