Differences in Wind Forecast Accuracy in the German North and Baltic Seas

D. Zastrau, M. Schlaak, T. Bruns, R. Elsner, and O. Herzog

***Abstract*—This work assesses the accuracy of the wind speed and wind direction forecast in the German North and Baltic Seas by comparing measurements from offshore observation stations in the sea with forecasts data by the German Weather Service which have been linearly interpolated in time. The seasonal and geographical variations are discussed by evaluation of the RMS error and the bias of the forecast look-ahead period up to 174 hours. The statistical evaluation allows the forecast of threshold exceedance probabilities for the purpose of risk analysis. The analysis is based on data from 2005 to 2010. It shows that wind speed and direction forecast accuracy seasonally vary by 25%. Also the evaluation revealed significant geographical variation of the wind direction forecast bias. A negative wind speed assimilation bias was found in both North and Baltic seas.**

***Index Terms*—Offshore, risk analysis on sea weather forecast, wind speed and wind direction.**

I. Introduction

Shipping as well as industrial offshore construction and maintenance operations require risk management which is mostly concerned with the inherent uncertainty in weather forecasts. The state of the art solution to model uncertainty in weather forecasts is an ensemble prediction which can identify insufficient initial conditions of the forecast model or errors in the model equations. However ensemble predictions are computationally intensive and have to be interpreted to be used for risk management [1]. In this work uncertainty is simply defined by the expected error and bias for a given forecast horizon. Overestimation of those variables will likely cause an increased number of "false alarms" whereas underestimation can implicate even more drastic consequences. Therefore it is beneficial to estimate the uncertainty as accurate as possible. To this end the seasonal and geographical conditions should be considered. This work compares the wind forecast accuracy in the Baltic inland sea with the forecast accuracy in the North Sea. The wind conditions in the North Sea are expected to differ from those in the Baltic Sea due to the long wave fetches and the stronger impact of Atlantic wind storms in the North Sea [2]. It will be subject to this work to investigate the impact of the differing wind conditions on the wind forecast accuracy.

Manuscript received March 2, 2014; revise May 12, 2014. This work has been supported by the government of Lower Saxony (Niedersächsisches Vorab. F.A.), Germany.

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II. Data and Methodology

The data in this work are wind forecasts by the German Weather Service (DWD) [3] and measurements from FINO 1, 2 and 3 from 2005 to 2010 [4].

A. FINO Measurements

Since 2003 three research stations (FINO 1,2,3) in the North and Baltic Seas have successively been set up to acquire accurate regional wind data, in order to assess the wind potential for offshore wind farms. To assess the uncertainty in wind forecasts measurements data from three offshore research stations (Fig. 1) are compared with weather forecast data from the German Weather Service (DWD) over a period of 5 years (2005 - 2010). The measurements allow evaluating the accuracy of wind forecast data. This gives in addition the opportunity to evaluate seasonal and geographical effects on the forecast accuracy. The FINO 2 measurements allow verifying the offshore forecast accuracy in the Baltic Sea whereas previous similar research was conducted based on measurements from coastal waters [5].

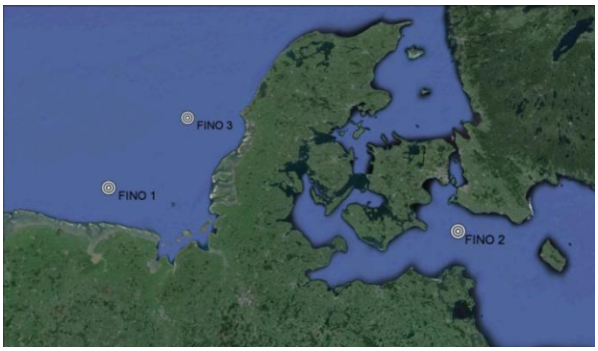

Fig. 1. Wind measurement stations in the German North (FINO 1 and 3) and Baltic (FINO 2) Seas (Source: Google Earth 2013 (v.6.2.2.6613)).

Although not all of the platforms have been operational since 2005 (Table I), almost all of the selected measurement time series cover at least one complete year which is obviously a precondition to evaluate statistical seasonal forecast error variations.

