A method for probabilistic icing modelling

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Abstract— **For planning and trading wind power in cold climates, reliable forecasts of icing on wind turbines and related production losses are needed. Probabilistic forecasting is commonly used to address uncertainties in weather forecasting and can provide the statistically best forecast and its uncertainty, allowing for optimal usage of the forecast information. As a step towards a full uncertainty quantification of the modelling chain, a probabilistic forecast addressing uncertainties in the applied ice growth model formulations was generated and tested for four wind parks in Sweden. The method is here compared with a probabilistic forecast created using a numerical weather prediction ensemble as input to the icing model.**

Keywords— ***Icing modelling, probabilistic forecasting, icing-related production losses, deterministic sampling, ensemble forecasting***

I. Introduction

In the end of 2015 nearly 30% of the global wind energy capacity was installed in cold climates [1]. In these regions, icing on the wind turbine blades can cause serious problems, both as a safety risk when ice falls of the blades and because it can lead to substantial production losses. Forecasts of the next-day wind energy production is a vital tool for energy companies for trading and to balance energy production and demand. It is therefore important to forecast the icing-related production losses accurately. The modelling chain presented in Fig. 1a is commonly used when modelling icing-related production losses (e.g. [2], [3]). It contains several steps, all of which have error sources such as uncertain initial conditions or simplified model physics. Icing-related production loss forecasts are therefore often uncertain.

Here we use probabilistic forecasting to address uncertainties of five parameters within the icing model. Using probabilistic, or ensemble forecasts, commonly reduces the forecast error and also provide some information of the forecast uncertainty at each forecast step. With deterministic sampling a nine-member icing model ensemble was generated [4]. A detailed description of the approach can be found in [5]. This method is compared with an ensemble forecast created using a numerical weather prediction (NWP) model prediction ensemble as input to the icing model.

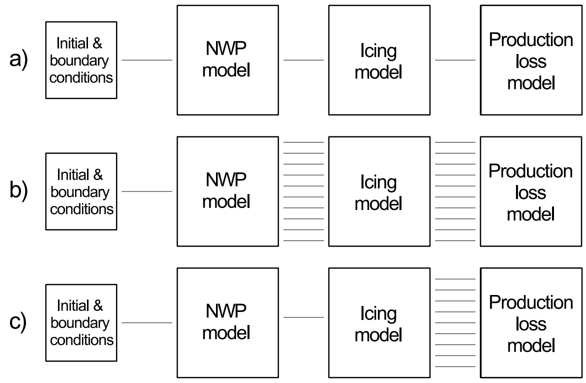

Fig. 1. Modelling chain for the modelling of icing-related production losses. a) represent the single forecast baseline, b) represent the NWP ensemble method and c) represent the icing model ensemble method.

II. Method

This paper and thus also the models and observational data closely follows [5].

A. Data

1) NWP data: Input to the icing model came from the regional NWP model HARMONIE-AROME. HARMONIE-AROME uses boundary conditions from ECMWF and has a horizontal resolution of 2.5. The model was run daily at 06 UTC +42 hours for 29 weeks during the cold seasons 2013-2014 and 2014-2015, producing hourly outputs. For 10 of the weeks, also a 11-member NWP ensemble initiated with initial perturbations based on the global ensemble prediction system at ECMWF was run.

2) Icing and production loss model: The icing model is based on [6] but with possible ice accretion due to all available hydrometeors, cloud water, graupel, cloud ice, snow and rain. It also has an ice loss term containing shedding, melting, sublimation and wind erosion.

Based on the forecasted ice load, icing intensity and wind speed a production loss in percent was calculated.

B. Observations

Observations of meteorological parameters and power production from wind turbines were available from four wind parks (referred to as A-D) in Sweden for the 29 weeks. All wind parks are located in hilly terrain and between 58-68°N. Since icing observations were not available, only the production loss forecast was validated and used as a proxy for the icing.

C. Probabilistic forecasting methods

Five parameters within the icing model and their uncertainty were assessed in this study:

- The Median Volume Diameter of the hydrometeors
- The Nusselt number used in the calculation of the ice accretion efficiency
- The wind erosion term
- The empirical shedding factor
- The sticking efficiency for ice particles

Based on estimation of the parameter uncertainty distributions, an icing model ensemble was generated using deterministic sampling. With deterministic sampling the estimated uncertainty distributions can be exactly represented with only nine ensemble members and propagated through the icing and production loss model (Fig. 1c). The resulting production loss forecast then consists of an ensemble mean and a standard deviation (or spread) that can be used as a measure of forecast uncertainty. The deterministic sampling method was compared with the more commonly used uncertainty quantification method random sampling, the results were similar [5].

For 10 of the 29 weeks a 11-member NWP ensemble forecast was also run with each member serving as input to the icing and production loss model (Fig. 1b).

