

# Applying Model Output Statistics (MOS) in the new German Project EWeLiNE for enhanced windforecasting for renewable power generation

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## Abstract

Model Output Statistics (MOS) is a powerful tool for optimizing the direct output of numerical weather forecast models. By developing multiple linear regressions with predictors, derived from observations and model output at DWD (German Meteorological Service) a reduction of 50% of the error variance in the forecast has been achieved. Moreover, statistical post-processing yields numerous advantages in forecasting, e.g. down-scaling on point forecasts at observation stations with specific topographic and climatological characteristics, correction of biases and systematical errors produced by numerical models, the derivation of further predictands of interest (e.g. probabilities) and the combination of several models.

In the recently founded German project EWeLiNE (Simultaneous improvement of weather and power forecasts for the grid integration of renewable energies), which is fulfilled in collaboration of DWD and IWES (Fraunhofer Institute on Wind and Energy Systems), one of the main goals is an adjustment of the DWD-system MOSMIX (combining the global models IFS and GME) to the demands of the transmission system operators. This includes the implementation of new predictands like wind elements in altitudes > 10m.

After the processes of converting raw data of acquired point measurements of observation masts and the implementation of their data into the MOS algorithms, studies have been accomplished investigating the fit of forecasts to observations by means of wind speed at 30m and 100m at selected locations, the choice of the predictors and the weighting of employed weather forecast models. By the implementation and pre-processing of the measured data, e.g. changing the length of training periods and the vertical interpolation of wind speed in heights of absent measurements, uncertainties develop, which require sensitivity studies, as the accuracy of the statistical forecast is affected. Amongst others these studies have been conducted by assessments of the RMSE.

## Objectives

According to (BEDARD et al. 2013) great potential in improving power forecast is ascribed to an enhancement of weather prediction. As introduced in the abstract and as it is also recommended in the science community a combination of physical and statistical methods achieves better results (GIEBEL et al. 2011). In the operative MOS-system by the DWD required variables for power-forecasting, as e.g. wind speed in heights > 10m are not processed yet. Thus, besides the ambitions of advancements in modeling and the application of probabilistic scores and data assimilation EWeLiNE aims at upgrading MOS by e.g. increasing the temporal resolution of the forecast, by implementing new physical models, by transferring the punctual forecasts of the MOS to a gridded network comprising Germany and by broadening the MOS-system by the implementation of required variables. Finally it will be attempted to use power measurements directly as additional predictors for meteorological variables within the MOS. Afterwards the data will be subject to improvement studies in the power forecast itself conducted by IWES.

## Methods & Data

The MOS at DWD is forced by the two global models GME (DWD) and IFS (ECMWF). The variables of the direct model output (DMO) are then trained as predictors on the observation data (as predictand –see below). This is done by a Multiple Linear Regression (MLR) (formula 1), where the coefficients  $a$  and  $b$  and the choice of predictors  $X$  are dependent on season (stratified MOS), station, forecast horizon and the daytime of the MOS initiation (depending on the most recent DMO forecast).

$$Y = a + b_1 X_1 + b_2 X_2 + \dots + b_n X_n + \varepsilon$$

The screening regression is developed by iterative sampling of the predictors with the selection of the predictor which exhibits the greatest reduction of variance (and from its residuals in the consecutive sampling steps). After too low reductions of variances, too small improvements of the RMSE or more than a certain number of active predictors the sampling is aborted to prevent overfitting.

The observed wind variables in upper heights have been derived by a network of wind measurement towers and additional masts. Figure 1 depicts the network of wind measurements we are able to use to obtain historical data. We plan to extend the persistent network constantly for the acquisition of historical data, where external contributions are greatly appreciated.

