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Forecasting of Icing Related Wind Energy Production Losses

Probabilistic and Machine Learning Approaches

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Abstract
Molinder, J. 2021. Forecasting of Icing Related Wind Energy Production Losses. Probabilistic and Machine Learning Approaches. *Digital Comprehensive Summaries of Uppsala Dissertations from the Faculty of Science and Technology* 1994. 53 pp. Uppsala: Acta Universitatis Upsaliensis. ISBN 978-91-513-1088-6.

Icing on wind turbine blades causes significant production losses for wind energy in cold climate. Next-day forecasts of these production losses are crucial for the power balance in the electrical grid and for the trading process, but they are uncertain due to lack of understanding of, and simplifications, in the modelling chain. In the present work, uncertainties in the modelling chain for icing related production losses are addressed with the aim to increase the utility of next-day production loss forecasts. Probabilistic and machine learning methods are applied both to improve the forecast skill and to estimate reliable forecast uncertainties. The different methods enable uncertainties in different parts of the chain to be addressed. A Numerical Weather Prediction (NWP) ensemble captures uncertainties in the initial conditions of the forecasts while a neighbourhood method describes uncertainties in the spatial representation of the NWP forecast at the exact locations of the wind parks. An icing model ensemble is generated in order to address uncertainties in the icing model parameters. Finally, machine learning approaches are employed to both deterministically and probabilistically address uncertainties in the modelling chain. Production data from wind parks in Sweden were used to evaluate all methods. The physically based probabilistic methods; the NWP ensemble, the neighbourhood method and the icing model ensemble, increase the forecast skill and provide valuable uncertainty estimations. The largest forecast improvement is obtained when the different probabilistic approaches are combined. On the other hand, machine learning approaches for icing related production losses demonstrate large potential. The probabilistic machine learning method employed generally outperforms every other single probabilistic method mentioned above. By applying the different methods of uncertainty quantification, the utility of icing related production loss forecast in the trading process is improved since related costs can be reduced and usage of the produced power can be optimised. These methods can also be beneficial when planning for site maintenance and for the use of de-icing systems, since icing on the wind turbines are directly or indirectly forecasted. Thus, the improved representations of uncertainties in the modelling chain contributes to an enhanced usage of wind power in cold climates.

Keywords: Wind energy, Icing on wind turbines, Machine learning, Probabilistic forecasting

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List of papers

This thesis is based on the following papers, which are referred to in the text by their Roman numerals.

I Molinder J., Körnich H., Olsson E., Bergström H. and Sjöblom A. 2018. Probabilistic forecasting of wind power production losses in cold climates: A case study. *Wind Energy Science. **3 (2)**: 667–680*, https://doi.org/10.5194/wes-3-667-2018.

II Molinder J., Körnich H., Olsson E. and Hessling P. 2019. Uncertainty quantification for the modelling of wind turbine icing. *Journal of Applied Meteorology and Climatology (JAMC). **58**, 2019-2032.* doi:10.1175/JAMC-D-18-0160.1. © American Meteorological Society. Used with permission.

III Scher S., Molinder J. 2019. Machine Learning-Based Prediction of Icing-Related Wind Power Production Loss. *IEEE Access, **7**, 129421-129429.* doi:10.1109/ACCESS.2019.2939657.s

IV Molinder J., Scher S., Körnich H., Nilsson E., Bergström H. and Sjöblom A. 2020. Probabilistic forecasting of wind turbine icing related production losses using quantile regression forests *Under review in Energies*

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Contents

1. Introduction

Wind energy is a fast growing source of renewable energy and thus plays a large role in the renewable energy development for the future. When building new wind parks there are several geographically related aspects to take into account in addition to the wind climate. First, since wind turbines can cause disturbance for people, for example due to the sound level, it is desirable to place a wind park far away from highly populated areas. Secondly, the higher air density in cold climates means a potential greater power production which makes cold climate areas of interest. Thirdly, building offshore wind parks has several advantages including minimising human disturbance, but with high maintenance costs as a trade off. Based on this, several wind parks have been constructed in cold climate regions where low density populated areas and higher potential power production is found. Cold climate wind parks can, however, experience severe problems due to periods of icing on the turbine blades. Icing changes the aerodynamic balance, generates vibrations and increases the load on the blades [1]. Icing can therefore result in significant production losses and increased maintenance costs. Figure 1.1 shows the mean potential power production based on the observed wind speed at a wind park in Sweden 2014. The figure also presents the observed power production for the same period. The site clearly suffers from substantial production losses during the whole period, showing how severe the icing related production losses can be. Malmsten [2] estimated annual production losses due to icing at Swedish wind farms, and found that two wind parks located in the northern parts of Sweden experienced annual production losses of nearly 20%. The influence of icing on the annual energy production was also investigated by Barber et al. [3] for sites located in Switzerland, finding that a site at high altitude experienced 17% production losses.

By the end of 2015, 30%, 127 GW, of the globally installed wind energy capacity was in cold climates [4]. This capacity is constantly increasing and is expected to have reached around 186 GW by the end of 2020 [5]. Most of these turbines experience icing, even if some of them only have light icing events which does not affect the power production significantly.

Icing on the turbine blade can be caused by in-cloud supercooled water droplets, freezing rain or wet snow and graupel. The most critical temperatures are a few degrees below, or around zero, since the ice accumulation requires sufficient liquid water in the air. The ongoing climate change towards higher temperatures does therefore not necessarily mean less icing for wind parks in cold climates. Some of the parks located in areas currently experiencing extremely low temperatures would instead be more affected by icing in a warmer climate [6]. Many of the newer wind turbines have de-icing systems, but due to the cost of running a de-icing system there is currently no solution available that definitely solves the problem of icing.

On a short time scale, of a few days, an additional cost and problem with icing arise if the ice is not forecasted correctly. A poorly forecasted next-day wind power production increases the trading costs for the energy companies and can result in an unstable grid. It can also be a problem when planning the usage of de-icing systems. Furthermore, ice falling off the blade is a safety risk for the public and during maintenance. Short-range forecasts of icing and related production losses are therefore crucial for the wind energy community. IEA Wind Task 19 [7] specifies the great need for site specific forecasts of icing provided at least once a day. For the trading process, next-day production is preferably predicted before noon one day ahead. Here the focus is on the next-day icing related production loss forecasts, but the methods presented can also be used for next-day icing forecast.

Forecasting wind turbine icing and/or related production losses has been done in several previous studies (e.g. [8, 9, 10, 11]). The forecasting involves several modelling steps and simplifications due to lack of understanding of ingoing modelling processes or computational costs. The resulting forecasts have thus been found to be uncertain. For example, Bergström et al. [9] used different Numerical Weather Prediction (NWP) models as input to an icing model showing that the NWP model formulations can have a large effect on the resulting icing forecast. Davis et al. [8] showed that different sizes of cloud droplets, which often are estimated within an icing model, also have a large effect on the forecasted icing amount. In this thesis, different methods are tested to improve the icing related production loss forecasts and/or estimate the uncertainty of these forecasts in each step.

In the meteorological community a commonly used approach to address and estimate model uncertainties is using probabilistic forecasting [12]. With probabilistic forecasting, not only one single forecast is issued at each forecast step, but a range of possible forecasts. A probabilistic forecast can thus be used both to estimate the likelihood for a specific event and for estimations of forecast uncertainties. Probabilistic forecasts can be generated using different methods depending on the addressed uncertainty source and have previously been used for wind energy purposes mainly focusing on the wind speed forecast (e.g. [13, 14, 15, 16]). A probabilistic forecasting method was for example shown by Kim and Hur [15] to improve wind power forecasts both in terms of better deterministic forecast results when using an ensemble mean forecast and with the additional information of forecast uncertainty for the next-day power production. Traiteur et al. [14] studied the use of short-range ensemble prediction systems for wind speed forecasting on a one-hour ahead approach and showed that their calibrated ensemble forecast outperformed other forecasting methods. Four probabilistic forecasting methods described in Section

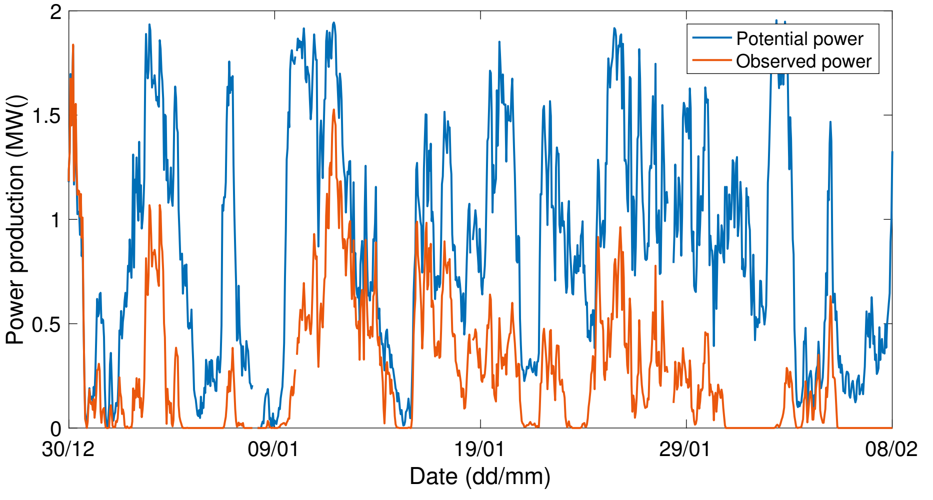

Figure 1.1. Potential power production vs observed power production for a one-month period 2013-2014 measured at a site in Sweden.

2 were applied here addressing uncertainties in different parts of the modelling chain for icing related production losses.

An ideal probabilistic forecast represents the forecast uncertainty and provides probabilistic estimations that can be used for risk assessments and decision making. A probabilistic forecast can, for example, be presented to users similarly to a deterministic forecast, showing a time series of the following days production loss. The forecasted uncertainty can then be visualised either by showing all ensemble members, or by adding the forecasted spread or standard deviation of the forecast. Figure 1.2 presents an example of forecasted production losses, forecasted uncertainty in terms of standard deviation for each time step, and the observations for this period. In this example, and using the uncertainty estimation, the forecast would be more uncertain for 4 January than for 9 January.

In the last decades, machine learning has been a fast growing field in geosciences [17]. It has successfully been applied in a variety of meteorological applications, such as forecasting aviation turbulence, for renewable energy, for post-processing of weather forecasts, to predict the forecast uncertainty and even for generation of complete weather forecasts [18, 19, 20, 21, 22]. Haupt and Monache [23] discuss the potential value of machine learning approaches in wind energy and more specifically probabilistic machine learning approaches. Kreutz et al. [24] used machine learning for icing related issues in wind energy with success, but to forecast the actual wind turbine icing and not the related production losses. Machine learning has also been applied to create a model for icing related production loss forecasting in e.g. Davis et al. [25] with input from a physical icing model. Here, machine learning meth-

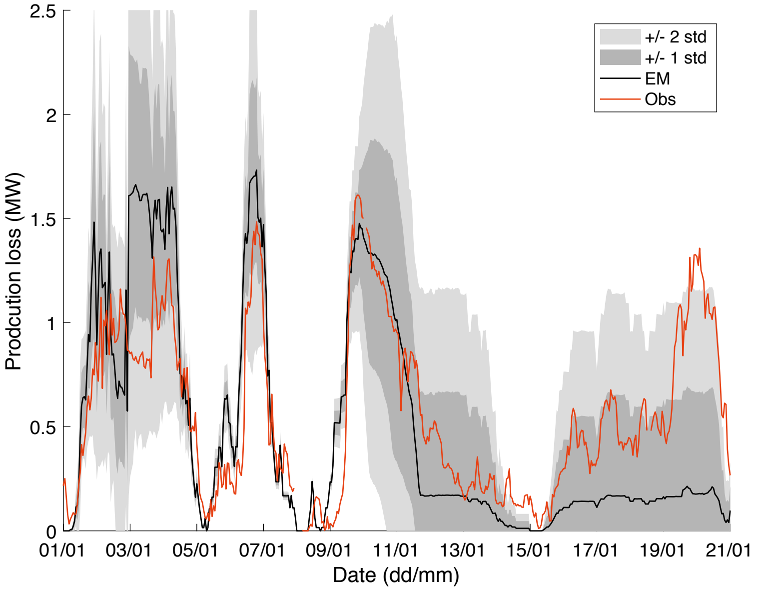

Figure 1.2. Production loss forecast including icing model ensemble mean (black) and ensemble spread in terms of two standard deviations (dark grey = 1 SD, light grey = 2 SD). Observed production loss in red. Reproduced from Figure 5 in **Paper II**. Molinder J., Körnich H., Olsson E. and Hessling P. 2019. Uncertainty quantification for the modelling of wind turbine icing. *Journal of Applied Meteorology and Climatology (JAMC). **58**, 2019-2032.*. doi:10.1175/JAMC-D-18-0160.1. © American Meteorological Society. Used with permission.

ods were applied to generate a production loss model both with and without the physical icing modelling step. Moreover, a probabilistic machine learning method was employed to forecast the next-day production loss together with the forecast uncertainty. Probabilistic machine learning methods have also been utilised previously for wind energy related forecasting but mainly focusing on the wind speed [26, 27].

The thesis is presented as follows. An overview of the modelling chain, related uncertainties and how these uncertainties were addressed is given in Section 2, followed by a description of the experiment periods and verification data in Section 3. Some of the verification tools are presented in Section 4. In Section 5, the main results are outlined. Finally, discussion and conclusions are presented in Section 6 and future perspectives in Section 7.