III. Results

The results from the probabilistic methods are compared with the single forecast method (Fig. 1a) since this is the commonly used approach. The focus in the verification is the next-day forecast, namely the +19-42 h forecast. This choice was made based on the delivery time for the next-day production estimations at 12 UTC.

In Table I the unbiased forecast error (square root of $RMSE^2$ minus $bias^2$) of the single forecast method and the icing model ensemble mean are presented for both seasons. Table I follows Table 4 in [5]. The ensemble mean production loss forecast is better than the single forecast at all wind parks and for both seasons. This means that the parameter uncertainties in the icing model are valuable to address in the modelling, and that the icing model ensemble is well constructed.

Table I. Average unbiased production loss forecast error (MW) for both seasons. The difference between the single forecast and the ensemble mean are significant for site A, C and D on a 95% level.

Wind park	**A**	**B**	**C**	**D**
2013-2014				
Single forecast	0.52	0.48	0.33	0.44
Icing model ensemble mean	0.42	0.45	0.29	0.42
2014-2015				
Single forecast	0.44	0.38	0.40	0.42
Icing model ensemble mean	0.33	0.31	0.31	0.32

For the 10 weeks with available NWP ensemble data, the icing model ensemble mean production loss forecast was also compared with the NWP ensemble mean production loss forecast. Fig. 2 show the average unbiased forecast error using the two probabilistic methods ensemble mean forecast and the single forecast approach. Both probabilistic methods outperform the single forecast. At wind park A and C the icing model ensemble method is also better than the NWP ensemble method. This gives confidence in that it is important to not only consider uncertainties in the input parameters, but also icing model uncertainties.

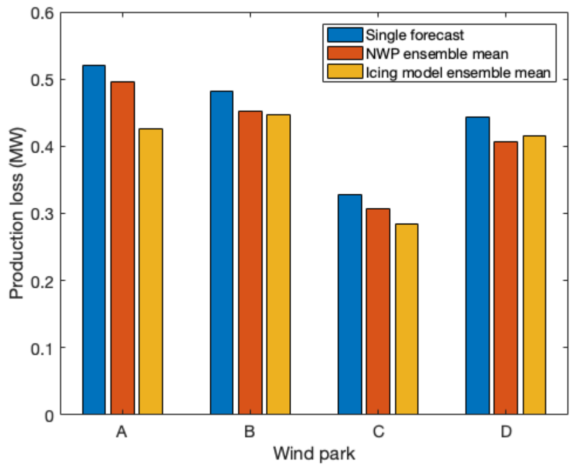

Fig. 2 Averaged unbiased forecast error of the production loss forecasts (MW) for the four wind parks during the 10 weeks of season 2013-2014 with available NWP ensemble data.

The probabilistic forecast also provides valuable information in terms of forecast spread for each time step. The forecast spread can be used as an estimation of forecast uncertainty at each time step. If all uncertainty sources are accounted for the spread and the forecast error should be similar for each forecast length on average. Fig. 3 present the forecast spread and error for the 10 weeks with NWP ensemble data. Both probabilistic methods clearly provide underestimated production loss forecast uncertainty.

However, interestingly the icing model ensemble method provide higher spread-skill relationship than the NWP ensemble method. This can partly result from the fact that the NWP ensemble does not have perturbed model physics, but once more stressing the importance of addressing the icing model uncertainties.

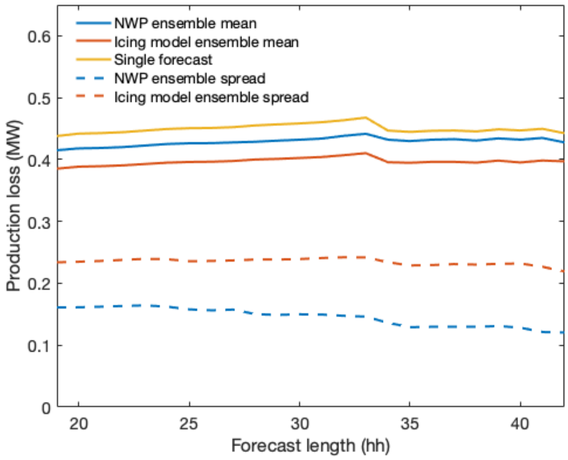

Fig. 3. Forecast error (MW) of the single forecast, the NWP ensemble mean and the icing model ensemble mean together with the average spread as a function of forecast length. The results are the average of the 10 weeks of season 2013-2014 with available NWP ensemble data.

IV. Summary and Discussion

An icing model ensemble was successfully constructed using a deterministic sampling method. The ensemble mean production loss forecast using this method outperform a single forecast approach. For two of the four wind parks it also outperforms the ensemble mean production loss forecast generated using a NWP ensemble as input to the icing and production loss model. We believe that the best results would be achieved using a combination of the methods and also addressing other parts of the modelling chain. For example, in [7] also the uncertainty of representation of the NWP forecast at the wind park was addressed.

Acknowledgment

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