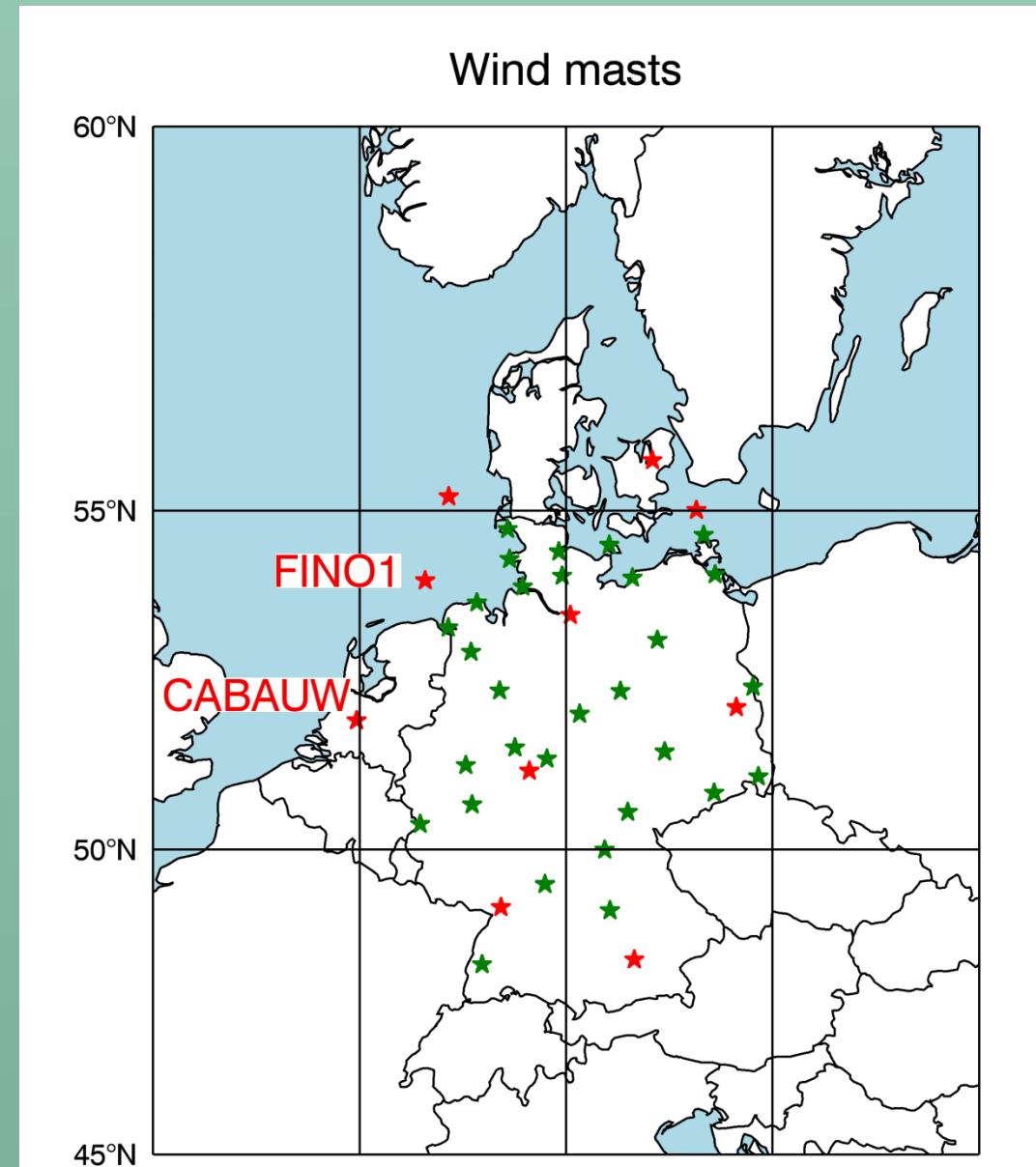


Figure 1: Observation stations

Red stars in figure 1 exhibit wind masts we gathered additional to the persisting network established by collaboration of IWES and DWD with measurements of windspeed in 10m, 30m, and in some cases also 50m and wind direction in 10m (green stars).

Here, we show first results related to two chosen stations (FINO1 and Cabauw – figure 1). Table 1 exhibits the measurements of the two depicted stations.