TABLE I: FINO Platform Positions

FINO ID	Longitude	Latitude	Operational since
1	6.58E	54.01N	2003
2	13.15E	55.00N	2007
3	7.15E	55.19N	2009

The FINO platforms are equipped with wind vanes, cup

anemometers and ultrasonic anemometers in different heights between 30m and 106m. Most heights have multiple instruments with different orientations to the mast, also using different technologies [6]. Table II shows the selected instruments for this work. They give the wind speed and direction. Studies have found average wind speed measurement errors of 1% which are related to the influence of the measurement mast [7]. Also the anemometer accuracy can slightly differ from the wind vanes accuracy, depending on the weather conditions. Still those effects should be insignificant compared to errors caused by the forecasting model. Compared to the forecast date the experimental data are set as "true/accurate", allowing on this bases to assess the accuracy of the DWD forecasts.

TABLE II: FINO INSTRUMENTS AND MEASURING HEIGHTS

FINO ID	Wind speed	Wind direction
1	Wind cup (33 m)	Wind vane (33 m)
2	Wind cup (32 m)	Wind vane (31 m)
3	Wind cup (30 m)	Ultrasonic anemometer (60 m)

B. DWD Wind Forecasts

The wind forecasts were generated by the DWDs Global-European Model (GME). The "E" for *European* refers to the historic European forecasting model (EM). The GME is one out of 14 global weather forecasting models. It operates on triangular grid elements with a resolution of 346 square kilometres. Four times a day all meteorological reports available within a few hours of the datum time (known as t+0) are assimilated by the model ́s analysis scheme to define conditions at the datum time. This assimilation describes the current condition. The forecast is calculated based on this assimilation in 3-hourly intervals out to 174 hours, i.e. more than 7 days. The wind field forecasts in this work are given in terms of the forecasting look-ahead time t_i: $t + t_1$. It is noteworthy that the forecasts are mean values which describe whole regions and are fitted against each other to provide a coherent global representation. The measurements on the other hand are punctual; therefore the forecast error is also linked to the grid resolution of the forecast model. However the model resolution should not affect the geographical and seasonal variance of the forecast error between the North and Baltic Seas.

C. The Approximation of the Vertical Wind Profile

Since the measurements have been collected in heights between 30m and 60m (Table II) and the forecasts refer to a height of 10m the forecasts are being extrapolated to the measurement heights using a vertical wind profile. The approximation of the vertical wind profile depends on the temperature gradient (water-air) and the water surface ́s roughness length. The logarithmic wind profile [8] is used to approximate the true wind profile in the atmospheric surface layer, which is up to 60-100 m. It is a simplification of the true wind shear but the measured data at different heights of the FINO stations can be described sufficiently well for our purposes by this wind profile. It defines the wind speed v_2 in height h_2 above sea level given a known wind speed v_1 at height h_1 at the same time. This accommodates for the fact that the wind speed generally increases with height. The coefficient z_0 is the surface roughness. It depends on the weather situation (wave forms and temperature). In the North Sea z_0 = 1 cm has been found to be an adequate mean value [2].

$$v_2 = v_1 \frac{\ln\left(\frac{h_2}{z_0}\right)}{\ln\left(\frac{h_1}{z_0}\right)} \tag{1}$$

To minimize the conversion error between forecasts and measurements the data from the instruments installed at the lowest height were chosen (Table II).

D. Analysis of the Data

The data are compiled and evaluated by statistics which may be applied in risk management. The seasonal variance of the forecast error is shown by comparing the forecasts with wind speed and direction measurements from FINO 1. Subsequently the results from FINO 1 will be contrasted with the analogous statistics obtained from FINO 2 and 3. Given the different geographical conditions the wind speed and direction forecast accuracy potentially vary between those sites. Risk analysts who are confronted with large-scale weather forecast uncertainty statistics thus might learn about the geographical variance, here demonstrated by comparing data between the Baltic (inland) Sea and the North Sea. The deviations between forecast values and measurements origin from inaccurate measurements, incorrect weather forecasts and the approximation of the vertical wind profile. The effects are superimposed and do not add a significant bias to the forecast error as can be observed in Fig. 2. The wind speed forecast error distribution in Fig. 2 also complies with general knowledge that the wind speed assimilation error resembles a Normal Distribution. Its first and second moments, the expected value and standard deviation, are the common parameters to describe the historical wind forecast uncertainty. Knowing its dependence on geographical and seasonal variation helps to estimate these parameters more appropriately. A seasonal bias and greater variance in stormy waters are common examples.