2. Modelling chain and sources of uncertainties

The modelling chain commonly used for the modelling of icing related production losses employed, or partly employed in **Paper I-IV**, is shown in Figure 2.1. The figure also presents several sources of uncertainty in the modelling chain. This section describes the modelling chain, the uncertainties, and how some of the uncertainties were addressed applying different methods.

2.1 Numerical weather prediction model

Modelling icing on wind turbines requires high resolution NWP data. Since these forecasts are computationally demanding, a regional model with high resolution was applied using input from a global model with lower resolution. More specifically, the ensemble prediction system (EPS) at the European Centre for Medium range Weather Forecasts (ECMWF) was utilised as boundary condition for the regional model. The ECMWF EPS version applied has a horizontal resolution of 30 km, and the boundary conditions were updated at 00 UTC and 12 UTC. Uncertainties in the model formulations of the global model are one source of uncertainty in the modelling chain contributing to uncertainties in the initial conditions and boundaries of the regional model (Figure 2.1).

The HARMONIE-AROME model [28, 29], operationally used at e.g. the Swedish Meteorological and Hydrological Institute (SMHI), was employed as the regional NWP model over a domain covering Sweden (Figure 2.2). The model is non-hydrostatic, convection-permitting, with a horizontal resolution of 2.5 km and has 65 vertical levels. In a two-week case study in **Paper I** model cycle 38h1.2 was applied while in **Paper II-IV** the applied model cycle was 40h1.1. The regional model was initialised every 6^{th} hour, 00:00, 06:00, 12:00 and 18:00 UTC, with hourly output. In the two-week case study all model runs were 42 hours long while for other periods, specified in Section 3, only the 06 UTC initialisation was run for 42 hours and the others only 6 hours ahead. This choice was made only to limit computational costs and allowed for longer re-forecasting periods of NWP model data. The 06 UTC model run was chosen to remain 42 hours since this allows for next-day production estimations before noon as often necessary for the trading process. The forecasted values from +18 to 42 hours then serve as the next-day forecast. The initial

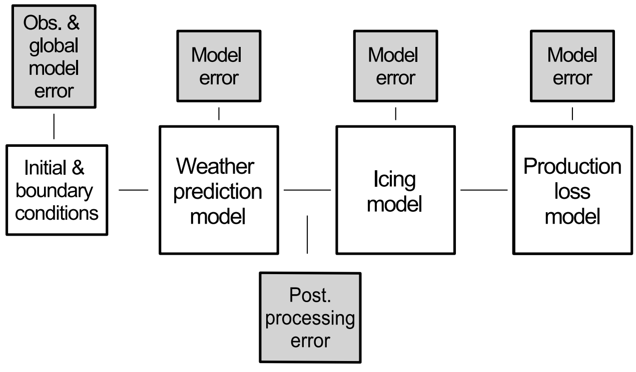

Figure 2.1. Schematic figure of the modelling chain often used for the modelling of icing related production losses and the respective sources of uncertainty (reproduced after **Paper I** Figure 1, CC BY 4.0)

conditions of the model were based on earlier model runs and observations using 3-dimensional-variational data assimilation.

Even if the data assimilation can generate the best possible estimation of initial conditions based on the available information, both the observations and the earlier model run are uncertain making a perfect initial condition impossible. It is known that for a non-linear dynamical system such as weather, a large part of the uncertainty results from initial errors that grow fast with forecast time [30]. This, together with assumptions in the data assimilation, contributes to uncertainties in the forecast [31] and are therefore another uncertainty source in the modelling chain (Figure 2.1). Uncertainties in the initial conditions of an NWP model are commonly addressed using ensemble forecasting which is a kind of probabilistic forecast. Basically, the model is run several times with slightly different initial conditions. The differences of the initial conditions are estimated based on approximations of observation and model errors. An advantage of an ensemble prediction system is that the ensemble mean forecast generally has a lower error than a single forecast because the less predictable parts have been filtered out when averaging the ensemble members [32]. The spread of the ensemble members can be used as a prediction of forecast uncertainty. In the two-week case study (**Paper I**) and for some additional results presented here, the uncertainties of the initial and boundary conditions were addressed using the EPS version of HARMONIE-AROME, HarmonEPS. Ten ensemble members with perturbed initial conditions based on boundary conditions from different members of the global EPS together

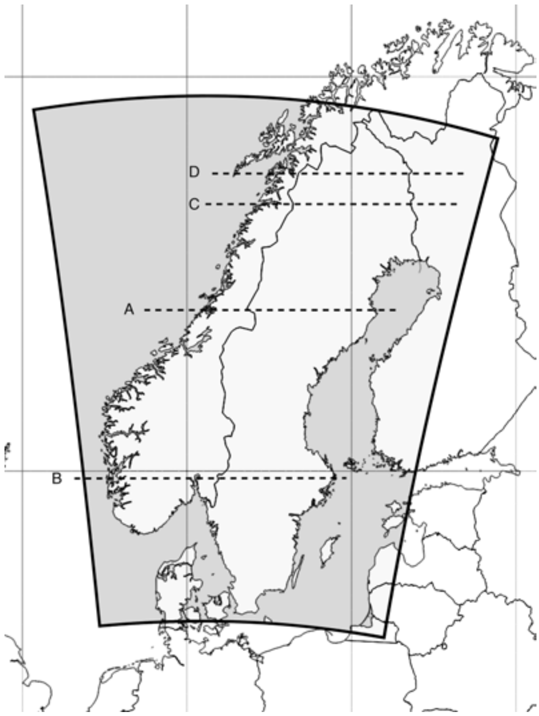

Figure 2.2. NWP model domain. The domain is centred over Sweden and to a large extent covers the rest of Scandinavia. Dashed lines mark approximate location of the 4 wind parks A-D with available production observations and no de-icing system. Reproduced from Figure 2 in **Paper III**. Molinder J., Körnich H., Olsson E. and Hessling P. 2019. Uncertainty quantification for the modelling of wind turbine icing. *Journal of Applied Meteorology and Climatology (JAMC). **58**, 2019-2032..* doi:10.1175/JAMC-D-18-0160.1. © American Meteorological Society. Used with permission.

with one control member were applied. The resulting modelling chain can be seen in Figure 2.3a.

The regional NWP model also suffers from uncertainties in the model formulations and from simplifications to make the model computationally affordable for operational usage [33]. This uncertainty was however not fully addressed here, even if these uncertainties are partly addressed by the initial condition perturbations.

Despite the high horizontal resolution of the NWP model, the model terrain in the mountainous areas, where wind parks often are located, often deviates from the real terrain. To account for this, a vertical interpolation method was utilised that averages the meteorological parameters, based on the difference between the model terrain and actual terrain height according to:

$$P_i = \frac{P(h_m + \Delta h + h_{nacelle}) + P(h_m + h_{nacelle})}{2} \tag{2.1}$$

where h_m is the model terrain height, Δh is the difference between the model terrain and the actual terrain height, $h_{nacelle}$ is the height of the turbine nacelle, and P_i is the interpolated parameter (Figure 2.4). The forecast made at the actual terrain height plus nacelle height and the forecast made at the model terrain height plus nacelle height are basically averaged.

An additional uncertainty in the modelling chain arises in the usage of grid point data from the NWP model to represent the weather at the exact location of the wind parks (Figure 2.1). This is a problem due to both the difference between model terrain and real terrain discussed above, and due to the fact that the closest grid point to the wind park can be several kilometres distant. Local weather phenomena can also easily be missplaced by a few kilometers by the NWP model. Unless otherwise stated, the forecasted meteorological parameters at the closest grid point to the wind park were used as input to the icing model or in some cases directly to a machine learning model. However, to address the uncertainties related to this, a neighbourhood method, following Mittermaier [34], was applied in the two-week case study in **Paper I**. In this case, instead of only using the closest grid point of the NWP forecast to the wind park, the 25 closest grid points were utilised as input to the icing model, creating a 25-member ensemble forecast (Figure 2.3b). All of the 25 grid points predictions were assumed to forecast equally likely meteorological parameters and the grid point forecasts were thus not weighted by distance. The combination of the initial condition ensemble and the neighbourhood method was also tested (Figure 2.3c). The combination results in a total of 275 ensemble members - 25 neighbourhood members for each of the 11 initial condition ensemble members.

2.2 Icing model

The meteorological parameters forecasted by the NWP model serve as input to an icing model, if not directly into a machine learning model as discussed below. The icing model calculates the ice load on a cylinder of 30 mm in diameter according to International Organization for Standardization (ISO) 12494 [35]. It is based on an in-cloud icing equation commonly referred to as the Makkonen equation [36] and already discussed in Kuroiwa [37] for the use of forecasting icing on wires, with an additional ice loss term and ice accretion due to other hydrometeors than cloud water:

$$\frac{dM}{dt} = \sum_{i=1}^{5} \alpha_{1_i} \alpha_{2_i} \alpha_{3_i} W_i v A - L \tag{2.2}$$

where M is the mass of ice, t is the time. The sum contains the contributions of the ice accumulation due to the different hydrometeors (i): rain, cloud water, snow, graupel and cloud ice. Basically, the ice load is calculated for each hydrometeor separately using the setup of the model suitable for the specific hydrometeor. Differences in their calculations are found in the efficiency coefficients, α_1, α_2 and α_3 further described below. W_i is the water content, v is wind speed, A is the cross-sectional area of the cylinder on which the ice accumulation is calculated and L is the ice loss term. L includes functions for melting, sublimation, wind erosion and ice shedding.

α_1*, Collision efficiency:* – Describes the ratio between the number of e.g. cloud droplets that collide with the surface of an object and the total number of cloud droplets on the windward side of the cylinder [38]. It depends on the particle size, the velocity of the particles, the shape of the object and the temperature. The median volume diameter (MVD) is used instead of the actual particle size of each particle. The MVD is derived from the mass concentration of the hydrometeors forecasted by the NWP model and the particle number concentration, according to a scheme for cloud water by Thompson et al. [39]. Larger MVD or higher v results in larger collision efficiency, while larger A results in smaller collision efficiency.

α_2*, Sticking efficiency:* – Describes the ratio of particles that stick to the blade after colliding with it. For snow, graupel and cloud ice it is often called β here calculated according to $1/v^{0.75}$ based on discussions in Nygaard et al. [10]. However, ice particles easily bounce off the surface. To account for this ice accretion due to snow, graupel and cloud ice was limited to when liquid water was present. For cloud water and rain the sticking efficiency is unity.

α_3*, Accretion efficiency:* – The heat balance of the icing process determines the accretion efficiency. It is unity if the water or ice particle that sticks to the surface freezes immediately. If it instead takes some time for the particle to freeze, some will fall off the surface and the accretion efficiency will be smaller than unity [38]. When MVD is small and T and v is low, the accretion efficiency is high.

The model contains several simplifications and uncertainties due to lack of knowledge of the ingoing processes ([8, 10, 40]) which are therefore another source of uncertainty in the modelling chain (Figure 2.1). Improvements of icing models are also not trivial due to the generally uncertain measurements of icing on wind turbines. To address some of these uncertainties, an icing model ensemble with perturbations in the model physics was generated in **Paper II**. Five model parameters were perturbed based on literature studies: IFP- the ice shedding factor, WE- wind erosion factor, MVD - median volume diameter, Nu - Nusselt number and β- sticking efficiency for ice particles (Figure 2.6). Two of the parameters affect the ice loss, two of them the ice accumulation and one of them, Nu, have an effect on both the ice loss and the ice accumulation. The IFP describes the amount of ice that will fall off the blade during melting while the WE factor determines the amount of ice that will fall off the blade due to strong wind. The parameter Nu affects the accretion efficiency, α_3, and the calculations of the rate of sublimation. MVD and β are central parts in the calculations of the efficiency coefficients as described above.

The perturbations were added to the parameters based on their estimated uncertainties in terms of standard deviation using a deterministic sampling method. A description of the estimated uncertainty distributions of the parameters and the deterministic sampling method can be found in **Paper II**. When using deterministic sampling, a sampling rule is applied, providing an accurate description of the uncertain parameter probability density function with only a few optimally sampled ensemble members. For five uncertain parameters, eight ensemble members and one control member are then enough to represent the whole uncertainty distribution [41]. Deterministic sampling methods have previously been used e.g. for nuclear power purposes in Rahman et al. [42]. The resulting forecast is one mean value and an estimation of the forecast uncertainty for each forecast step in terms of standard deviation. The modelling chain can be seen in Figure 2.3d. In some of the new results presented in Section 5, the icing model ensemble was further combined with the initial condition ensemble; the resulting modelling chain is presented in Figure 2.3e. This combination was tested to see whether the icing model ensemble addresses different uncertainties compared to the initial condition ensemble, or if the uncertainties were already accounted for using the initial condition ensemble.

The icing model is currently based on the equation for ice accumulation on a cylinder as described above and not a wind turbine blade, which also contribute to uncertainties in the ice accumulation calculations. However, since this uncertainty rather should be addressed by re-writing the model physics and not perturbing it, it was not part of the direct perturbations here.

2.3 Production loss model

The production loss model uses input from the previous modelling steps, estimating a production loss based on the potential production. In **Paper I** and **Paper II** a simple empirical production loss model was utilised, while machine learning models were applied in **Paper III-IV**. The simple empirical production loss model was also used in the baseline approach further described in Section 4. Both the empirical model and the machine learning based models suffer from uncertainties due to the limited amount of historical data, and from uncertainties in the model formulations (Figure 2.1).