Table 1: Characteristics of the two depicted stations

station	FINO1	Cabauw
heights of windspeed	33, 40, 50, 60, 70, 80, 90, 100m	10, 20, 40, 80, 140, 200m
heights of wind direction	33, 40, 50, 60, 70, 80, 90m	10, 20, 40, 80, 140, 200m
lat	54,0143°	51,97°
lon	6,5876°	4,926°
height above ground	0m	-0,7m

For first attempts wind speed in heights of 30m, 80m and of 100m have been assessed. Furthermore the wind direction in 80m is introduced from the observations into the MOS. Amongst others these variables have been suggested by literature (e.g. RANABOLDO et al. 2012). As individual masts do not account for these heights missing speed has been interpolated by a quadratic polynome from the measured heights. Wind direction is interpolated linearly by weighting the direction from two adjacent heights. For statistical reasons and with the application of severe quality checks the interpolation procedure has been proved to be sufficient. Extrapolation is not applied.

## References

- 1) BEDARD, J. et al. (2013): Development of a geophysical model output statistics module for improving short-term numerical wind predictions over complex sites. In: *Wind Energy*, vol. 16, pp. 1131-1147.
- 2) GIEBEL, G. et al. (2011): The state-of-the-art in short-term prediction of wind power – a literature overview, 2<sup>nd</sup> edn, *Project report for the Anemos.plus and SafeWind projects*, Risoe, Roskilde, Denmark, pp.110.
- 3) RANABOLDO, M. et al. (2013): Implementation of a Model Output Statistics based on meteorological variable screening for short-term wind power forecast. In: *Wind Energy*, vol. 16, pp. 811-826.
- 4) WILKS, D. S. (1995): Statistical Methods in the Atmospheric Sciences: An Introduction. Academic Press, New York.

## Results

In the first attempts we implement new meteorologic fields, which have not been addressed yet. These are windspeeds in heights of 30m, 80m and 100m and the direction of the wind in 80m height. Figure 2 exhibits the forecasts of these variables at two different sites for the 2012-12-13 and 2012-07-17. These dates have been chosen, as transmission operators reported high uncertainty concerning their power forecasts. Please note, that the training periods of the MOS algorithms have different lengths, as they depend on the time series of observations at the specific stations. Furthermore at the FINO1 platform no wind speed is measured at 30m or beneath that height (see table 1), why interpolation does not work and thus no forecast is available at this height.

