# Development of operational forecasting for icing and wind power at cold climate sites

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***Abstract*: Based on icing measurements from 12 meteorological stations in Sweden a methodology for calculating icing from meso scale model data has been developed over the past 5 years. Operational data from seven wind farms in cold climate regions in Sweden (total of 272 MW and 111 individual turbines) have in addition been utilized to develop a state-of-the-art model for estimating production losses due to icing (IceLoss).**

**Operational forecasting of energy production, icing and production losses due to icing has been carried out for the four wind farms which all experiences losses due to icing. The forecast simulations are run 4 times daily, each with a lead time of 48 hours. It is shown that the method is able to realistically describe the periods when ice is influencing the energy production for the wind farms. 63-82% of the time periods when icing is influencing the energy production are captured by the forecasts.**

**Essential to forecast icing events is the ability to forecast the events at the correct time. For 67-71 % of the strongest icing events the timing was correctly forecasted. These icing events accounted for approximately 90 % of the production losses from the wind farms.**

**The power forecasts with and without losses due to icing are compared to the hourly production data from the wind farm. It is evident that the accuracy of the forecasts is improved when the power losses caused by icing are taken into account, resulting in a reduction of the mean absolute error (MAE), reduction of the average bias and increase of hourly correlation coefficients. The results show that the number of cases when the produced energy is over-predicted is reduced when including power losses due to icing, while the cases of under-prediction the produced energy is somewhat increased.**

***Keywords: icing, wind power, forecast, production losses, validation***

## Introduction

As the number of wind farms installed in Sweden has increased over the recent years wind farms has also been developed in cold climate regions on exposed hills. At these hills the wind conditions are often quite favourable for wind energy generation, but also quite exposed to in-cloud icing which can disrupt the energy generation during the winter months.

The typical wind energy forecasts are dependent on the wind conditions only. If the icing is not considered these forecasts will be biased during the winter time. A high accuracy forecast can also be valuable information to be used for the control of wind turbine blade heating systems.

In this paper we present the validation of icing forecasts for four wind farms in Sweden. The validation considers the instrumental icing periods, timing of icing events and wind energy forecasts.

## I. Methodology

This chapter describes the model setup of the forecasts, the calculation of the ice load, the IceLoss methodology and identification of icing periods from SCADA data.

### *A. Meso-scale model data*

In this work we have used the Weather Research and Forecasting (WRF) model (version 3.2.1) run both with a hindcast setup, with input data from Final Global Data Assimilation System (FNL), and for forecasting using GFS (Global Forecast System) data as input.

The area covered by a 4 km x 4 km resolution grid is given as the inner domain showed in Figure 1. The simulations are setup with 32 layers in the vertical with four layers in the lower 200 m. We have used the Thompson microphysics scheme [1] and the Yonsei University Scheme [2] for boundary layer mixing.

In forecast mode the model is initiated 4 times daily and run for a period of 48 hours. Hourly data is stored for the simulation periods.

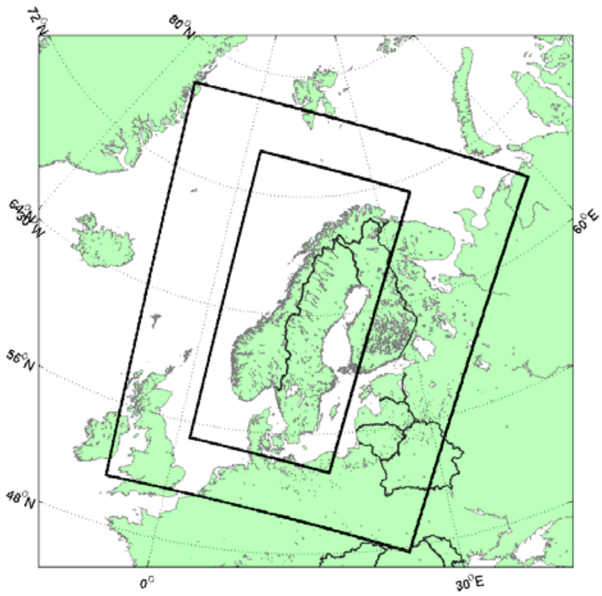


**Figure 1** The model setup used. The inner rectangle shows the area covered by 4 km x 4 km simulations.

### B. *Ice load calculations*

According to the standard ISO 12494 [3] icing has been calculated from:

$$\frac{dM}{dt} = \alpha_1\alpha_2\alpha_3 \cdot w \cdot A \cdot V$$

Here *dM/dt* is the icing rate on a standard cylindrical icing collector (defined by ISO 12494 as a cylinder of 1 m length and 30 mm diameter), *w* is the liquid water content (LWC), and *A* is the collision area of the exposed object. *V* is the wind speed and $\alpha_1$, $\alpha_2$ and $\alpha_3$ are the collision efficiency, sticking efficiency and accretion efficiency, respectively.

The topography in the simulations is represented by a computational grid that is too coarse to represent the real height of the mountain peaks. This means that the mountain tops in the model often are lower than in the real world. This discrepancy can lead to an underestimation of the icing amounts particularly for coarse model grids. The discrepancy in height is corrected for by lifting the air in the model to the correct terrain height. This lifting will contribute to lower the pressure and temperature in the air, and will lead to condensation in the cases when the air when reaching the saturation water vapor pressure. The lifting is performed according to the vertical profile of temperature and moisture locally in the model.

The modelled ice load at a given time, t, is defined as a function of the icing rate, melting rate ($dM_{melt}/dt$) and sublimation rate ($dM_{sublimation}/dt$) according to:

$$M(t) = \sum_{t=t_0}^{t}\left(\frac{dM}{dt}(t) + \frac{dM_{melt}}{dt}(t) + \frac{dM_{sublimation}}{dt}(t)\right)\Delta t$$

The time step, Δt, used in the calculations of icing are 3600 s. A detailed description of the terms for the melting rate is given in [4]. Sublimation is defined as the transfer of ice from solid state directly to water vapour, which occurs in situations with dry and cold air. The sublimation rate increases with wind speed as the ventilation of the iced object is high. This can allow for a faster ice removal from a rotating turbine blade compared to other fixed objects. The sublimation rate is calculated by evaluating the energy balance between outgoing long wave radiation and latent heat release from the sublimation process. Sublimation has been included in the icing calculations. During the process of sublimation we have observed that the accreted ice becomes brittle and that small ice-pieces are continuously shed from the cylinder. The shedding is included by multiplying the sublimation rate with a factor of 2.5.

### C. *Production losses caused by icing*

To estimate the production loss we assume that energy production will continue with ice on the rotor blades, and that there is a direct relation between the ice load on the standard ISO cylinder and the production loss experienced by the turbines. Ice on the blades will disrupt the aerodynamic structure of the blades which leads to a lower energy yield at any wind speed. The energy production follows the principle of a two-dimensional power curve as shown in Figure 2 The methodology is denoted IceLoss.

The curve is adjusted based on the operational data gathered for 3 wind farms in Sweden during 2009-2011. The power curve is adjusted using the ice load data calculated from WRF (and not the observed ice load data) to adapt the power loss calculation to WRF data.

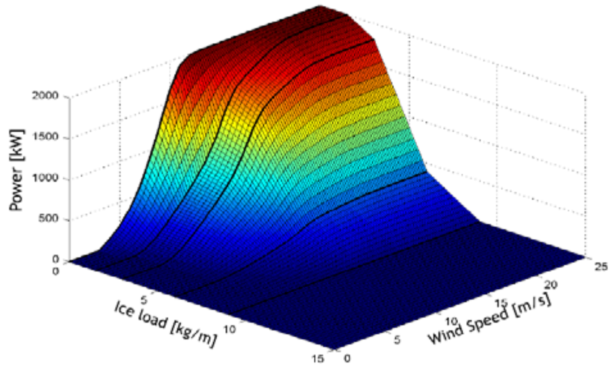


**Figure 2** Two-parameter power curve P(V,M), function of ice load and wind speed.

Observed weekly production losses from one of the wind farms are shown together with the modelled production losses using the IceLoss methodology in Figure 3. We note a high correlation between the observed and modelled production losses, but also a small underestimation of the losses for some winters.