2.3.1 Simple empirical production loss model

Ice load, icing intensity and wind speed are inputs to the empirical production loss model. The model consists of two matrixes derived from a two-month period with available icing observations in 2010, and was manually constructed by fitting 0 and 100% production losses. One part of the model deals with the production loss due to ice load and the other part with production losses due to icing intensity. Higher wind speed, ice load or icing intensity results in greater production losses. A production loss in percent is forecasted by both parts of the model separately, but only the highest forecasted production loss is used. If the ice load is increasing, meaning a positive icing intensity, this part of the model generally forecasts the greatest production loss.

2.3.2 Machine learning based production loss model

Four machine learning algorithms were tested for the forecasting of the icing related production losses in **Paper III**: multilinear regression, random forest regression, support vector regression and neural networks with one hidden layer. Since modelling icing and the development of the icing models are challenging, as previously discussed, it would be beneficial if icing related production losses could be forecasted directly from NWP data. The machine learning algorithms were therefore applied without the icing modelling step to evaluate whether this approach can produce well performing icing related production loss forecast. The NWP data forecasted by the control member of HarmonEPS together with observations at the forecast initialisation time served as input to the machine learning based production loss models in this approach (Figure 2.5c). The exact input features can be found in detail in **Paper III**. The random forest regression method outperformed the other three tested machine learning algorithms. This method was therefore further used throughout the study.

Random forest regression was also applied in a following study presented in **Paper IV**. The focus in **Paper IV** was on forecasting uncertainties in addition to the mean production loss forecast. It was however found in **Paper IV** that it is beneficial to include the icing model in the modelling chain when using the random forest regression method based on the amount of training data available. Therefore, the output from the icing model, ice load and icing intensity, together with the wind speed, wind direction, temperature, air pressure and relative humidity from the NWP model served as input to the machine learning model throughout **Paper IV**. A probabilistic extension of the random forest regression algorithm, quantile regression forest (QRF), was applied for the uncertainty estimations (Figure 2.3f).

Random forest regression [43] is a commonly used machine learning method. It is based on decision trees which has been utilised for a range of meteorological applications the last decades (e.g. [21, 44, 45]). Basically, several decision trees are created based on a random subset of the training data. The final prediction is the average of the predictions made by each tree. The baseline random forest regression algorithm was applied using the stickit-learn implementation [46]. The algorithm can only forecast values in the range of the training data. This can be seen as an advantage since in the case of production losses the range is fixed to minimum-maximum production. However, since the training data is limited, the lack of extrapolation can also be a disadvantage.

The probabilistic random forest regression method QRF [47] was mainly applied to address uncertain parts in the production loss estimation step themselves, but since the training of the machine learning model is performed at the end of the modelling chain, uncertainties in the rest of the modelling chain are also addressed with this method. The QRF model forecasts chosen quantiles, and hence uncertainties, in addition to the mean forecast. The number of and exact output quantiles can be defined at each model run.

Many machine learning algorithms are sensitive to overfitting. Overfitting means that the model works very well on the training data, but not on new data. Training and test data therefore have to be clearly separated. Because of autocorrelation in weather forecasts randomly splitting up the individual forecasts into training and test sets is not useful. The data was instead divided into 10-day chunks and randomly chosen chunks were used for training and test sets. This is further discussed in **Paper IV**. For the deterministic random forest regression approach, 80% of the total amount of data was used for training the model and 20% for testing. When applying the QRF, 5-fold cross validation was used resulting in five different training and test sets, meaning that all data was used as test data once.

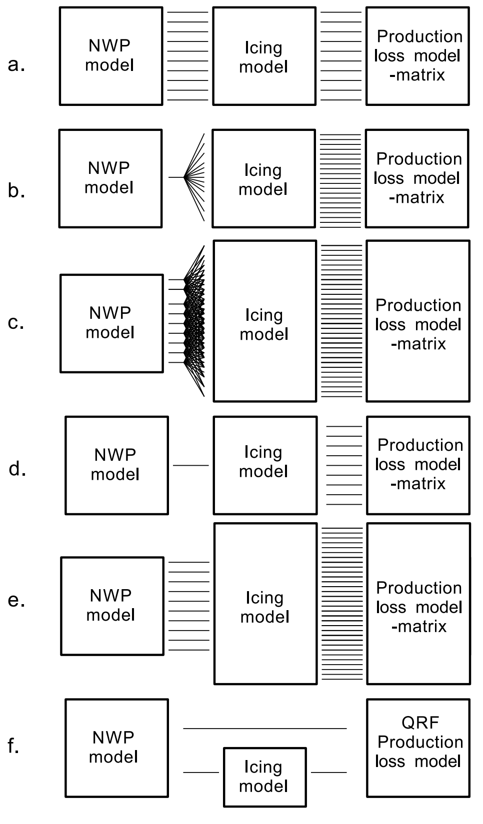

Figure 2.3. Probabilistic modelling chains applied in **Paper I, II & IV**. NWP model refers to the regional NWP model. Production loss model - matrix refers to the empirical production loss model and QRF production loss model refers to the machine learning based model. a. Initial condition ensemble approach, 11 NWP ensemble members. b. The neighbourhood method, resulting in a 25 member ensemble. c. The combination of the initial condition ensemble and the neighbourhood method - 275 ensemble members. d. Icing model ensemble, 9 icing model ensemble members. e. The combination of the initial condition ensemble and the icing model ensemble - 99 ensemble members. f. Probabilistic machine learning approach, generates quantiles representing forecast uncertainty.

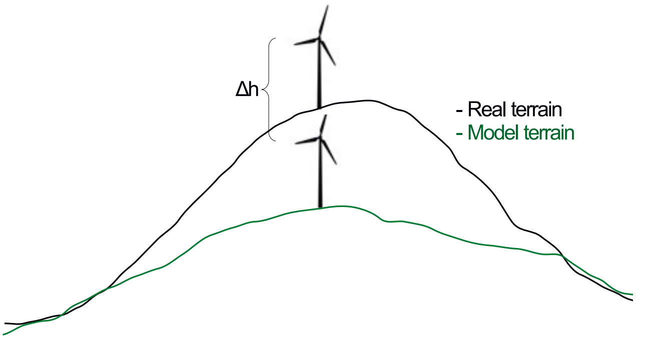

Figure 2.4. Illustration of the interpolation used for the meteorological parameters to account for differences between model terrain and actual terrain according to Equation 2.1.

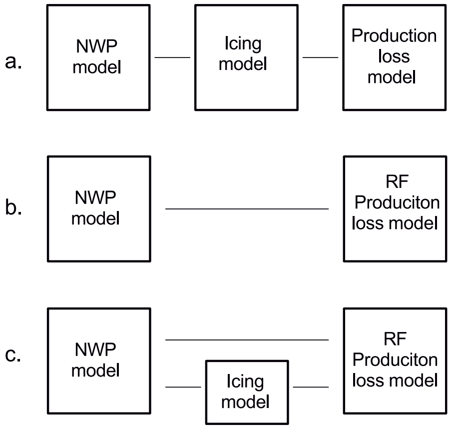

Figure 2.5. Deterministic modelling chains applied in **Paper I-IV**. a. Baseline modelling chain also used as deterministic reference forecast. b. Random forest based modelling chain without the icing model step. c. Random forest based modelling chain also including the icing model forecast step.

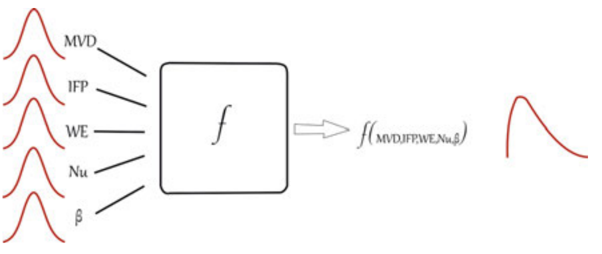

Figure 2.6. Estimated uncertainty distributions for the five parameters, MVD, IFP, WE, Nu and β described in the text, are used instead of a single parameter and generate an uncertainty distribution of the icing related production loss forecast. Reproduced from Figure 3 in **Paper II**. Molinder J., Körnich H., Olsson E. and Hessling P. 2019. Uncertainty quantification for the modelling of wind turbine icing. *Journal of Applied Meteorology and Climatology (JAMC).* ***58****, 2019-2032..* doi:10.1175/JAMC-D-18-0160.1. © American Meteorological Society. Used with permission.

3. Experimental periods and available data

Meteorological observations and production data were available for some winter periods between 2011 and 2015 from several wind parks in Sweden (Table 3.1). The wind parks cannot be specified by name or exact location due to contractual reasons, but the approximate locations of four wind parks with no de-icing system and available production data referred to as site A-D can be seen in Figure 2.2. The results here are mainly based on these four sites. In the two-week case study (**Paper I**) meteorological observations from a total of ten sites were used in the verification of the initial condition ensemble. For this verification of the forecasted meteorological parameters all model runs, 00:00, 06:00, 12:00 and 18:00 UTC + 42 hours were used. Throughout all papers, the 06:00 UTC + 42 hour model run was utilised when the icing related production loss forecasts were verified since this model run would allow for next-day forecast before noon as needed for the electricity trading process, as mentioned above. In the first paper that applies machine learning methods (**Paper III**), data from the four wind turbine sites in Figure 2.2 together with additional data from two sites with available production observations was used in the verification. The two additional wind parks do have de-icing systems, but since the de-icing systems are imperfect it is also of interest to evaluate the performance of the machine learning based model also at these sites. All parks are located between 250 and 1,000 meters above sea level and the measuring heights for the meteorological observations are between 60 and 150 meters above ground. The meteorological observations were available for every 10-minute period, but only data from every full hour were used.

The parks with available production data have several wind turbines, but production data from the running turbines was averaged for each wind park per hour. Only turbines with no current error code were used. Some of the sites also have observations of ice load as presented in **Paper I**. The observations of icing are, however, uncertain and could not be used for evaluation of the methods. Instead the forecasted production loss compared to the observed production loss was seen as a measure of the performance of the icing model. Both the production loss in percent and the absolute production loss were used.

The observed production loss (ploss) was based on potential power production compared to actual power production according to Equation 3.1. The potential production (p_potential) was estimated using power curves constructed from ice-free periods and observed wind speed. The observed production loss (p_observed) can, unfortunately be affected by errors in the observed wind speed, for example due to icing on the measuring instruments. Some additional uncertainty arises since the forecast potential production and production

Table 3.1. *The four periods with available NWP and observational data and in which paper the periods were used. The version of the NWP model used for re-forecasting Period 1 differs from the model version used for the other periods. More details can be found in* ***Paper I-II****.*

Period	Date	Used in Paper
1	27 Dec 2011 - 9 Jan 2012	I
2	30 Dec 2013 - 28 Feb 2014	II & III
3	12 Sept 2014 - 12 Jan 2015	II & III
4	14 Jan 2015 - 18 Feb 2015	II-IV

losses in percent assume no wake and blockage effects that can give positive biases in the derived production losses. This can lead to unavoidable over- or underestimation of the observed production loss and thus contributes to errors in the verification not related to the modelling. Some quality controls was performed, removing constant wind speeds in the data for example, and are further described in **Paper I**. Due to the complexity of this issue, no further action was taken to account for this. Some evaluation was undertaken regarding the resulting power production forecast in addition to the production loss forecast (**Paper I** and **Paper III**). This forecast step, however, involves the wind speed observation to an even larger extent and, because of the mentioned problem with the wind speed observations, the production loss forecast is mostly discussed here.

$$ploss = p_{potential} - p_{observed} \tag{3.1}$$

NWP models are computationally demanding to run and therefore limited time periods of re-forecasts were available. New periods were run when the opportunity was given. Historical NWP data from ECMWF EPS were only available for a two-week period when the first study was carried out (**Paper I**). This two-week period is referred to as period 1 in Table 3.1. During period 1 only production loss observations from three wind parks, parks A-C, were available. Results should due to the extremely limited amount of data be seen as a case study and proof-of-concept. The icing model ensemble and the first tested deterministic machine learning methods (**Paper II** and **Paper III**) were verified using data from period 2 and 3 in Table 3.1 and the results regarding the QRF method (**Paper IV**) using data from period 2-4. Period 1 was not utilised in the later studies (**Paper II-IV**) since the NWP model cycle differ in this period which means that the effect of different model versions cannot be neglected when comparing methods.

4. Verification methods

4.1 Reference forecasts

The control member (CM) of the ensemble prediction system, HarmonEPS, used as input to the icing model and further into the empirical production loss model has been used as baseline and deterministic reference forecast approach throughout the papers (Figure 2.5a). This allows a direct comparison with other methods since the same NWP model formulation is used. Another reference forecast applied for the machine learning approaches is a persistence forecast. The persistence was calculated assuming that the observed production loss in percentage at the initialisation time of the forecast is the same throughout the whole forecast length. This is not an unreasonable assumption since when the ice has accumulated on the turbine it can cause similar production losses for several days.

4.2 Verification scores

Comparison with deterministic forecast skill – Often when constructing probabilistic forecasts one of the aims, in addition to the probabilistic advantage of the forecasts, is to reduce the mean forecast error. The ensemble mean, i.e. the mean of the ensemble members, can be directly compared with a deterministic forecast in terms of forecast performance, e.g. using RMSE. The ensemble mean often outperforms a deterministic reference forecast on average since less predictable parts of the forecasts are filtered out. It is however important to take the smoothing of the forecast into account when using the ensemble mean. Even if it usually is a better single forecast, the ensemble mean should therefore not be used alone but instead together with the ensemble members or the uncertainty estimations.