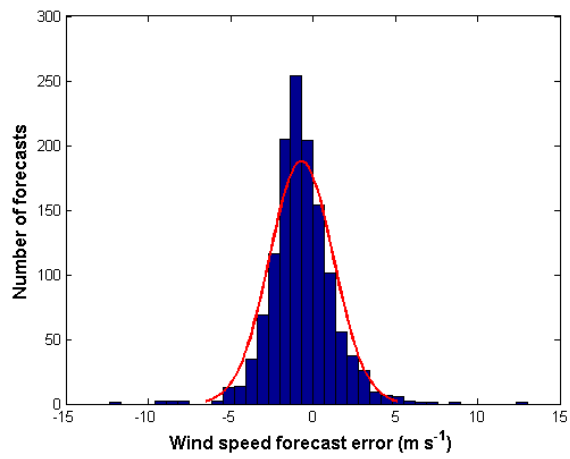

Fig. 2. The histogram (blue) and a normal density function fit (red) show the deviation between DWD wind speed assimilations and FINO 1 measurements (wind vane at 33m) from 2005 to 2010. The number of bins is equal to the square root of the number of forecasts.

In general weather forecast validation is not straight-forward because forecasts are only available as mean

values in fixed time slots for whole regions inside the weather model. Measurements on the other hand are acquired punctually. The root-mean-square error (RMSE) and the mean error, also called bias, are common metrics to evaluate the forecast accuracy. For risk analysis purposes it is also useful to know the statistical probability that the mean absolute forecast error (MAE) will remain below a certain threshold. Given a time series with n predictions $\hat{y}_t$ and observations y_t at point t in time the RMSE in (2) is a robust estimator of the errors standard deviation.

$$RMSE=\sqrt{\frac{\sum_{t=1}^{n}(y_t-\hat{y}_t)^2}{n}} \tag{2}$$

The MAE in (2) is used to compute the threshold exceedance statistic which is computed for different thresholds anyway so there is no need to give higher weights to large errors as the RMSE does. It should be mentioned that exceedance probabilities of less than 5 % can be regarded as being unreliable because of temporary biases [9]. The mean error is essentially the MAE, just without the absolute value signs. Since it sums both positive and negative forecast errors it is useful to identify forecast error biases.

$$MAE=\frac{\sum_{t=1}^{n}|y_t-\hat{y}_t|}{n} \tag{3}$$

III. Evaluation

The first part of the evaluation investigates the wind forecast uncertainty at FINO 1. The second part assesses the uncertainty for all three observation sites thus comparing the forecast accuracy between North and Baltic Seas. The accuracy (RMSE and MAE) will be evaluated for both wind speed and direction. The seasonal relevance and the dependence of the look-ahead time t_i will be analyzed. To evaluate the prediction by forecast values the 3 hourly wind forecasts have been linearly interpolated (between 3 hrs) before comparing them to the 10 minutely measurement intervals. Linear interpolation is the standard procedure for gridded wind speed values since there is no motivation to assume a non-linear gradient [10].

A. Assessment of the Wind Speed Forecast Precision

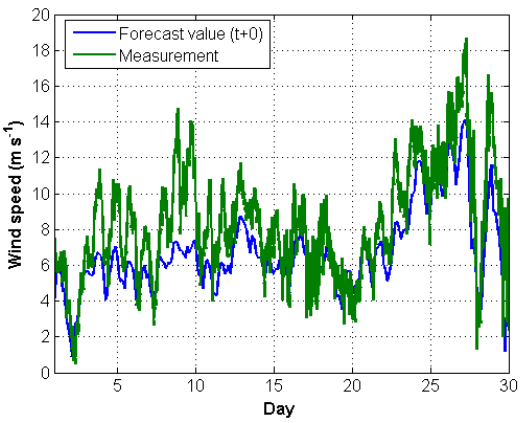

Fig. 3. Wind speed measurements from FINO 1 and corresponding interpolated datum time forecasts (t+0) in April 2010.

Aside from satellite data only few direct measurements from the open sea are usually incorporated into the initial forecast assimilation process that generates the datum time (t+0) forecast. The incorrect input data is a main reason why the forecast sometimes fails to model the true wind conditions. Fig. 3 shows as an example the datum time forecast values compared with the measured data. Single measurements deviate by up to 7ms^{-1} from the forecast values. However wind farms for example are shut down when wind speeds exceed 8 Beaufort so the peak at the end of the month (18 ms^{-1}= 8 Beaufort) would be a critical situation which would not have been identified as such by the forecast values. Therefore risk management requires adding a statistical worst-case error value to the forecast.