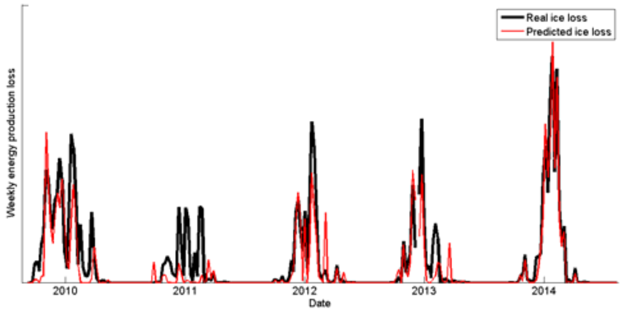


**Figure 3** Observed (black curve) and modelled (red curve) weekly production loss values for one wind farm.

### D. *Identification of icing from wind turbine SCADA data*

For each of the turbines in the available wind farms a power curve representative for the winter season has been calculated from the nacelle anemometer and power data. The power curve has been calculated using the median power values for wind speeds binned with 0.5 m/s intervals. When an alarm code is given the data is removed along with the pro- and preceding 10 minute time steps. Data for periods with curtailed power output is also removed in the analyses.

A threshold power curve has also been defined based on the associated 10-percentile value in each wind speed bin. When the power output from the turbine is below the threshold power curve, then the period is flagged as icing given that the operational codes also indicates normal operation and that the temperature measured at the nacelle is below 3 ºC. Only indications that are lasting more than 3 consecutive time steps (30 minutes) are used.

According to [5] this is the preferred method for defining periods of icing based on power data from the wind farm SCADA system.

## II. WIND FARM DATA

In this work data from four wind farms in Sweden have been used. All four wind farms experiences considerable amounts of icing and icing losses during the winter. For all wind farms more than 2 years of data has been available for the analyses. The four wind farms are denoted A, B, C and D.

III. RESULTS

### E. *Validation of icing periods*

According to [6] the periods of meteorological icing is defined as the periods when the meteorological conditions result in buildup of ice on structures, instruments, turbine blades etc. In the model these periods are defined by $dM/dt > 0$ g/hr. Instrumental icing is defined as the period when icing is influencing the wind measurements or the wind turbine production. Typically for modelled ice loads, M, larger than 100 g/m on the standard ISO cylinder we often observe that ice is influencing the energy production. In these analyses we compare the periods with ice loads larger than 100 g/m from the model with icing identified from the wind turbine SCADA data.

In Table 1 the percentages of time when ice was detected from the SCADA data for the four wind farms are displayed in the first line. We note that wind farm A has clearly a higher percentage of icing compared to the other 3. For wind farm A icing is found to influence energy production 22 % of the time. The probability of the model to also detect the periods when ice was found to influence wind power production was found to be 63-82% of the time for the four wind farms. The cases when the model falsely detected icing although no icing was detected from the SCADA data were 5-7 % of the time.

Note also that there are considerable uncertainties in the method for detecting icing from the SCADA data. During periods with low wind speeds it can be difficult to identify icing from the method described above. By reducing the threshold value of 100 g/m used for the modelled icing we were able to detect a higher number of the icing periods, but resulting also in a larger number of false alarms. An increase of the icing threshold had the opposite effect. The duration of the instrumental icing periods is also influenced by ice shedding that is difficult to model due to its stochastic behaviour. This also influences the probability of detection and false alarm percentages given.

**Table 1** Percentage of time when instrumental icing is detected from SCADA data, the probability of detection of instrumental icing from the forecasts, and percentage of false alarm cases from the forecasts

| | A | B | C | D |
|---|---|---|---|---|
| Ice detected from SCADA | 22 % | 9% | 10 % | 13 % |
| Probability of detection | 74 % | 82 % | 79 % | 63 % |
| False alarm percentage | 6 % | 7 % | 6 % | 5 % |

### F. *Timing of icing events*

Timing is essential in order to forecast icing and when the influence wind energy production is expected to start. If icing is successfully forecasted this can be valuable information to be used for the control of blade heating systems to be able to heat up the blade before the meteorological icing occurs.