Spread/skill relationship – The probabilistic forecast should optimally have a spread in the size of the actual forecast uncertainty at each forecast step. The spread is here defined as the mean difference between the ensemble mean and the ensemble members or forecasted standard deviation. A probabilistic forecast with a too low spread, often referred to as underdispersive, results in underestimated forecast uncertainty while a too large spread, an overdispersive forecast, can be useless since the forecast uncertainty is overestimated. Forecast uncertainty is however impossible to observe directly. A commonly used verification tool when the forecasted uncertainty is evaluated is the so called spread/skill relationship. If the forecast bias and the observational error are neglected, the mean spread and the mean RMSE should be of equal size. Due to the observational error and the bias a somewhat lower mean spread compared to the RMSE is however expected. The bias of the forecast can roughly be accounted for if the unbiased forecast error is used, here defined as $STD = \sqrt{RMSE^2 - bias^2}$. The unbiased forecast error was therefore employed for evaluations of the initial condition ensemble and the neighbourhood method in **Paper I** and the icing model ensemble in **Paper II**. For the forecasts based on machine learning algorithms in **Paper III** and **Paper IV** the unbiased forecast error was not applied (except in one comparison in **Paper III**) since the machine learning algorithms should be able to account for biases.

ROC diagram – A receiver operating characteristic curve (ROC) illustrates the ability of a probabilistic forecast to predict a certain parameter threshold. It compares the hit rate with the false alarm rate and shows if the probabilistic forecast is useful. Basically, for cases when the forecasted probability for a certain threshold, for example production losses higher than 0.5 MW, is high, the observation should agree in most cases. For cases when the forecasted probability is low, the observation should instead agree on fewer occasions. The ROC curve shows if this is generally true. However, to construct a ROC curve enough data, or available forecasts of the threshold, is required. The curve will otherwise be irregular and difficult to interpret. A higher area under the ROC curve is desirable, since this means less false alarm rates and a higher hit rate. A perfect forecast would have an area under the curve close to one. If the curve has a 1-1 relationship or even lower area under the curve, the forecast is not useful.

5. Main findings

5.1 Initial condition ensemble and the neighbourhood method

The initial condition ensemble and the neighbourhood method address uncertainties in the beginning of the modelling chain. This means that the forecasted meteorological parameters by the NWP model can also be improved with this method in terms of better forecast skill of the ensemble mean and uncertainty estimations of the parameters. Figure 5.1 presents the mean unbiased temperature forecast error (STD, solid lines) for forecast length +0-42 hours using the control member, the initial condition ensemble mean, the neighbourhood method ensemble mean and the combination of the two methods. The figure also shows the mean spread of the ensemble members for the probabilistic approaches (dashed lines). It is expected that the forecast error increases with forecast length which is seen for temperature shown in the figure. This was not the case for the wind speed and relative humidity forecast error (not shown) which is further discussed in **Paper I**. The initial condition ensemble spread also increases with forecast length (dashed black line in Figure 5.1), while the neighbourhood method shows a nearly constant spread (dashed green line). The constant spread of the neighbourhood method is a result from that the weather does not vary more between grid points on average for longer forecast lengths than for shorter. All three probabilistic approaches, the initial condition ensemble, the neighbourhood method and the combination, improve the forecast skill compared to the control member, i.e. the deterministic reference forecast. Combining the two probabilistic methods reduces the forecast error most compared to the control member, suggesting that the two methods actually address different uncertainties. The spread/skill relationship is, however, lower than it would be for a perfect ensemble forecast for all methods, meaning that the forecasted uncertainty is underestimated. This implies that the ensemble is not perfect. This is expected since other uncertainties, such as uncertainties in the physics of the NWP model, are not fully accounted for in the initial condition ensemble or by using the neighbourhood method. It should also be noted that the observational error is not accounted for in this comparison as discussed in Section 4. Some probabilistic verification tools, such as the ROC curve and the rank histogram are not suitable to use for the two-week period due to the limited amount of data and were thus not applied.

Figure 5.2 presents the production loss forecast in percentage for both the control member and the initial condition ensemble mean, and the related ensemble spread using the initial condition ensemble at site B for the two weeks.

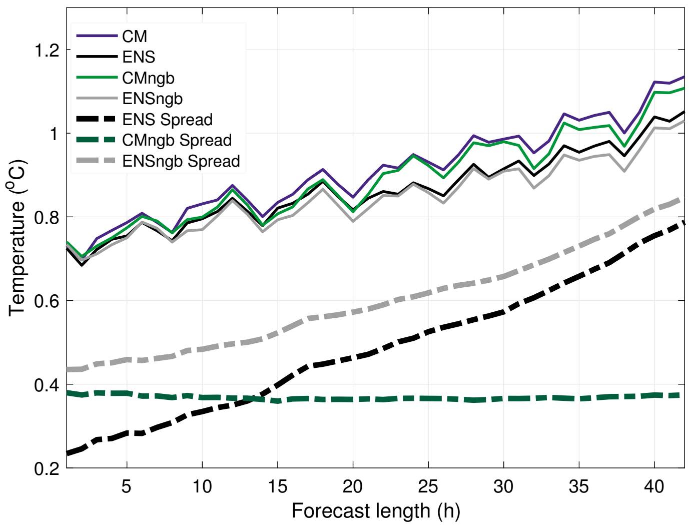

Figure 5.1. Unbiased forecast error, STD, for the control member (CM), the initial condition ensemble (ENS), the neighbourhood method (CMngb) and the combination of the initial condition ensemble and the neighbourhood method (ENSngb) for the temperature in ^{o}C and the spread for the three approaches consisting of multiple forecasts described in the text (Reproduced from Figure 5 in **Paper I**, CC BY 4.0).

It can be seen that the control member shows a more spiky behaviour than the ensemble mean. This is a result from the averaging of the ensemble members filtering out less predictable parts of the forecast. The forecasted uncertainty, or ensemble spread (Figure 5.2b), is clearly higher during ice accumulation and during ice loss. Forecasting the end of an icing period has been shown to be challenging due to the difficulties in modelling ice loss (e.g. [8]). This implies a well forecasted timing of high forecast uncertainty in this case. Some problems with the forecasted uncertainty were, however, seen especially at the start of one icing event during a frontal passage, where the ensemble was too confident with all ensemble members forecasting the start with the same time, but 12 hours later than the observations showed. By combining the initial condition ensemble with the neighbourhood method, there was some improvement in this case, but still not sufficiently accurate to observations (not shown here). This is further discussed in **Paper I**.

On average for the three sites, the initial condition ensemble, the neighbourhood method and the combination of them outperform the control member both regarding the production loss forecast and the final production forecast in terms of STD (Table 5.1). The average spread/skill ratio of the power production forecast applying the combination of the two methods was found to be around 0.7, compared to 0.5 for the initial condition ensemble alone and

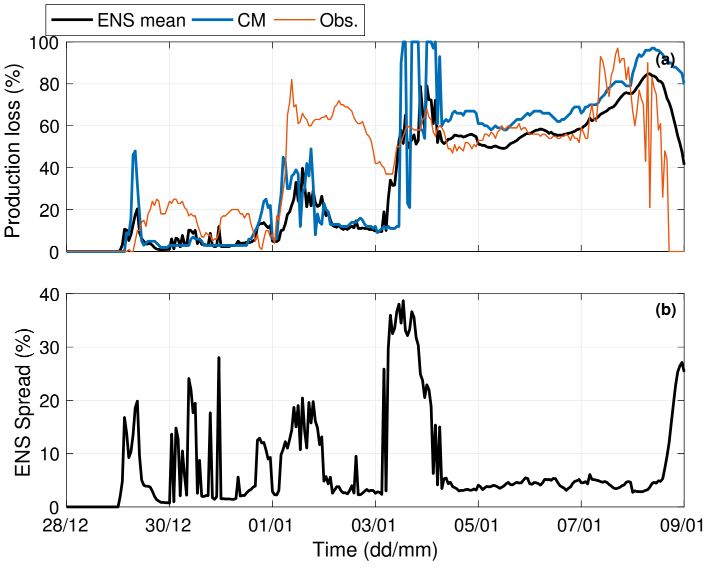

Figure 5.2. a) Forecasted production loss in percent for site B. Black line is the initial condition ensemble mean (ENS mean), blue is the control member, i.e. the deterministic reference forecast (CM) and red line is the observed production loss. b) The related spread of the ensemble members of the initial condition ensemble. (Reproduced from Figure 10 in **Paper I**, CC BY 4.0).

even lower for the neighbourhood method. Based on this, the combination of the methods provides the best estimate of the power production forecast uncertainty, even if the model still underestimates the uncertainty. Some additional results from using the initial condition ensemble, in this case for a longer period, are presented in Section 5.2.

5.2 Icing model ensemble

The icing model ensemble was tested over periods 2 and 3 (Table 3.1). The mean effect of the parameter perturbations on the production loss forecasts varies for five different parameters, WE, IFP, MVD, β and Nu. Table 5.2 shows the mean sensitivity of the icing model in terms of mean spread/standard deviation of the ensemble production loss forecast when perturbing each of the parameters separately. It is clear that β, MVD and Nu are the most important parameters since the model is more sensitive to perturbations of them in general. The Nu has an effect on both the sublimation, Subl, and the accretion efficiency, AE, which can be seen in the parentheses. It should be noted that the icing model is constructed for the NWP model version used here, which has a tendency to transform the cold droplets or rain to snow, graupel and ice

Table 5.1. *Unbiased RMSE for the control member, i.e. the deterministic reference forecast (CM), the initial condition ensemble (ENS), the neighbourhood method (CMngb) and for the combination of the initial condition ensemble and neighbourhood method (ENSngb) for production and for production loss forecasts averaged over the three sites with production data. The results are based on the two-week period (Period 1 in Table 3.1.)*

Method	Prod. (MW)	Prod. loss (%)
CM	0.49	26
CMngb	0.44	23
ENS	0.44	21
ENSngb	0.41	21

particles too fast when the temperature decrease ([28]; B. J. K. Engdahl 2019, personal communication). This means that the model sensitivity of perturbations of β probably would be lower if another NWP model and icing model was used.

Table 5.2. *Model sensitivity in terms of ensemble spread for the five perturbed parameters. Subl refers to the part of the Nu perturbation that affects the sublimation and AE refers to the part that affects the accretion efficiency (see text for explanation).*

Parameter	Mean spread of production loss forecast (MW).
WE	0.02
IFP	0.03
β	0.12
MVD	0.16
Nu (Subl, AE)	0.11 (0.08, 0.03)
All	0.22

Even if the effect of perturbing the ice loss parameters, WE, IFP and $Nu-subl$, is generally small, it could be seen visually for some periods that the perturbations can have a positive effect on the ensemble mean forecast skill, especially when combined. This positive effect that the perturbations can have on an ice loss event, separately and together, is shown in Figure 5.3. WE and IFP (Figure 5.3a and b) only result in a small difference in the mean forecast (ensemble mean, black lines) compared to the control member forecast (blue lines), while the Nu (Figure 5.3c) has a much larger effect. However, when combining the three of them (Figure 5.3d) the ensemble mean forecast shows closest behaviour to the observations, implying that all three perturbations are valuable.

On average over all sites, using the icing model ensemble mean forecast instead of the control member, i.e. the deterministic reference forecast, reduced the unbiased forecast error, STD by 12 % and 21 % for periods 2 and

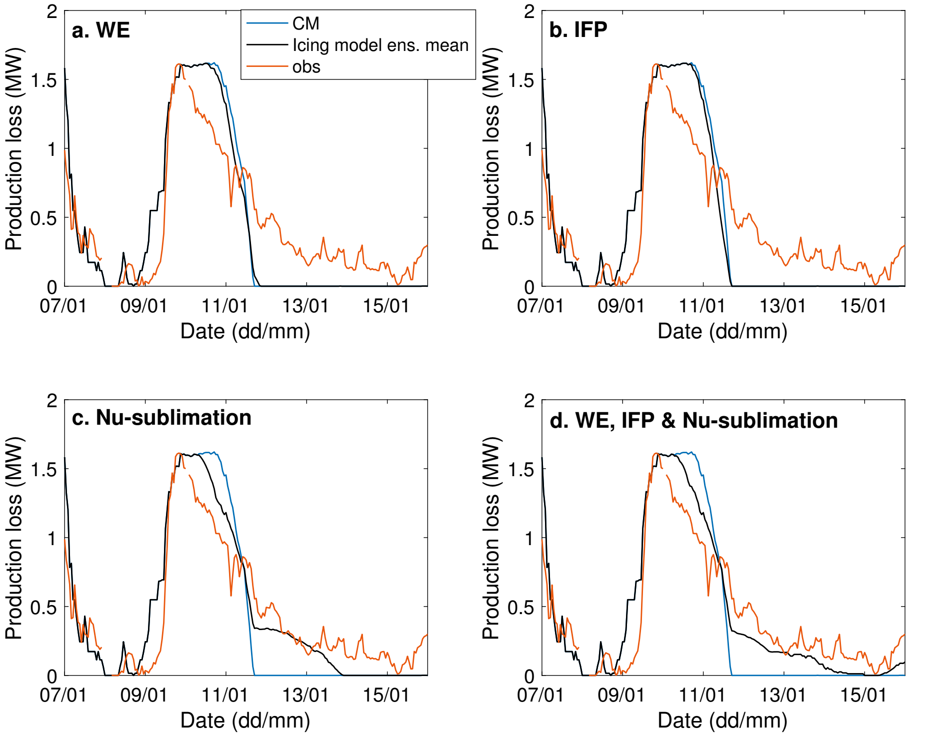

Figure 5.3. Ensemble mean production loss forecast using the icing model ensemble when perturbing icing model parameters separately, the control member forecast, i.e. the deterministic reference forecast (CM) and the observed production loss (obs). a. Perturbing only WE. b. Perturbing only the IFP. c. Perturbing only the sublimation part of the Nu-sublimation part. and d. Perturbing WE, IFP and Nu-sublimation. Each panel shows the observation (red), the control member forecast (CM) (blue) and the icing model ensemble mean forecast (black) for a one week during Period 1. Reproduced from Figure 6 in **Paper II**. Molinder J., Körnich H., Olsson E. and Hessling P. 2019. Uncertainty quantification for the modelling of wind turbine icing. *Journal of Applied Meteorology and Climatology (JAMC). **58**, 2019-2032.*. doi:10.1175/JAMC-D-18-0160.1. © American Meteorological Society. Used with permission.