The forecast accuracy degrades with the look-ahead time (Fig. 4). Whereas the mean datum time forecast error (t+0) remains almost constant throughout the year (2ms^{-1}) the subsequent forecast errors (up to t+168) show a seasonal pattern with highest forecast accuracy during spring. The percentage of large errors increases towards winter, corresponding to the increase in wind speed during that time of the year. The RMS error increases with the look-ahead time t_i due to an assimilation of input data errors (and model limitations). Fig. 4 also shows that a high assimilation error is passed through to the subsequent forecast. The assimilation error is considered critical because assimilation errors are likely to propagate through the whole subsequent forecast period. Usually a high assimilation error also indicates an even higher forecast error throughout the year. It should be noted that the forecast horizons layered above each other which indicates a gradual degradation of the forecast accuracy over the forecast horizon.

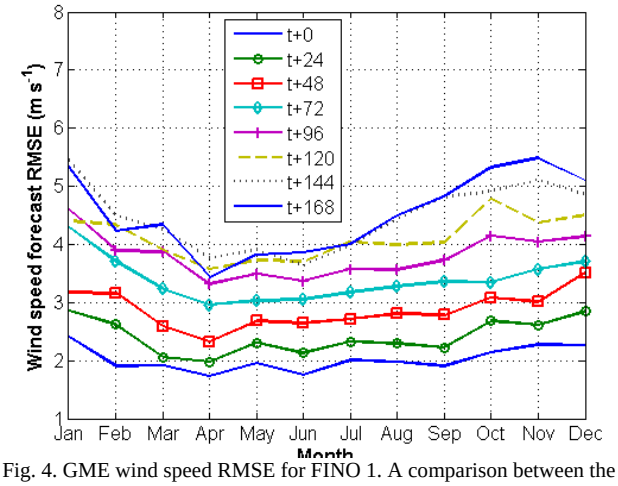

Fig. 4. GME wind speed RMSE for FINO 1. A comparison between the datum time forecast and up to 168 hours forecasts. The $t+k$ plot line refers to the mean forecast error for forecasts k hours ahead in time.

FINO 1 wind speed forecasts are negatively biased by up to –1 ms^{-1} as shown in Fig. 5. Also during spring the bias tends to grow with the forecast horizon which indicates amplifying errors in the forecast model equations. In terms of risk analysis the bias should be added to the expected forecast error. Thus the bias in combination with the standard deviation of the historical forecast error is used to calculate the confidence interval of the expected error distribution.

All three sites exhibit a negative wind speed forecast bias (Table III). In the Baltic Sea (FINO 2; -1.1) it is a bigger than

in the North Sea (-0.66 and -0.89). Also it shows that the bias amplifies with the look-ahead time t_i especially during spring and summer (Apr – Aug). Surprisingly the wind direction forecast bias on the other hand varies between FINO 1 and 3 although both sites are located in the North Sea: This shows the regional variability of the wind direction forecast bias. As opposed to the wind speed forecast bias the wind direction forecast bias does not systematically amplify with t_i.

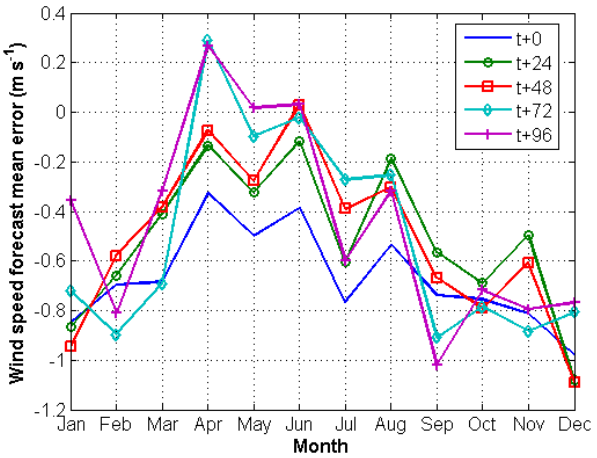

Fig. 5. GME wind speed bias for FINO 1. For clearness the plot has been limited to forecasts of up to 96 hours.