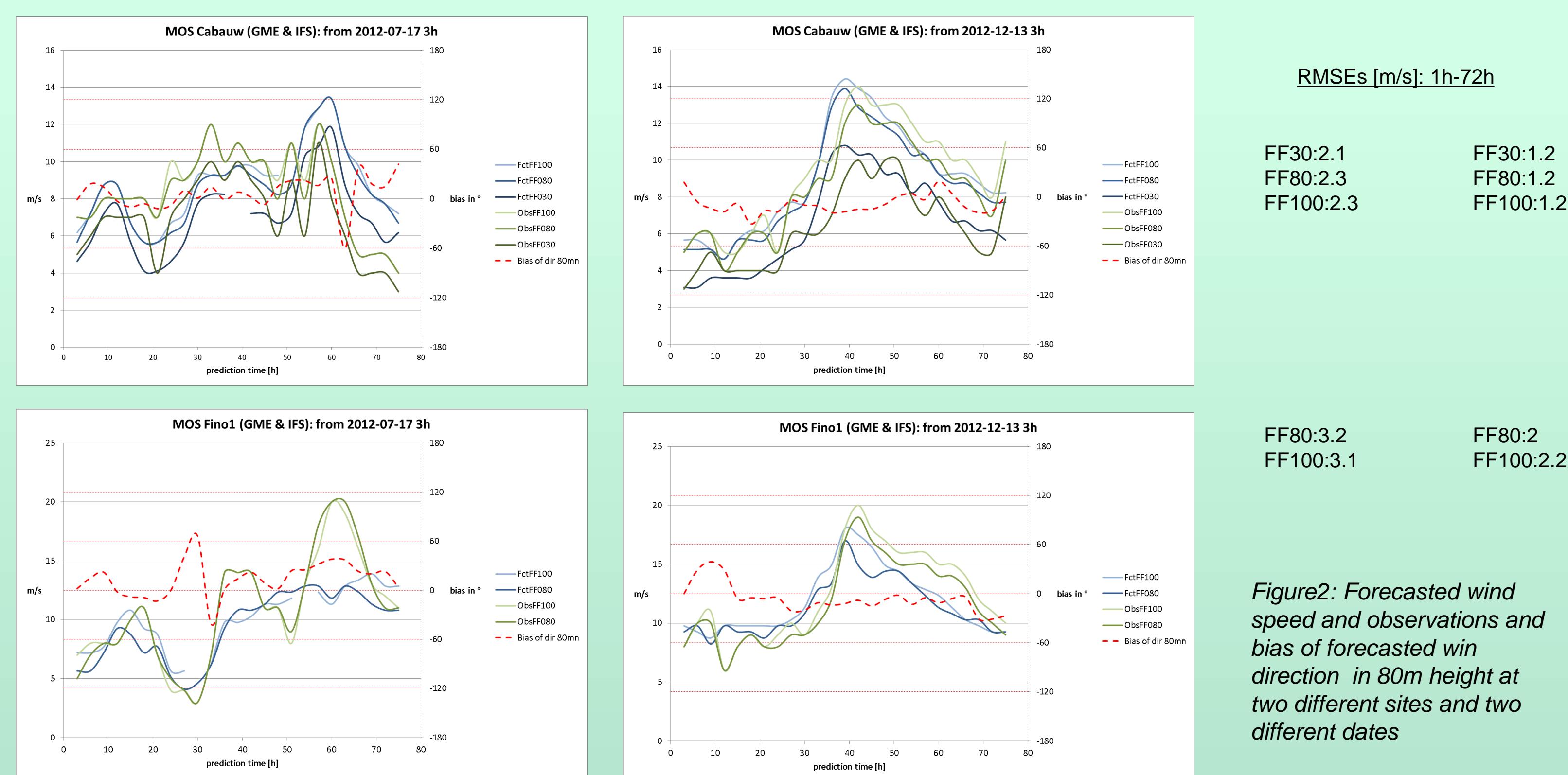


Figure 2: Forecasted wind speed and observations and bias of forecasted wind direction in 80m height at two different sites and two different dates

These first assessments show clearly that MOSMIX reproduces the observations quite well. Though the RMSEs (as shown above) are relatively bad, they have been calculated for the whole forecast horizon. Concerning the first hours of forecast, they become better and in some cases even undermatch the 1m/s threshold. With respect to more sites and dates right now no conclusions can be drawn about differing forecast quality within the seasons. Table 2 shows the main predictors, which have been chosen by the iterative screening regression for FF80. Please note that it is planned to implement further predictors.

Predictor 2012-12-13	Weighting in %	Predictor 2012-07-17	Weighting in %
Statistical Forecast FF100	82,62	Statistical Forecast FF100	61,13
DMO FF10 (-3h)	2,24	DMO FF10 (+3h)	4,95
DMO FF1000	1,86	DMO FF1000 (+3h)	1,75
Observations FF80 (-3h)	1,71	Observations FF100 (-3h)	1,46
Observations FF100 (-3h)	1,71	DMO FF100 (-3h)	1,38
DMO FF850 (+3h)	1,27	DMO FF10	1,24
...	...	...	...

Table 2: Display of chosen predictors with highest weighting for FF80. Averaged over the total forecast horizon of 72h.

In our MOSMIX, we distinguish the predictors into different groups. Besides the values of the DMO and the observations, which have highest impact on the first hours of the forecast, also the forecasted values themselves are used as predictors in further progression of the forecast horizon. Furthermore empirical predictors, date and time functions and climatological expectations are involved into the MOS equations. In table 2, it is evident that the statistical forecast of windspeed in 100m dominates the predictor group. The weighting of the predictors has been averaged over the whole forecast horizon of 72hours. Naturally the observations loose their weighting by a progression of the forecast, while the impact of the statistical forecast and of the DMO increases.