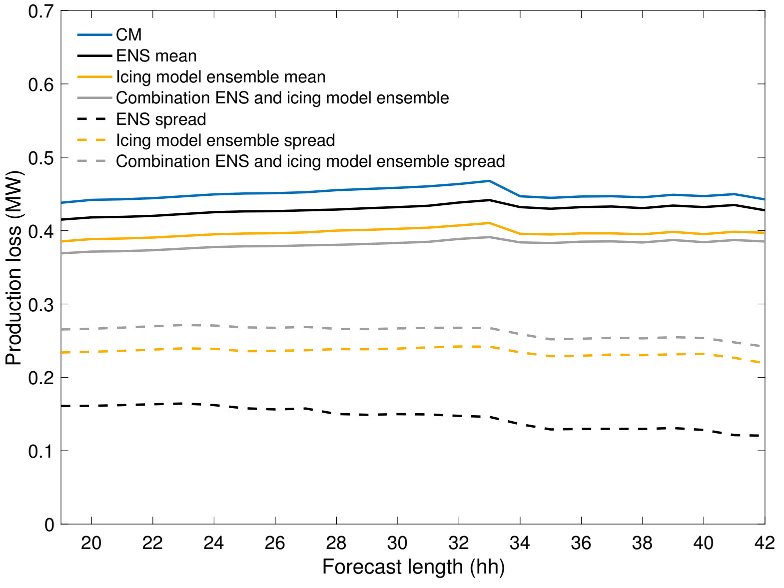

Figure 5.4. Mean forecast error (solid lines) and mean spread/standard deviation (dashed lines) of the probabilistic approaches, the initial condition ensemble mean (ENS mean), the icing model ensemble mean and the combination of the two approaches. Also shown is the mean forecast error using the control member (CM), i.e. the deterministic reference forecast.

3 respectively (Table 3.1). The mean STD, using the icing model ensemble mean and the control member averaged for site A-D and how this varies with forecast length are presented in Figure 5.4. The figure shows results based only on period 2 since this also enabled for a comparison with an initial condition ensemble available for the same period. This allows to present the initial condition ensemble mean and the combination of the two approaches STD in the figure. The mean forecast spread of the probabilistic approaches is also shown. First, it can be seen that both the initial condition ensemble and the icing model ensemble mean outperform the control member in terms of forecast skill. The icing model ensemble also outperforms the initial condition ensemble both in terms of forecast skill and in terms of spread/skill relationship. By applying the combination of the two methods, the forecast error decreases and the forecast spread increases leading to an even better spread/skill relationship. These results imply that the icing model ensemble actually address different uncertainties than the initial condition ensemble. Figure 5.5 shows the forecast error in terms of STD for the different approaches and the combination for all four sites separately. It is clear that the combination of the two methods is the preferred approach for all sites.

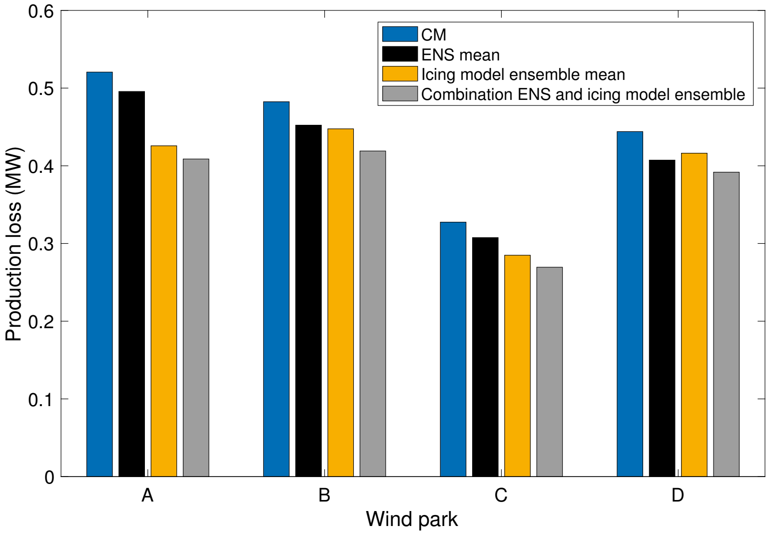

Figure 5.5. Average unbiased forecast error for wind turbine site A-D using the control member (CM), i.e. the deterministic reference forecast, the initial condition ensemble mean (ENS mean), the icing model ensemble mean and the combination of the initial condition ensemble and the icing model ensemble mean. Results are based on period 2 (Table 3.1).

A ROC diagram was used to verify that the icing model ensemble uncertainty forecast was of value compared to the deterministic reference forecast approach. Figure 5.6 presents both the ROC curve for the control member, i.e. the reference forecast, and for the icing model ensemble, averaged for period 2 and 3 (Table 3.1) and all four sites. The area under the curve is clearly higher for the ensemble forecast compared to the control member which means that the forecasted uncertainty is valuable, even if the forecast is not perfect.

5.3 Machine learning based forecasting

Periods 2 and 3 (Table 3.1) were used in the training and testing of the deterministic machine learning approach applied without the icing modelling step according to modelling chain Figure 2.5c. 20% of the data was used in the testing and 80% for training the random forest machine learning model. Figure 5.7 presents a comparison of forecast skill in terms of mean absolute error (MAE) of the power production forecast between the machine learning based forecast, the persistence forecast described in Section 4 and a production forecast made solely on forecasted wind speed from the NWP model. It is clear that the random forest regression model has some forecast skill since it outperforms both of the other methods in the relevant forecast lengths, 18-42 hours.

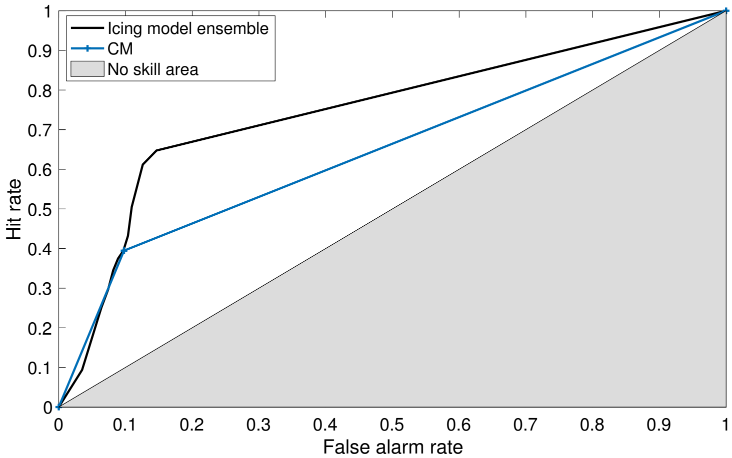

Figure 5.6. ROC diagram of the production loss forecasts for the threshold of 0.5 MW. The icing model ensemble forecast is given with the black line, while the blue line with marker shows the control member. Based on site A-D and data from period 2 and 3 (Table 3.1). The grey area marks the area of no skill. Reproduced from Figure 11 in **Paper II**. Molinder J., Körnich H., Olsson E. and Hessling P. 2019. Uncertainty quantification for the modelling of wind turbine icing. *Journal of Applied Meteorology and Climatology (JAMC).* ***58****, 2019-2032..* doi:10.1175/JAMC-D-18-0160.1. © American Meteorological Society. Used with permission.

The resulting forecast skill using this approach was also of similar magnitude as when applying the deterministic reference forecast. The average STD of the random forest regression forecasts for the four sites without de-icing system can be seen in Figure 5.8 (green bar). The figure also presents the control member, i.e. the deterministic reference forecast error (blue bar). It should be noted that the results regarding the machine learning approach are only based on the 20% test data compared to the deterministic reference forecast results which are based on all data from periods 2 and 3. The comparison clearly shows the potential of applying machine learning approaches for the modelling of icing related production losses. Moreover, production data from two wind turbine sites that have de-icing systems were compared to modelled production losses. Interestingly, the random forest regression model seems to be able to forecast the icing related production losses with some forecast skill at these sites despite the lack of knowledge about the de-icing system (not shown here). Some problems with underestimations of high production losses were, however, observed applying the method. This is further shown in **Paper III**.

The importance of the input parameters for the machine learning based model result was evaluated. Naturally, the forecasted wind speed was found to be the most important input parameter since this is crucial to determine the

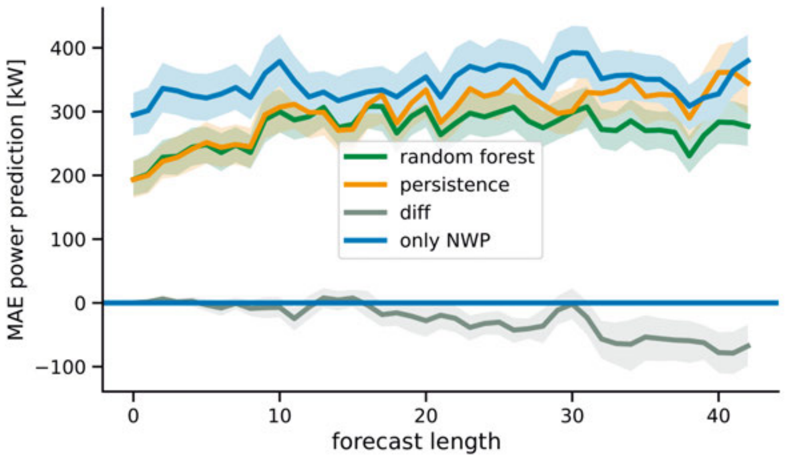

Figure 5.7. Mean absolute production forecast error (MAE) for the random forest forecasts (green) (modelling chain Figure 2.5c), the persistence forecast (orange) and the power prediction using only NWP forecasted wind speed (blue). The shading shows the uncertainty estimated via bootstrapping (5-95 confidence interval). (Figure reproduced from Figure 4 in **Paper III**, CC BY 4.0).

potential production and production loss. After wind speed, forecasted snow was found to be one of the most important parameter for the algorithm. However, if snow was removed from the training, the other ice particles, cloud ice and graupel, were instead most important and the forecast skill was shown to be approximately the same. An increased forecast error was first seen when removing all of the ice particles, snow, cloud ice and graupel. Thus, the model seems to compensate and to be able to forecast the icing related production losses solely based on one of the ice particles combined with the other input features. The importance of ice particles shows that the model captures some of the real physics in modelling icing. It was also found that if observations in the initialisation were not part of the input features, the forecast skill is only slightly negatively affected while removing the NWP data has a higher impact.

Even if the random forest regression model was found to perform well without the icing model in the modelling chain in **Paper III**, the forecast skill was substantially improved when using the NWP forecasted parameters together with the icing model output as input features to the machine learning model according to modelling chain Figure 2.5d (**Paper IV**). The resulting forecast error for each of the four sites are presented, and can be compared to the setup without the icing model in the modelling chain, in Figure 5.8 (grey bar).

The probabilistic machine learning approach QRF was applied and tested using 5-fold cross validation in **Paper IV**. All data was thus used as test data in the verification at some point. The results are based on periods 2-4 in Table 3.1. The machine learning algorithm was trained either separately for

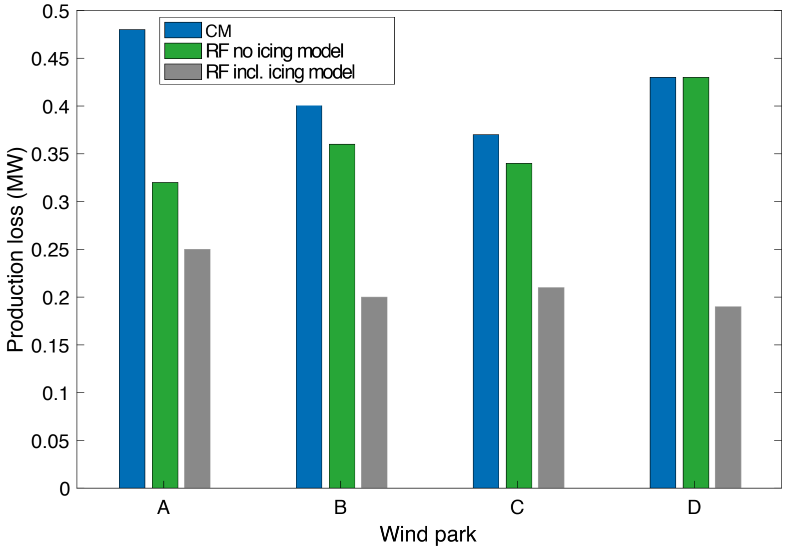

Figure 5.8. Average forecast error, *RMSE* or unbiased *RMSE*, for wind turbine site A-D using the control member (CM), i.e. the deterministic reference forecast, deterministic random forest regression trained only on NWP data and observations (RF no icing model) and random forest regression trained on both NWP data and output from the icing model (RF incl. icing model).

each wind park, by using all data together, or by using all data and adding a training parameter specifying the station name. The mean difference between these station splitting options in terms of deterministic forecast skill was small, but the options specifying station name or separating the stations performed slightly better overall. The RMSE of the QRF modelled mean production losses are presented in Figure 5.9, asterisks showing the average forecast RMSE of the 5-fold cross validation and bars the maximum and minimum of the five test sets resulting from the cross validation.