TABLE III: WIND FORECAST BIAS AT FINO SITES

FINO ID	Direction (ms^{-1})	Speed (°)	grows with t_i	
			Speed	Direction
1	4.2	-0.66	Yes	No
2	-0.2	-1.10	Yes	No
3	-4.3	-0.89	Yes	No

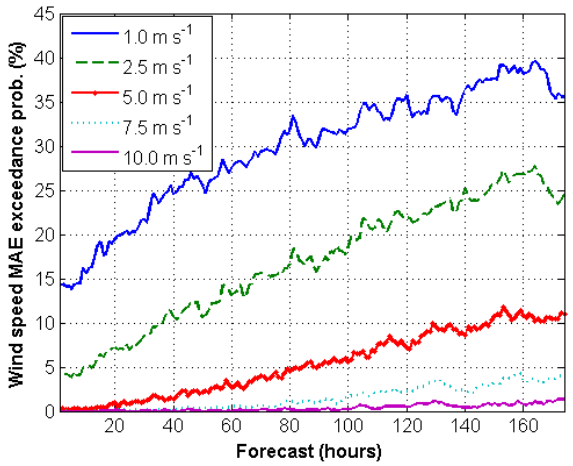

Fig. 6. GME threshold wind speed exceedance probability for different thresholds. The error has been calculated from FINO 1 measurements and DWD forecast values.

Another possibly approach to risk analysis is to directly calculate the probability that the forecast error remains below a specific threshold. Returning to the example of an offshore wind farm the forecast might be a "fresh breeze" and the operator wants to know the probability that it won't become a storm (8 Beaufort). Fig. 6 shows the statistical probability that the mean absolute wind speed forecast error will not exceed a certain threshold (1.0 to 10.0 ms^{-1}) at FINO 1. For greater thresholds (>2.5 ms^{-1}) the probability increases almost linear with the forecasting horizon. Contrary the 1.0 ms^{-1} threshold probability curve is not in linear proportion to t_i but somewhat logarithmically. This indicates small random errors which are not associated to the look-ahead time of the forecast. While the exceedance probability for low errors of 1.0 ms^{-1} increases from 15 to 35 % after 174 hrs the exceedance probability for medium errors of 5.0 ms^{-1} rises from 1 % to 11 %.

B. Assessment of the Wind Direction Forecast Accuracy

While the wind direction forecast accuracy is of lesser interest to the wind energy industry it is of great interest to the shipping companies. In contrast to the wind speed forecast (Fig. 4) the wind direction forecast accuracy (Fig. 7) is seasonally almost invariant. The up to *t*+48 forecasts are slightly less accurate during summer (Jun – Jul) than in November. The forecast error in November might origin from erroneous measurements or an unfavourable wind direction with respect to the measurement mast: If the measurements orientation with respect to the mast is opposite to the wind direction the mast will tamper the wind measurements. On the contrary the forecast error is only above-average for the first 96 hrs lookout period which implies that the high error during November is rather related to an insufficient model initialization.

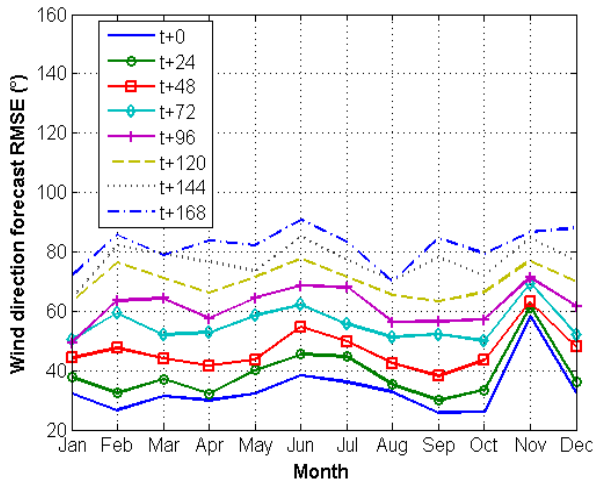

Fig. 7. GME wind direction RMS error for FINO 1. A comparison between the datum time forecast and up to 168 hours forecasts. The *t*+*k* plot line refers to the mean forecast error for forecasts *k* hours ahead in time.