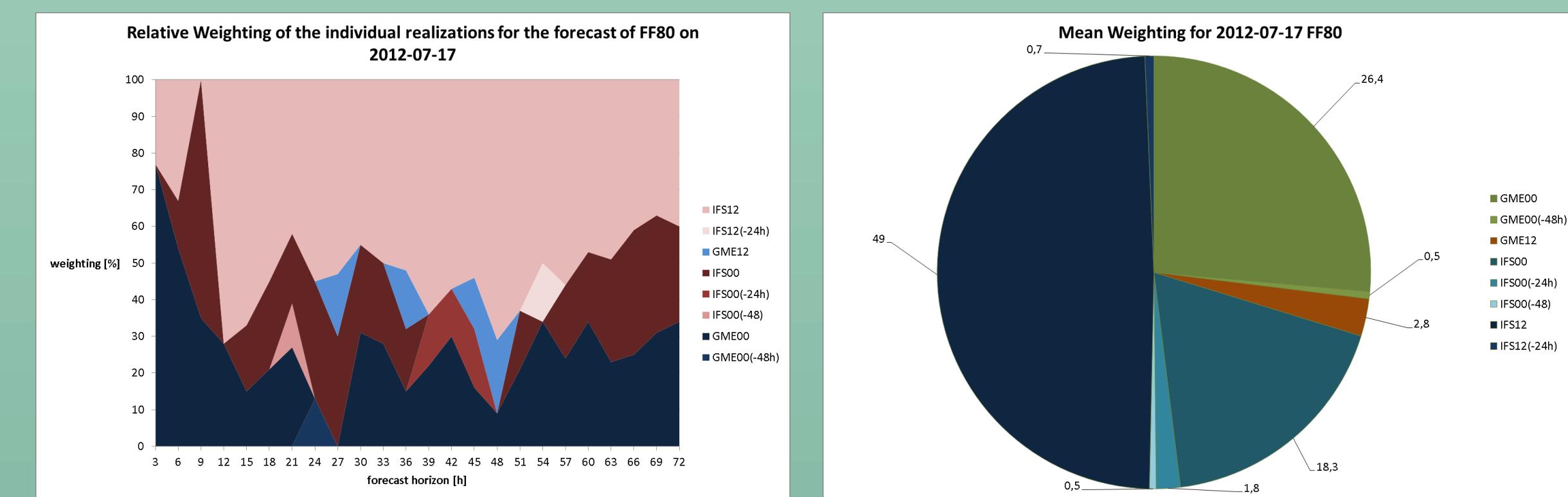


Figure 3: Temporal and overall distribution of the weighting of the two applied models IFS and GME

As the MOSMIX combines the DMO of two models (GME and IFS) a weighting of the individual models and their time specific simulations is applied. Figure 3 depicts the individual weighting of the involved realizations. Please note, that the IFS12 realization is the most current one, as the forecasts in figure 1 are calculated from 0h. That is why this model has the highest impact on the forecast.