The aim of using the QRF was mainly to obtain useful probabilistic forecasts of icing related production losses. An example of such a probabilistic forecast for site A can be seen in Figure 5.10. The model performs relatively well over the six weeks presented but has some problems forecasting the high production losses during some icing events. This agrees with results regarding the random forest regression model in **Paper III** presented previously and is probably a result from the fact that the model is not able to extrapolate. With a limited amount of training data, and thus few really high production loss events, it has not seen each specific weather situation.

Figure 5.11 shows a ROC diagram where both the ROC curve for the QRF probabilistic forecasts (green line) and the ROC curve for the icing model ensemble are presented (black line) based on the four sites and period 2-4. It

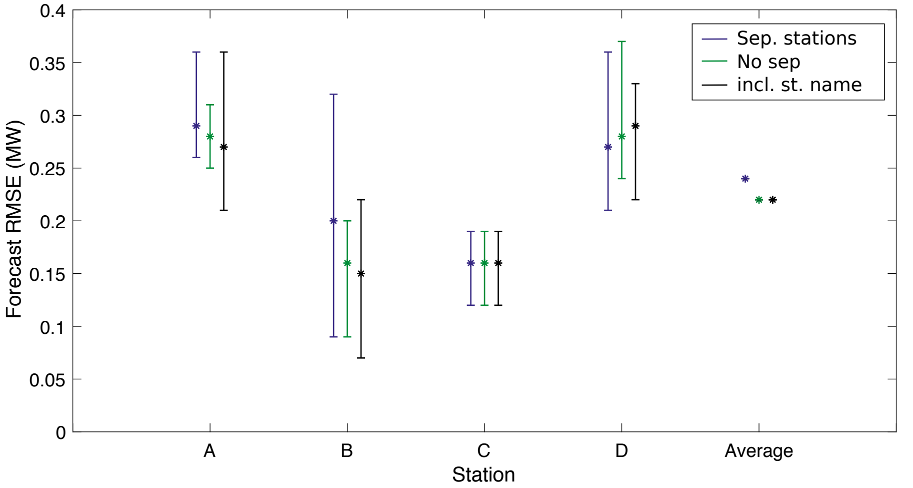

Figure 5.9. RMSE of the production loss forecast in MW for sites A-D, the mean of the sites, and the three station data splitting options. The markers show the mean *RMSE* and the bars present the minimum-maximum of the five test/training sets. Based on data from period 2-4 in Table 3.1. Figure reproduced from Figure 6 in **Paper IV**.

can be seen that the QRF probabilistic forecast outperforms the icing model ensemble in general. The probabilistic forecast is also better than using only the mean QRF forest forecast (blue line) implying that the probabilistic part of the forecast adds value. A perfect forecast would, however, have an area under the curve close to one and there is clearly room for improvement in both methods.

Other verification tools were applied for the probabilistic part of the QRF forecast and are described in detail in **Paper IV**. The verification implies that the forecast is slightly underdispersive. Since both the station splitting option used for the training of the model separating the stations and the option adding station name as input feature performed equally well on average in terms of forecast error, it was interesting to analyse which of them is preferred probabilistically. The station splitting option with the station name as input feature could possibly perform better than the splitting option separating all station data, since this allows for more training data to the model. One of the probabilistic verifications presented in **Paper IV** confirm this, with a better estimate of forecast uncertainty. Another verification tool however shows that the option separating the station data performs better in terms of forecast probabilities. It is therefore not clear which splitting option is preferred.

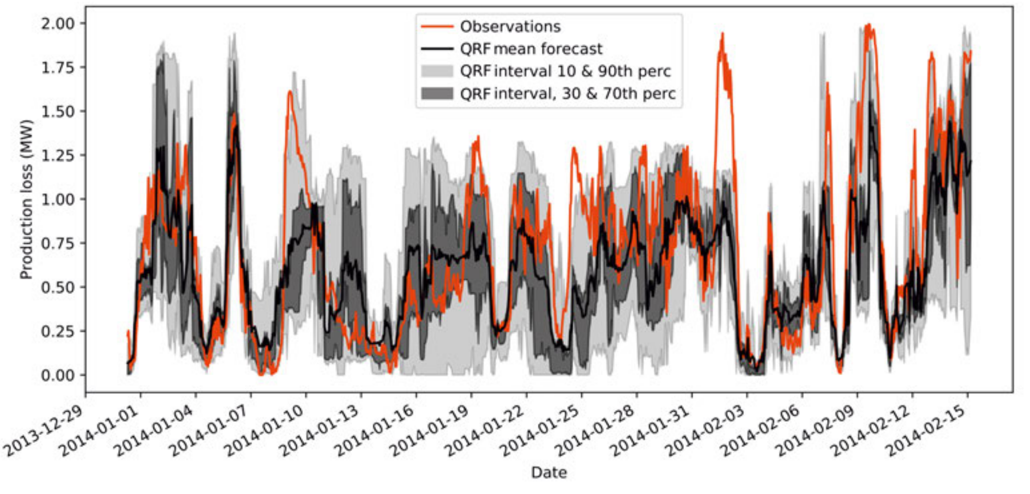

Figure 5.10. Probabilistic forecast with the QRF (site A). Light shaded area show 10-90th percentile range and dark shaded area 30-70th percentile of the forecast. Figure reproduced from Figure 8 in **Paper IV**.

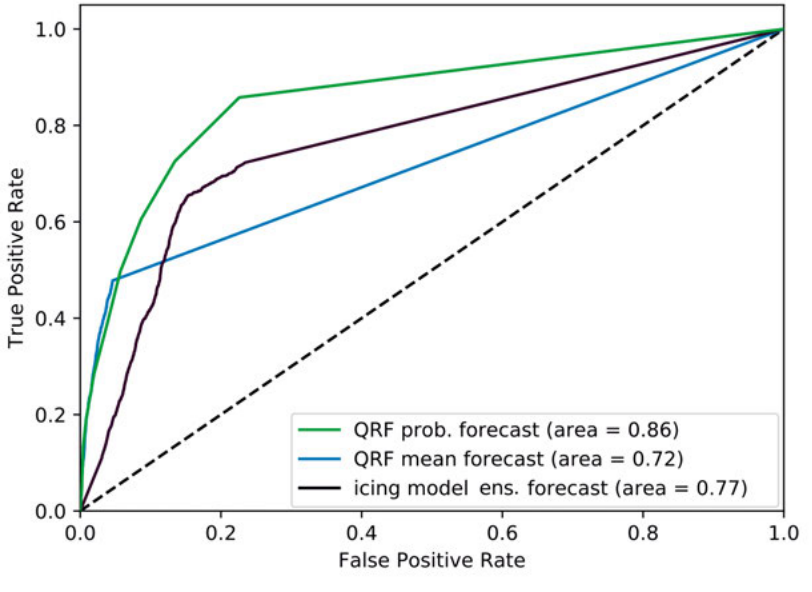

Figure 5.11. ROC diagram of the production loss forecasts for the threshold of 0.5 MW for the splitting option including station name, deterministically and probabilistic, and the icing model ensemble. Based on data from period 2-4 in Table 3.1. Figure reproduced from Figure 12 in **Paper IV**.

6. Discussion and conclusions

The results from four papers are summarised and some additional results are presented. Different probabilistic and machine learning methods were applied with the aim of improving the skill and usability of short-range forecasts of icing related production losses for wind energy. If probabilistic methods are utilised when icing on the wind turbine blade is present or possible, both a better mean production loss forecast and a cost-loss estimation can be obtained, allowing for improved decision making.

A NWP ensemble was employed in **Paper I** to generate a probabilistic forecast addressing uncertainties in the initial and boundary conditions of the NWP model. A neighbourhood method was applied to address uncertainties in the representativeness of the NWP forecast at the wind turbine site (**Paper I**). An icing model ensemble was developed in **Paper II** to address uncertainties in the physics of the icing model. A deterministic machine learning method was applied in **Paper III** without the icing modelling step in the modelling chain showing the potential of machine learning for these predictions. Finally, a probabilistic machine learning method was employed and optimised including an icing model in the modelling chain in **Paper IV**.

Both the initial condition ensemble and the neighbourhood method, as well as the combination of the two methods, were shown to outperform a deterministic reference forecast in terms of mean forecast skill (Table 5.1)(**Paper I**). The estimated uncertainty from the initial condition ensemble partly agreed with expectations, with high forecast uncertainties around the start- and end of an icing event (Figure 5.2). The spread/skill relationship regarding the meteorological parameters and the power production forecast however showed that the forecasted uncertainty was underestimated. The lack of spread of the ensemble members was especially visible during a frontal passage where all members had the same timing of the passage and start of an icing event. Since this was based on a two-week case study no statistical significance could be shown. Some additional results presented here, based on 10 weeks of forecasts using the initial condition ensemble, however confirmed the results from the two weeks (Figure 5.5).

The underestimation of forecast uncertainty by the initial condition ensemble is expected since not all uncertainties in the modelling chain, such as NWP model formulations, are accounted for using this approach alone. No calibration of the forecasted uncertainty was tested here but this could be an option to reduce the underestimation and by that way increase the usability of the forecasts [48, 49]. Overall, the results show the possible benefit of using an

NWP ensemble or neighbourhood methods for the modelling of icing related production losses both in terms of mean forecast skill and for estimations of forecast uncertainty.

The icing model ensemble was generated by perturbing five uncertain parameters in the model, the size of the hydrometeors, the shedding factor, the sticking efficiency for ice particles, the wind erosion and the Nusselt number affecting the calculations of both the accretion efficiency and the sublimation, using a deterministic sampling method (**Paper II**). The resulting icing and related production loss forecast consists of a mean forecast and a standard deviation used as an estimation of forecast uncertainty. Out of the five perturbed parameters, the size of the hydrometeors, the sticking efficiency calculated for the ice particles and the Nusselt number were shown to have the greatest effect on the final forecast (Table 5.2). The large effect of perturbing the sticking efficiency for ice particles is probably partly caused by the exact models used in the modelling chain here. This is because the NWP model version applied to forecast input to the icing model has a tendency to transform the liquid particles to ice particles too fast as the temperature decreases in the model. However, the uncertainty of the sticking efficiency for snow is also stressed both in Nygaard et al. [10] and in ISO 12494 [35]. The great effect of perturbing the size of the hydrometeors in the model is confirmed by Davis et al. [8]. The role of the uncertain Nusselt number affecting the heat transfer coefficient was also expected based on the discussions in Makkonen [40] and Wang [50]. Perturbations of the wind erosion factor were shown to have a smaller effect. This agrees with Davis et al. [25] who stressed the uncertainty in estimations of the wind erosion factor, but also discussed the low sensitivity of changes in this. The generally low model sensitivity to perturbations of the shedding factor is expected since it is used only during melting and there were relatively few periods with temperatures above freezing.

The icing model ensemble mean production loss forecast was shown to outperform a deterministic reference forecast in terms of forecast skill (Figure 5.4 and 5.5). The icing model ensemble was also shown to have a higher spread/skill relationship compared to the initial condition ensemble alone for the 10 weeks where both methods could be compared. Additional results presented here also show that the combination of the two methods improves the mean forecast skill and the uncertainty forecast in terms of spread/skill relationship to an even larger extent (Figure 5.4). This implies that the two approaches address different uncertainties, at least partly, which is the aim. The forecasted uncertainty is however still underestimated according to the spread/skill relationship. This is likley due to the fact that uncertainties in other parts of the modelling chain are not addressed and stresses the need for a fully probabilistic approach. The icing model ensemble forecast could possibly also be further improved by using observations of icing related production losses to tune the uncertainty distributions estimated for the five perturbed parameters such that the icing model ensemble better represents the observed uncertainty [51].

Four deterministic machine learning methods were applied to forecast icing related production losses solely based on NWP forecast data and observations during the initialisation in **Paper III**. Out of the four methods, random forest regression performed best on the 20 % test data; total amount of data being around 29 weeks. Even without the icing modelling step, the random forest regression model was able to forecast production losses with at least similar forecast skill as the baseline deterministic modelling chain approach (Figure 5.8). It should be noted that the comparison is not based on the exact same amount of data and should therefore only be seen as a proof-of-concept. The method also outperformed the persistence forecast for the relevant forecast lengths in terms of mean absolute error (Figure 5.7).

Some problems with the random forest regression model were nonetheless seen for high production losses, probably also a result from the limited amount of data including high production loss observations. More training data might be able to reduce this problem. Despite this, **Paper III** clearly indicates the potential of machine learning approaches for the modelling of icing related production losses. Icing models are not trivially developed, mainly due to a lack of reliable icing observations and limited amount of available power production observations from wind parks. It would thus be valuable if this modelling step could be indirectly performed by a machine learning model. One drawback of using machine learning methods is that it is difficult to explain why an approach works well. However, based on results in **Paper III** showing that ice particles, snow, graupel and cloud ice, are one of the most important input features, the model does indeed seem to learn a connection that has a physical meaning.

Random forest regression was further used with input also from the icing model in addition to NWP data in **Paper IV**. It was shown that using the forecasted ice load and intensity as input parameters clearly improves the results (Figure 5.8). This means that at least with the limited amount of training data used here the icing model is a crucial step in the modelling chain to obtain the best machine learning based production loss forecast.