Wind direction threshold exceedance probabilities can be useful when optimizing ship routes. This will become even more relevant since current research investigates the applicability of new wind assisted cargo ships [11]. These drives will amplify the influence of the wind on the ship performance and require a more sophisticated risk management with regard to meteorological conditions.

The wind direction exceedance probability (Fig. 8) is very low for the datum time forecast (<5 %) but rises quickly for moderate forecast errors: The probability of errors less than 45° rises 6 times to more than 30° after the full forecast horizon of 174 hrs. In other words the datum time forecast seems to be very accurate while medium-term forecasts are of little use in one out of three cases.

It should be noted that the deviation between predicted and actual wind direction is a radial value and therefore it is ambiguous: A 90° deviation can implicate an error of either 90° or 270°. For the calculation of the risk exceedance

probabilities in Fig. 8 the smaller error has been chosen since in most applications (such as shipping) the worst possible wind direction forecast error is 180 °.

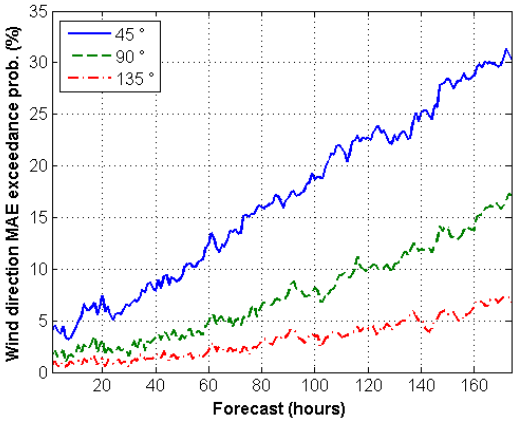

Fig. 8. Probability for the exceedance of different thresholds in wind direction scattering. The error has been calculated from FINO 1 measurements and DWD forecasts.

C. Comparison of the Forecast Accuracy between Different Geographical Locations

The distance between FINO 1 and 3 (both in the North Sea) is only 76 sea miles. Nevertheless the monthly mean wind speed RMSE varies by up to 0.4 ms^{-1} (Fig. 9). The wind speed forecasts are less accurate during winter by up to approximately 25 % (May: 3.2 ms^{-1}; Dec: 4.0 ms^{-1}). However the seasonal pattern is less pronounced in the Baltic Sea (FINO 2). Because of maintenance work no FINO 3 measurements were available in August. The *t*+174 forecast accuracy (Fig. 10) linearly decreases by a factor of $\frac{4.5}{2} = 2.25$ compared to the datum time (*t*+0) forecast accuracy. This implies a degradation of forecast accuracy by $24 \cdot \frac{4.5-2}{174} \approx 0.35 ms^{-1}$ per day. In comparison to FINO 3 the FINO 1 and 2 curves in Fig. 8 are smoother. This is probably related to the more substantial measurement data record which was available to generate the statistic for FINO 1 and 2 (Table III). Otherwise the differences between FINO 1 and 3 wind speed forecast accuracy are only marginal. It is noteworthy that the wind speed and direction seasonal forecast accuracy patterns are partially inverted: The wind direction forecast in Fig. 11 is least accurate in spring time (Apr – Jun) when the wind speed forecast accuracy is highest.

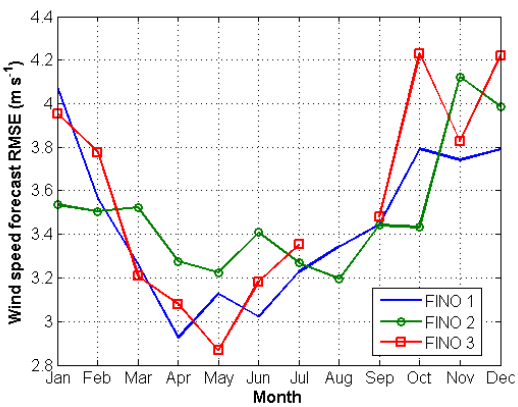

Fig. 9. Averaged wind speed forecast (up to *t*+174) RMSE for all FINO stations. Data from 2005 to 2010 has been compared to calculate the RMSE for every month.

However during winter (Nov – Dec) wind direction forecast accuracy also decreases by approximately 25% (Sep: 45 °; Dec: 60 °).