For each icing event identified from the wind farms we perform a check to see if the event starts within a period when meteorological icing is forecasted. The meteorological icing events can last from 1hr events to events lasting for 3 days or more. The average durability for the forecasted icing events are 12 hours. The forecast is shifted 6 hours as the observed icing event is more likely to start in the middle of the modelled icing period. If the observed icing event starts within the time period of the forecasted event we denote it as successful at forecasting the particular event. Otherwise we report the time lag between the forecasted icing period and the onset of the observed icing period.

In Table 2 the number of individual icing episodes for each of the wind farms is reported. We see that for wind farm A and C a higher number of icing episodes were identified. These are also the wind farms where the longest time series are available. The table also shows how many of these icing episodes the model was able to correctly forecast the timing of when the icing started to influence the energy production

**Table 2** The number of individual icing episodes identified for each of the four wind farms. The probability of the forecast model to correctly detect when the icing episode starts is also given. The number of severe episodes is also given along with the probability of the forecast model to detect when the severe icing episodes starts.

| | A | B | C | D |
|---|---|---|---|---|
| Total number of icing episodes | 273 | 161 | 254 | 122 |
| Probability of detection | 52 % | 63 % | 63 % | 42 % |
| Number of severe episodes | 109 | 57 | 115 | 27 |
| Probability of detection | 67 % | 70 % | 71 % | 70 % |

For wind farm B and C the forecast model was able to correctly describe the timing for 63 % of all icing episodes. For wind farm A and D a lower number is found.  A large number of the identified icing episodes results only in minor losses, influences only a few turbines in the wind farm or only last for a short time period. For the four wind farms studied the 55-80 % of the icing episodes are related to such minor episodes. The total losses during these minor icing episodes equals to only around 10 % of the total production losses observed in these wind farms.

The individual cases when icing causes the aggregated production losses in the wind farm to be higher than 20% as an average over a period of 12 hours is then identified and defined as “severe” icing episodes. The remaining events includes only around 20-45 % of the total individual cases, but equals a total of 90 % of the total production losses in the wind farms and are therefore the events that are most important to capture with the icing forecasts. From Table 2 the number of severe events and the probability of detection are given as the third and fourth row. We note that the probabilities for the model to forecast the timing of these events are starting are 67-71 % for the four wind farms.

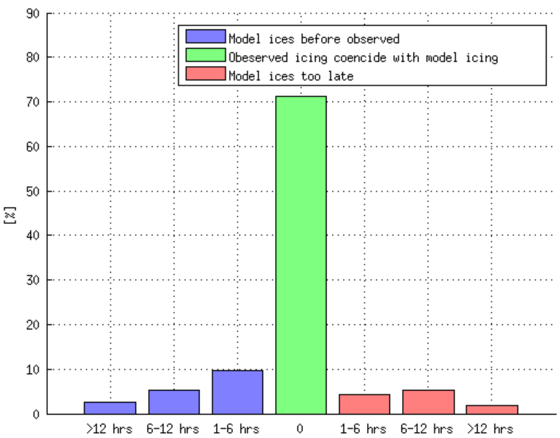


**Figure 4** Percentage of observed severe icing episodes forecasted with corrects timing (green bar), percentage of observed icing episodes when the model forecast icing too early (blue bars) and percentage of observed icing episodes when the model forecast icing too late (red bars). The figure displays the results for site C.

For the cases when the model is unable to correctly forecast the timing the icing event will either be forecasted too late, too soon or not at all. For wind farm C a histogram showing the percentage of timing biases in the forecast is shown in Figure 4. The blue bars denote the cases when the icing event is forecasted too soon, while the red bars denote the number of cases when the icing event is forecasted too late.

### G. *Forecasting of wind energy production*

The wind energy production for each of the four wind farms have been forecasted on a daily basis during the last two winter seasons. The forecast have been delivered at 10:00 every day in time to make use of the forecasts for bids at the NordPool spot market for the next day. The forecasts are made both for energy production assuming clean blades, depending only on the forecasted wind conditions, and for ice reduced forecast where we assume the icing influences the energy production according to the IceLoss model described in Section C.