A probabilistic extension of the random forest regression algorithm, quantile regression forest, was also applied here, in this case on around 34 weeks of data with 5-fold cross validation. The obtained probabilistic forecast was shown to perform better compared to the icing model ensemble forecast for the same period according to a ROC diagram (Figure 5.11). Some results however imply that the forecasted uncertainty is still underestimated with this method. Different station splitting options in the training of the model were also tested. The options of either separating the stations in the training of the machine learning model or specifying the station name by adding a training feature usually performed best deterministically. This is expected since the wind parks are situated at different locations with different terrain and have different wind speed forecast biases for example; a perfect model should differ between the sites. Probabilistically, the verification deviates between which option is generally preferred out of the two deterministically best options. The conclusion regarding splitting options is that overall both options seem to perform similarly, but that for some stations it could be valuable to also include data from other stations when training a quantile regression forest model since this allows for more training data.

To summarise, the main conclusions are:

– All of the probabilistic methods improve the usability of the production loss forecast, both in terms of deterministic forecast skill using the mean forecast and in terms of additional uncertainty estimations compared to a single forecast.
– Combinations of the probabilistic methods improved the results to an even greater extent as a result of several addressed uncertainty sources.
– The random forest regression method can obtain a similar production loss forecast skill solely with input from a NWP forecast and observations as a forecast based on a physical icing model together with an empirical production loss model. Adding parameters forecasted by the icing model however improves the forecasts.
– The probabilistic extension of the random forest regression algorithm, quantile regression forest, can produce well performing probabilistic production loss forecasts of better skill compared to the icing model ensemble.

The methods presented here were constructed to be suitable for usage for real-time trading. The NWP forecast initialised at 06 UTC is usually available for users within three hours and the other models in the modelling chain can if necessary be run on a laptop in minutes. The forecast can therefore be presented well before noon when the first next-day production forecast is required in the trading process. NWP ensemble prediction forecasts are available at the large weather centres. An advantage of applying the icing model ensemble or the machine learning based method compared to the NWP ensemble is however that they are not as computationally demanding.

Both the physically based probabilistic methods and the machine learning methods have room for improvement, with neither of them providing perfect probabilistic or deterministic forecasts. A combination of all of the probabilistic methods presented here would probably result in the most usable production loss forecast. This is supported by some of the results where the methods are partly combined. Such a combination would not necessarily result in a single forecast and single uncertainty estimation, but different approaches or methods could be used for different weather situations and calibrated for a certain wind park if the user is experienced with the performance of the methods in different situations. Knowing the likelihood for icing and related production losses, the end-user can employ site-specific cost-loss ratios in the decision-making and trading processes. This is also valuable for the efficient use of de-icing systems, and for the safety of people working at the wind farm.

7. Future perspectives

Increased knowledge about uncertainties in the modelling of icing related production losses and how these can be addressed has been presented in this thesis together with the potential of machine learning methods in this field. Both machine learning and probabilistic methods have previously been applied for wind energy but mainly focusing on the wind speed forecasts. Developments of probabilistic and machine learning methods for icing related production losses are valuable contributions to the field of wind energy in terms of improved decision-making in the trading process, for operations of de-icing systems and when planning for site maintenance.

Nonetheless, there remain uncertain elements in the modelling chain that need to be investigated to obtain a full uncertainty quantification of these forecasts. Moreover, the use of machine learning methods can be further developed with different methods, other combinations of training data or be focused more on the correction of the NWP ensemble for example.

Specifically, an aspect to examine is the uncertainty of the height interpolation of the NWP model data. The neighbourhood method could be extended to include points at different model heights, for instance up to a few hundred meters above ground. Parameters forecasted at different heights by the NWP model could also be used as input to a probabilistic machine learning model, in order to provide additional background information for the uncertainty estimation combined with each other.

The methods presented here can also be combined with each other to a greater extent. Both the machine learning based probabilistic approach and the more physical probabilistic approaches have pros and cons, but if they are merged together as an extra last step in the modelling chain the advantages of both methods can possibly be usefully employed. Furthermore, since many wind turbines are equipped with de-icing systems, additional steps can be added in the modelling chain if de-icing usage data is available. For this also a longer forecast, up to a week, would be of interest. Cost-loss estimations of the best timing to use the de-icing systems could also be provided based on the probabilistic forecasts. This also applies to the trading process where cost-loss estimations would be beneficial.

In addition to studies of the next-day forecasting, planning of wind power sites could be studied with probabilistic methods. This would provide an understanding of uncertainties in production estimations for planned wind power plants which is valuable since wind turbines have a lifetime of several decades and require considerable investment to construct. In this case uncertainties of future climate projections could be included. The methods that have been developed here can also be employed in other areas, e.g. solar energy production or electrical grid balance including wind, solar and battery power.

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9. Sammanfattning på svenska

Vindenergi är just nu en av våra främsta källor till förnybar energi. Att förbättra förutsättningarna för vindenergi är därför av största vikt för den förnybara energins fortsatta utveckling. Vindkraftparker placerade i kallt klimat stod år 2015 för cirka 30% [4], av den globala vindenergiproduktionen. Dessa parker är placerade där på grund av bland annat den låga befolkningstätheten i dessa områden och högre luftdensitet i lägre temperatur, vilket resulterar i högre produktion. Även om placeringen av en vindpark i kallt klimat har flera fördelar finns också utmaningar. Under vintermånaderna skapar isbildning på vindkraftverkens blad omfattande produktionsförluster. [2] uppskattade en årlig produktionsförlust för två vindkraftparker i Sverige till närmare 20%. En annan studie, av [3], visar på att vindparker i hög terräng i Schweiz kan ha upp emot 17% produktionsförluster på grund av isbildning på bladen.

För det kommande dygnet, kan isbildning resultera i onödiga kostnader under själva elhandelsprocessen. Felprognostiserad produktionsförlust ökar nämligen handelskostnaderna. Det kan även resultera i ett instabilt elnät och problem för planeringen av användandet av avisningssystem. Bra prognoser av isbildning samt isrelaterade produktionsförluster är därför av största vikt för vindenergin i kallt klimat [7].

I denna avhandling summeras fyra artiklar som alla har målet att öka användbarheten av prognostiserade isrelaterade produktionsförluster, både i form av träffsäkrare prognoser och genom uppskattningar av osäkerheten i prognoserna. Olika metoder applicerades och validerades mot data från vindparker i Sverige. Fyra parker med tillgängliga produktionsdata användes till största del för validering av produktionsförlustprognoserna, även om data från fler stationer användes för validering av vissa modellerade meteorologiska parametrar prognostiserade av en vädermodell i **Artikel I** samt delvis för validering av maskininlärningsmodeller i **Artikel III**.

Att modellera isrelaterade produktionsförluster kräver med den vanligast använda modellkedjan flera prognossteg. En numerisk vädermodell används för att prognostisera meteorologiska parametrar, en ismodell för att prognostisera själva isbildningen, samt en produktionsförlustmodell som baserat på isbildningen beräknar en produktionsförlust. Alla steg i denna modellkedja innehåller osäkerheter i form av osäkra initialtillstånd, modellfysik och hur väl vädermodellen kan prognostisera vädret på den exakta platsen av en vindpark. Detta resulterar i osäkra produktionsförlustprognoser. Inom meteorologin är det vanligt att använda sannolikhetsprognoser för att adressera osäkra prognoser. Här har olika sannolikhetsprognosmetoder, också kallat probabilistiska prognosmetoder, som adresserar olika osäkra delar i modellkedjan därför använts för att skapa riskprognoser. I **Artikel I** testades en ensembleprognosmetod som adresserar osäkerheterna i initialtillståndet av väderprognosmodellen samt en grannmetod som adresserar osäkerheterna av hur väl platsen för vindparken representeras av vädermodellen. I **Artikel II** skapades en ismodellensemble för att adressera osäkerheter i ismodellens ingående parametrar. Ismodellensemblen skapades genom en deterministisk samplingsmetod som resulterar i en medelprognos samt en standardavvikelse för varje tidssteg av prognosen[41].

En deterministisk prognos skapad med vädermodellen användes som indata till en deterministisk ismodell och vidare in i en statistisk produktionsförlustmodell användes genomgående som referensmetod vid verifikationerna. Både medelprognoser gjorda med vädermodellsensemblen, grannmetoden samt kombinationen av de två metoderna visade sig ha högre träffsäkerhet jämfört med den deterministiska referensmetoden i medeltal över de två veckorna metoderna testades på i **Artikel I**. Detta gäller både för meteorologiska parametrar prognostiserade av vädermodellen samt produktionförlustprognoserna. Osäkerhetsprognosen skapad med vädermodellensemblen prognostiserade även till viss del större osäkerheter vid start och slut av isperioder vilket tyder på att metoden fungerar då detta är den mest osäkra delen av prognosen. Osäkerhetsuppskattningen av de meteorologiska parametrarna och den prognostiserade produktionen verkar dock vara underskattad baserat på en vanlig verifikationsmetod för sannolikhetsprognoser. Detta är dock förväntat eftersom osäkerheter i vädermodellens formulering inte adresseras med dessa metoder utan enbart osäkerheterna i starttillståndet. Vädermodellensemblen testades även på ytterligare 10 veckors data och resultaten tyder på samma slutsatser som ovan.

Ismodellensemblen testades på två vintersäsonger i **Artikel II**, totalt cirka 29 veckor. Medelvärdet av ismodellensemblens produktionsförlustprognos var även det mer träffsäkert jämfört med den deterministiska referensprognosen. Ismodellen skapades genom att perturbera fem osäkra parametrar i modellformuleringen. Utav dessa fem parametrar var storleken på droppar och ispartiklar, en parameter som beskriver hur väl ispartiklar klibbar fast på vingen, samt en parameter som påverkar sublimering och sammansättningshastigheten av partiklar, de som påverkade utfallet av prognosen mest. Den prognostiserade osäkerheten visades även vid användandet av ismodellensemblen vara underskattad, detta beror troligtvis på att alla osäkerheter i modellkedjan inte heller här är adresserade.

Ismodellensemblen kunde även jämföras och kombineras med vädermodellensemblen då båda metoderna körts för samma 10-veckorsperiod. Ismodellensemblens medelprognos hade högre träffsäkerhet jämfört med vädermodellensemblens medelprognos och även bättre osäkerhetsuppskattningar. Kombinationen av de två metoderna resulterade i allra bäst prognoser och osäkerhetsuppskattningar. Detta tyder på att de två metoderna faktiskt adresserar olika osäkerheter och visar vikten av att adressera alla osäkerheter i modellkedjan för att få bästa underlag för beslutsfattare.

Senaste decenniet har användandet av maskininlärning ökat inom olika delar av meteorologin. I **Artikel III** applicerades maskininlärningsmetoder tränade endast på parametrar från vädermodellen samt tidigare observationer av produktionsförluster. Ingen isbildning prognostiserades i det här fallet i modellkedjan utan endast den isrelaterade produktionsförlusten. Utvecklingen av ismodellen är utmanande på grund av svårigheten att observera isbildning. Det vore därför värdefullt om man med maskininlärning kunde prognostisera isrelaterad produktionsförlust utan ismodelleringssteget. Maskininlärningsalgoritmen random forest regression[43] gav prognoser med liknande träffsäkerhet eller bättre i medeltal jämfört med den deterministiska referensmetoden för de 20% testdata som användes. Studien baserades även här på totalt 29 veckors data, varav 80% användes som träningsdata för modellen. Vissa problem kunde dock ses vid höga produktionsförluster, där modellen hade en tendens att underskatta produktionförlusten. Resultaten visade trots detta tydligt på potentialen av att använda maskininlärning för isrelaterade produktionsförlustprognoser.

Random forest regression applicerades även i **Artikel IV**. Huvudfokus i **Artikel IV** var dock att testa den probabilistiska expansionen av random forest regression, quantile regression forest[47]. Random forest regression-metoden visades dra fördel av att tränas även på islast och isintensitet från en ismodell tillsammans med parametrar från vädermodellen. Därför inkluderades även ismodellen i modellkedjan när den probablilistiska versionen av random forest regression användes. Det ska dock tilläggas att detta skulle kunna ändras om mer träningsdata var tillgänglig och modellen då själv skulle kunna indirekt uppskatta istillväxt bättre. Metoden quantile regression forest testades på totalt 34 veckors data. I detta fall användes även en 5-delad korsvalidering vilket betyder att all data användes som testdata men vid olika uppdelningar av test och träningsdata. På så sätt validerades metoden mot alla 34 veckors data. Quantile regression forest modellen prognostiserade produktionsförlusterna och dess osäkerheter bra. Jämfört med den deterministiska referensprognosen och ismodellensemblen beskriven ovan hade medelprognosen från quantile regression forest-metoden betydligt lägre prognosfel och osäkerhetsuppskattningarna var i medel bättre. Vissa problem kunde dock ses även här vid höga produktionsförluster. Problemet vid höga produktionsförluster är troligtvis ett resultat från att en begränsad mängd träningsdata är tillgänglig, speciellt för de högsta produktionsförlusterna, i samband med att random forest regression algoritmen inte kan extrapolera.