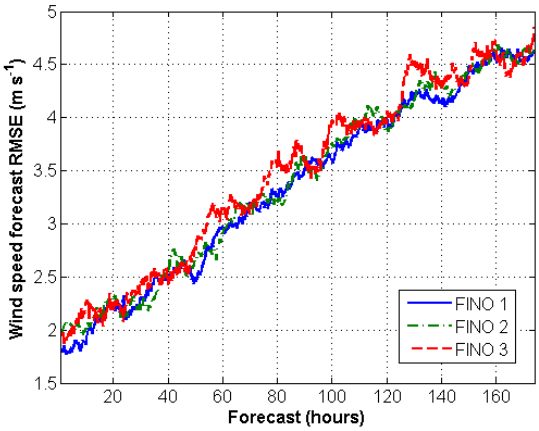

Fig. 10. Mean GME wind speed forecast error for every hour in 174 hrs forecasts for all three FINO stations. Data has been compiled from 2005 to 2010.

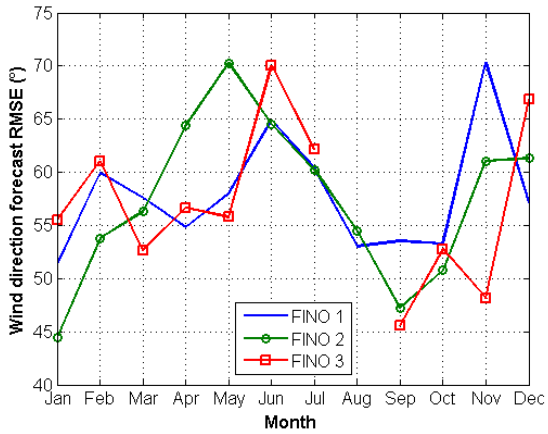

Fig. 11. Averaged wind direction forecast (up to *t*+174) RMSE for all FINO stations. Data from 2005 to 2010 has been compared to calculate the RMSE for every month.

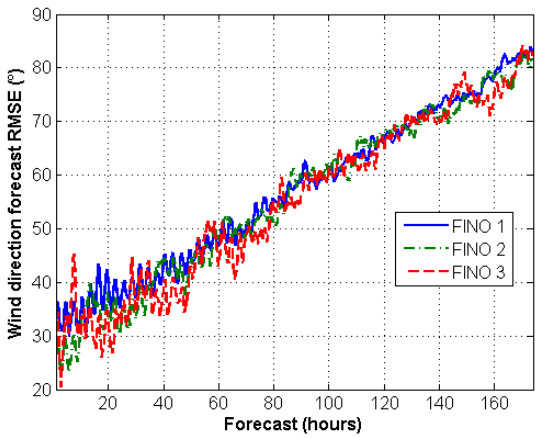

Fig. 12. Mean GME wind direction forecast error for every hour in 174 hrs forecasts for all three FINO stations. DWD and FINO data from 2005 to 2010 has been compiled.

Initial differences in wind direction forecast accuracy (Fig. 12) which are related to assimilation errors are almost smoothed out after 96 hrs. Especially the nearly congruent FINO 1 and FINO 2 curves show no significant difference between forecast accuracy in the North and Baltic Seas. This is surprising since FINO 1 and 3 in the North Sea are subject

to predominantly westerly winds [2] which may have been assumed to be more predictable. The t+174 forecast accuracy (Fig. 10) linearly decreases from 30 ° to 80 ° compared to the datum time (t+0) forecast accuracy. This implies a degradation of forecast accuracy by $24 \cdot \frac{80-30}{174} \approx 7°$ per day.

IV. Conclusion

Assessment of the Quality of the DWD Forecast Model

Whereas seasonal forecast variability could be observed significant geographical differences between North and Baltic Sea have not been verified with the exception of the wind direction forecast bias which varied between all three sites in the North and Baltic Seas. The wind speed forecast bias was similar for all sites and showed a tendency to amplify with the forecast horizon. The DWD forecast model RMSE scales linearly in the forecast horizon.

V. Use for Risk Management for Ship Routing

This work also showed that mean weather forecast errors can be modelled as linear curves over the forecast horizon. Statistics have been derived which may be of help to avoid risks in offshore engineering or ship routing. To describe forecast uncertainty based on scenarios the wind speeds seasonal correlation and the threshold exceedance probabilities provide useful information because the forecast error correlated non-linearly with the seasons and the different thresholds.

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