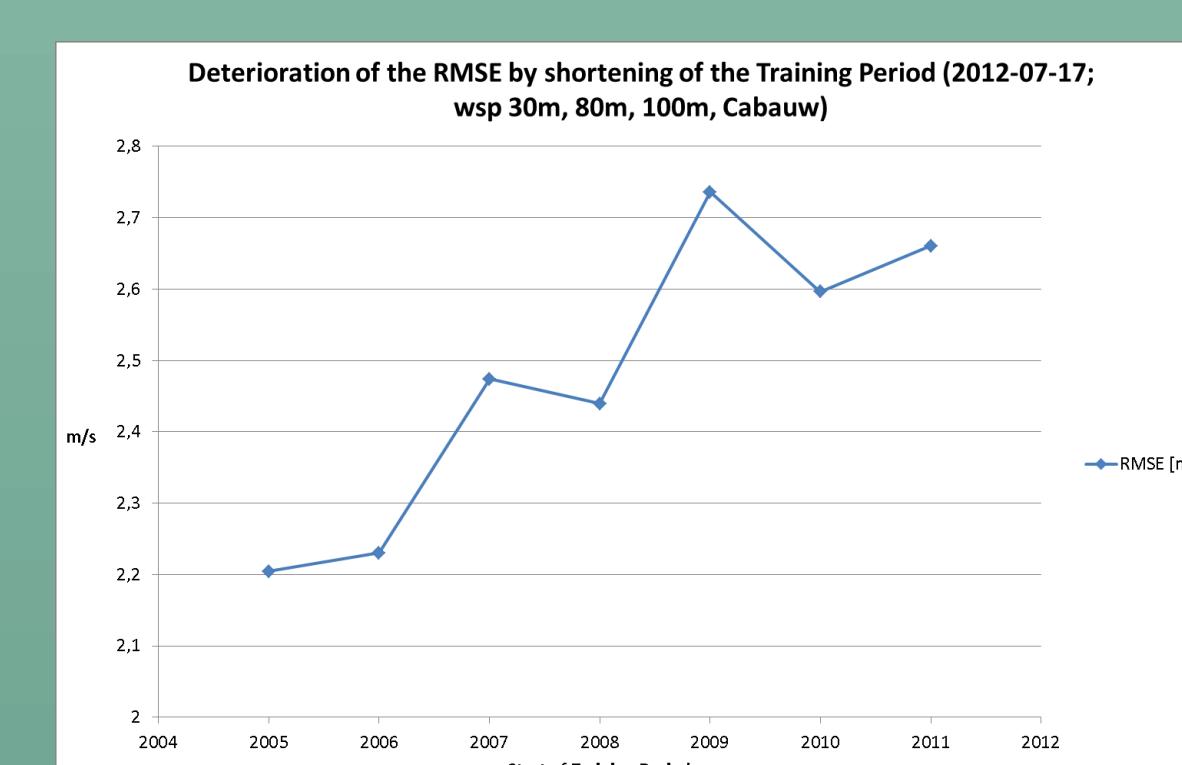


Figure 4: Enhancement of the RMSE by extending the training period

The length of the training period within the MOS equations are developed naturally depend on the length time series of the observed stations. As the DMO is available for more than ten years for GME and IFS this is not critical for the MOS. In figure 5 we show, how the RMSE is becoming worse with a yearly stepwise shortening of the training period for Cabauw. Thus it is desirable to achieve observed time series with a maximum in length. Please note that for certain forecasting dates, horizons and variables the RMSE even might get better by a further reduction of the length of the training period. This might be due to overfitting by less datasets (WILKS 1995), the higher chance of involvements of extreme situations in a longer training period, which disturbs the equations, and intermittent improvements of the parametrization schemes of the models. By extending the sampling, these effects of enhanced RMSEs by shortage of training periods vanish.

## Conclusions & Outlook

It is planned to improve meteorological forecast in terms of enhancing power forecasts for renewable energy. For this we expand the current MOS at DWD. We showed, that the MOS-system at DWD meets the requirements concerning the quality of the forecast, choice of accurate predictors and the mixing of two different models. Generally, a limiting factor of MOS-systems is the availability of observation data defining e.g. the accuracy of forecasts by limited periods of data series relating to the RMSE as verification score.

These first attempts show promise allowing following working advancements concerning the statistical post-processing of required meteorological parameters:

- Defining most crucial variables and their priority for power prediction
- Assessing the most accurate weather prognosis with the MOS concerning the new variables
- Enhancing the temporal resolution from 3h forecast steps to 1h forecast steps
- Transferring the new variables onto a spatial grid
- Implementing more models next to GME and IFS. Planned are GFS and COSMO-DE EPS with its probabilistic features
- Applying measured power as predictor
- → Transferring the data to the IWES Institute for power predictions