Data från olika vindparker kan delas upp på olika sätt vid träning av maskininlärningsmodellen. I **Artikel IV** testades tre olika uppdelningar, en där modellen tränades separat för varje station, en där all data slogs samman samt en där all data användes men stationsnamn lades till som träningsparameter. De olika metoderna testades eftersom det logiska vore att det bästa alternativet är att dela upp stationsdatan, men då det vid begränsad mängd data finns en möjlighet att modellen drar nytta av data också från andra stationer vid träningen. Bästa deterministiska resultat uppnåddes genom att separera stationsdatan eller ge modellen stationsnamn som träningsvariabel. Gällande uppskattningar av prognososäkerhet gav metoden som inkluderar all data med stationsnamn högst spridning, eller medel-standardavvikelse, på uppskattningarna men det kunde dock inte konstateras vilken av uppdelningarna som var att föredra.

Kort sammanfattat är huvudresultaten:

– Alla probabilistika prognosmetoder förbättrar träffsäkerheten av prognostiserad isrelaterad produktionsförlust. De kan även öka användbarheten av prognoserna genom osäkerhetsuppskattningar och riskprognoser.
– Genom att kombinera probabilistiska metoder som adresserar olika osäkerheter i modellkedjan kan prognoserna förbättras ytterligare.
– En maskininlärningsalgorithm kan prognostisera isrelaterade produktionsförluster baserat på observationer samt data från en vädermodell med liknande träffsäkerhet som referensmetoden om det används en fysikalisk ismodell samt en statistisk produktionsförlustmodell. Bättre resultat uppnås dock om en ismodell används i modellkedjan även för maskininläningsmetoden, i alla fall med den mängd data som är tillgänglig.
– Den probabilistiska maskininlärningsmetoden applicerad här kan skapa riskprognoser för produktionsförluster med bättre träffsäkerhet än ismodellensemblen.

En fördel med att använda en maskininlärningsbaserad probabilistisk prognos, jämfört med att använda en vädermodell-ensemble i modellkedjan är att det är mer lättillgängligt. Metoden testad här går att köra på en bärbar dator medan en vädermodell-ensemble oftast behöver köras av de stora vädercentren på grund av hur beräkningstunga de är. Detta gäller även ismodellensemblen som inte heller är beräkningstung jämfört med en vädermodellensemble. Det ska dock tilläggas att vädermodell-ensembleprognoser blir mer och mer tillgängliga för användare att hämta från vädercentren. Vädermodellen som användes här som första steg i modellkedjan initialiserades 06 UTC och data från prognoslängd +19-42 timmar användes som nästa dygns prognos. Detta tillåter att en färdig produktionsförlustprognos kan sammanställas före 12 UTC när en första uppskattning krävs inom elhandeln. Sammantaget kan alla metoder som presenterats här teoretiskt sett användas för elhandelsprocessen. Då flera av metoderna angriper prognososäkerhet i olika steg eller på olika sätt skulle en sammanslagning av flera metoder troligtvis ge bäst underlag för elhandeln.

References

[1] A. G. Kraj and E. L. Bibeau. Phases of icing on wind turbine blades characterized by ice accumulation. *Renewable Energy*, 35(5):966–972, 2010.

[2] K. J. Malmsten. Wind Turbine Production losses in Cold Climate Case study of ten wind farms in Sweden. Technical report, Wind Energy, Gotland University, Visby, 2011.

[3] S. Barber, Y. Wang, S. Jafari, and N. Chokani. The Impact of Ice Formation on Wind Turbine Performance and Aerodynamics. *Journal of Solar Energy Engineering*, 133(1), 2011.

[4] GWEC. Global wind energy statistics, 2017.

[5] V. Lehtomaki. IEA Wind Task 19, "Emerging from the cold", 2016.

[6] J. Lutz, A. Dobler, B. E. Nygaard, H. M. Innes, and J. E. Haugen. Future Projections of Icing on Power Lines over Norway. In *Proceedings - Int. Workshop on Atmospheric Icing of Structures*, pages 23–26, 2019.

[7] V. Lehtomäki, A. Krenn, P. J. Ordaens, C. Godreau, N. Davis, Z. Khadiri-Yazami, R. E. Bredesen, G. Ronsten, H. Wickman, S. Bourgeois, and T. Beckford. IEA Wind TCP Task 19, Available Technologies for Wind Energy in Cold Climates report. Technical report, 2018.

[8] N. Davis. *Icing Impacts on Wind Energy Production*. PhD thesis, DTU Wind Energy, 2014.

[9] H. Bergström, E. Olsson, S. Söderberg, P. Thorsson, and P. Undén. Wind power in cold climates, Ice mapping methods, 2013.

[10] B. E. K. Nygaard, H. Àgústsson, and K. Somfalvi-Tóth. Modeling Wet Snow Accretion on Power Lines : Improvements to Previous Methods Using 50 Years of Observations. *Journal of Applied Meteorology and Climatology*, 52:2189–2203, 2013.

[11] G. Ronsten, T. Wallenius, M. Hulkkonen, I. Baring-Gould, R. Cattin, M. Durstewitz, A. Krenn, T. Laakso, A. Lacroix, L. Tallhaug, Ø. Byrkjedal, and E. Peltola. IEA Wind Task 19, State-of-the-Art of Wind Energy in Cold Climates. Technical report, iea wind, 2012.

[12] C. E. Leith. Theoretical Skill of Monte Carlo Forecasts. *Monthly Weather Review*, 102(6):409–418, 1974.

[13] P. Pinson and G. N. Kariniotakis. Conditional Prediction Intervals of Wind Power Generation. *IEEE Tranactions on Power Systems*, (25(4)):1845–1856, 2010.

[14] J. J. Traiteur, D. J. Callicutt, M. Smith, and S. Baiday Roy. A Short-Term Ensemble Wind Speed Forecasting System for Wind Power Applications. *Journal of Applied Meteorology and Climatology*, October:1763–1774, 2012.

[15] D. Kim and J. Hur. Short-term probabilistic forecasting of wind energy resources using the enhanced ensemble method. *Energy*, 157:211–226, 2018.

[16] Y. Wu, P. Su, T. Wu, J. Hong, and M.Y. Hassan. Probabilistic Wind-Power Forecasting Using Weather Ensemble Models. *IEEE Transactions on indystry applications*, 54(6):5609–5620, 2018.
[17] M. Reichstein, G. Camps-Valls, B. Stevens, M. Jung, J. Denzler, N. Carvalhais, and Mr. Prabhat. Deep learning and process understanding for data-driven Earth system science. *Nature*, 566:195, 2019.
[18] S. Scher and G. Messori. Predicting weather forecast uncertainty with machine learning. *Quarterly Journal of the Royal Meteorological Society*, 144:2830–2841, 2018.
[19] S. Rasp and S. Lerch. Neural Networks for Postprocessing Ensemble Weather Forecasts. *Monthly Weather Review*, November:3885–3900, 2018.
[20] A. McGovernn, K. L. Elmore, D. J. Gagne II, S. E. Haupt, C. D. Karstens, R. Lagerquist, T. Smith, and J. K. Williams. Using artificial intelligence to improve real-time decision-making for high-impact weather. *Bulletin of the American Meteorological SocietyAmerican Meteorological Society*, (October):2073–2090, 2017.
[21] J. K. Williams. Using random forests to diagnose aviation turbulence. *Machine learning*, 95:51–70, 2014.
[22] S. Rasp, P. D. Dueben, S. Scher, J. A. Weyn, S. Mouatadid, and N. Thuerey. WeatherBench : A benchmark dataset for data-driven weather forecasting. *arXiv preprint*, submitted, 2020.
[23] S. E. Haupt and D. Monache. Understanding Ensemble Prediction: How Probabilistic Wind Power Prediction can Help in Optimising Operations. *WindTech*, 10(6):27–29, 2014.
[24] M. Kreutz, A. Ait-Alla, K. Varasteh, S. Oelker, A. Greulich, M. Freitag, and K.-D. Thoben. Machine learning-based icing prediciton on wind turbines. *Procedia CIRP*, 81:423–428, 2019.
[25] N. Davis, P. Pinson, A. N. Hahmann, N-E. Clausen, and M. Žagar. Identifying and characterizing the impact of turbine icing on wind farm power generation. *Wind Energy*, 16(September 2015):1503–1518, 2016.
[26] J. Lee, W. U. Wang, F. Harrou, and Y. Sun. Wind Power Prediction Using Ensemble Learning-Based Models. *IEEE Access*, In editing, 2020.
[27] D. Monache, F. A. Eckel, D. L. Rife, B. Nagrajan, and K. Searight. Probabilistic Weather Prediction with an Analog Ensemble. *Monthly Weather Review*, 141(10):3498–3516, 2013.
[28] L. Bengtsson, U. Andrae, T. Aspelien, Y. Batrak, J. Calvo, W. De Rooy, E. Gleeson, B. Hansen-Sass, M. Homleid, M. Hartal, K. Ivarsson, G. Lenderink, S. Miemelä, K. Pagh Nielsen, J. Onvlee, L. Rontu, P. Samuelsson, D. Santos Munoz, A. Subias, S. Tijm, V. Toll, X. Yang, and M. Ødegaard KØltzow. The HARMONIE - AROME Model Configuration in the ALADIN - HIRLAM NWP System. *Monthly Weather Review*, 145(5):1919–1935, 2017.
[29] M. Müller, M. Homleid, K.-I. Ivarsson, M. Køltzow, M. Lindskog, K. H. Midtbø, U. Andrae, T. Aspelien, L. Berggren, D. Bjørge, P. Dahlgren, J. Kristiansen, R. Randriamampianina, and M. Ridal. AROME-MetCoOp: A Nordic Convective-Scale Operational Weather Prediction Model. *Weather and Forecasting*, 32(2):609–627, 2017.
[30] M. Leutbecher and T. N. Palmer. Ensemble forecasting. *Journal of*

Computational Physics, 227(7):3515–3539, 2008.
[31] L. Megner, D. G. H. Tan, H. Körnich, L. Isaksen, A. Hor, A. Stoffelen, and G. Marseille. Linearity aspects of the ensemble of data assimilations technique. *Quarterly Journal of the Royal Meteorological Society*, 141(January):426–432, 2015.
[32] WMO. *Guidelines on Ensemble Prediction Systems and Forecasting*. Chair, Publication Board, Geneva, 2012.
[33] J.-I. Yano, L. Bengtsson, J.-F. Geleyn, and R. Brozkova. Towards a Unified and Self-Consistent Parameterization Framework. In R.S. Plant and J-I Yano, editors, *Parameterization of Atmospheric Convection*, chapter Chapter 26, pages 423–435. World Scientific, 1 edition, 2015.
[34] M. P. Mittermaier. A Strategy for Verifying Near-Convection-Resolving Model Forecasts at Observing Sites. *Weather and Forecasting*, 29(2):185–204, 2014.
[35] ISO 12494. Atmospheric icing of structures (ISO/TC 98/SC3). Technical report, International Organization for Standardization, Geneva, Switzerland, 2001.
[36] L. Makkonen. Models for the growth of rime, glaze icicles and wet snow on structures. *Philosophical Transactions of The Royal Society Lond.*, 358:2913–2039, 2000.
[37] D. Kuroiwa. Icing and Snow Accretion on Electric Wires. *Research report Volume 123, Cold Regions Research and Engeneering laboratory (U.S)*, 123, 1965.
[38] H. Dobesch, D. Nikolov, and L. Makkonen. *Physical processes, modelling and measuring of icing effects in Europe*. Zentralanst. für Meteorologie und Geodynamik, 2005.
[39] G. Thompson, P. R. Field, R. M. Rasmussen, and W. D. Hall. Explicit Forecasts of Winter Precipitation Using an Improved Bulk Microphysics Scheme . Part II : Implementation of a New Snow Parameterization. *Monthly Weather Review*, 136:5095–5115, 2008.
[40] L. Makkonen. A model of hoarfrost formation on a cable. *Cold Regions Science and Technology*, 85(October):256–260, 2013.
[41] J. P. Hessling. Deterministic Sampling for Propagating Model Covariance. *SIAM/ASA Journal Uncertainty Quantification*, 1:297–318, 2013.
[42] S. Rahman, D. R. Karanki, A. Epiney, D. Wicaksono, O. Zerkak, and V. N. Dang. Deterministic sampling for propagating epistemic and aleatory uncertainty in dynamic event tree analysis. *Reliability Engineering and System Safety*, 175(January):62–78, 2018.
[43] L. E. O. Breiman. Random Forests. *Machine learning*, 45(5-32), 2001.
[44] D. J. Gagne, A. Mcgovern, and J. Brotzge. Classification of Convective Areas Using Decision Trees. *Journal of Atmospheric and Oceanic Technology*, 26(7):1341–1353, 2009.
[45] A. Mcgovern, D. J. Gagne, J. K. Williams, R. A. Brown, and J. B Basara. Enhancing understanding and improving prediction of severe weather through spatiotemporal relational learning. *Machine learning*, 95:27–50, 2014.
[46] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, P. Matthieu, and E. Duchesnay. Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*,

12:2825–2830, 2011.
[47] N. Meinshausen. Quantile Regression Forests. *Journal of Machine Learning Research*, 7:983–999, 2006.
[48] B. A. Veenhuis. Spread Calibration of Ensemble MOS Forecasts. *Monthly Weather Review*, 141:2467–2482, 2012.
[49] J. M. Sloughter, T. Gneiting, and A. E. Raftery. Probabilistic Wind Vector Forecasting Using Ensembles and Bayesian Model Averaging. *Monthly Weather Review*, 141:2107–2119, 2012.
[50] X. Wang. Convective Heat Transfer and Experimental Icing Aerodynamics of Wind Turbine Blades. Technical report, 2008.
[51] M. C. Kennedy and A. O'Hagan. Bayesian calibration of computer models. *J. R. Stat. Soc. Ser. B Stat. Methodol.*, 63(3):425–464, 2001.

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