The change in mean absolute error (MAE), bias and correlation coefficient in the forecasts when we include the IceLoss model is shown for one of the four sites in Figure 5. The MAE for this site is reduced by from an average of 22.5 % to 15 %. The negative bias is also clearly reduced, while the correlation coefficient between the forecasted energy production and the actual production is increased. Similar statistics for all the sites (as an average of the two winters 2013/2014 and 2014/2015) is given in Table 3. The values given are the average errors for +6 h to +48 h lead time. It is clear that the forecasts using the IceLoss model reduces the errors for all wind farms and increases the correlation coefficient. The largest improvement is found for wind farm A.

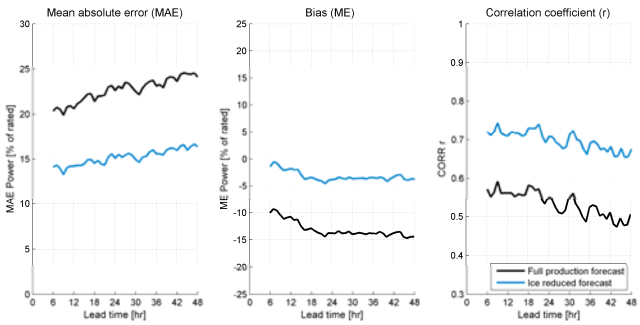


**Figure 5** Mean absolute error, bias and correlation coefficient for the forecasts. The forecasts assuming clean blades are shown in black curves, while forecasts using the IceLoss model are shown as blue curves. The forecast lead time is displayed on the horizontal axis. The results shown are for site A during the winter 2013-2014.

**Table 3** Mean absolute error, bias, and correlation coefficient, r, in the forecast of energy production for 4 wind farms as an average over the two winters 2013/2014 and 2014/2015.

| | A | B | C | D |
|---|---|---|---|---|
| MAE clean blades | 23 % | 17 % | 21 % | 16 % |
| MAE IceLoss | 16 % | 15 % | 17 % | 15 % |
| BIAS clean blades | - 14 % | -5 % | -5 % | -8 % |
| BIAS IceLoss | -5 % | -2 % | -1 % | -5 % |
| r clean blades | 0.60 | 0.78 | 0.72 | 0.80 |
| r IceLoss | 0.70 | 0.79 | 0.78 | 0.80 |

The distribution of forecast errors for site A is shown in Figure 6. The number of cases when the produced energy is forecasted within +/- 12.5 % is clearly higher when the IceLoss model is applied (ice reduced forecast) compared to the full production forecast derived using information about the wind conditions only. The number of cases when the forecast over-predicts the energy produced is also clearly reduced for the ice reduced forecast. On the other hand we see a somewhat larger number of cases when the forecast under-predicts the produced energy in the wind farm.

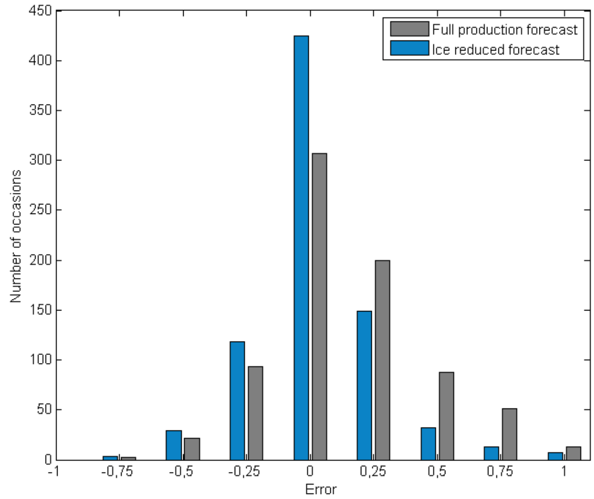


**Figure 6** Distribution of forecast errors. The results shown are for site A during the winter 2013-2014.

## IV. CONCLUSIONS

The WRF model has been configured to run operational 48 hour forecasts, initiated four times per day, in order to predict icing and wind farm energy production for wind farms located at exposed locations for icing in Sweden. The results of the analysis described show that the modelling system is able to correctly predict the periods when ice influences wind energy production in 63-82 % of the time of observed production losses in the considered wind farms. In 68-71 % of the severe icing events, which accounts for approximately 90 % of the observed production losses, the forecasted onset of the icing episodes were correct.

For all four wind farms the IceLoss model improved the energy forecasts and the associated icing losses.

## ACKNOWLEDGMENT

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