Combining Ensemble Icing Forecasts with Real-Time Measurements for Power Line and Wind Turbine Applications

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Abstract— **Ensemble icing forecasts and real-time measurements are powerful tools for many purposes. Here, the two are combined for two separate applications as a proof of concept. For power lines, measurements of ice loads using the sensor LoadTroll is used to calibrate the initial ice load in the model forecasts. For wind turbine applications, the IceSignal detection method is used to identify periods where there are false negatives in the model ensemble and subsequently initialize the model with a given ice load on all members. Such coupling of model forecasts and measurements ensures that there is a link between measurements and model and further strengthen the reliability of the forecasts.**

Keywords— ***ensemble, icing, power lines, wind turbines, forecast***

I. Introduction

Forecasting atmospheric icing on structures is inherently challenging due to the large sensitivity to several meteorological variables such as wind speed, wind direction, cloud water content, droplet size distribution temperature etc. When single or deterministic forecasts fail, they may cause poor or wrong decisions because the forecast uncertainty is unknown. Therefore, Kjeller Vindteknikk is developing a system for probabilistic short-term icing forecasts in parallel in two different research projects. Firstly, the R&D project Icebox, where real-time icing measurements are used as input to the probabilistic icing forecasts. Secondly, Wind Energy in Icing Climates (WEIC), where wind turbine SCADA data are analyzed in real-time and coupled to the probabilistic icing forecasts.

From a power grid operation perspective, icing is particularly challenging due to the limited information available in real-time. Often, the first indication of a severe icing event is an outage due to flashover from sagging conductors to the ground, or even worse, a sudden outage due to collapsed towers or tower components. Icebox is a research and development project lead by Statnett, the transmission system operator in Norway. In this project we develop a system for real-time monitoring and probabilistic forecasting of ice loads on overhead transmission lines that aims to limit outages due to ice and wind loads, by actively utilize de- and anti-icing technologies on the power lines when critical weather situations are detected or predicted by the ensemble forecast.

The WEIC project is an initiative by Kjeller Vindteknikk along with several wind farm operators in Norway and Sweden to improve the reliability of ice throw forecasts as well as communication platforms for such forecasts. Ice sensors within the wind farm as well as icing signals derived from SCADA data are used to validate/correct the initial conditions of each forecast iteration and thereby improve the reliability of icing nowcasts (forecasts for the very near future). Furthermore, real-time SCADA data are used to perform running calibration of icing forecasts. The icing forecast ensemble consists of 31 members, which yields a solid foundation for uncertainty quantification.

Probabilistic icing forecasts combined with real-time SCADA data open new possibilities within ice risk management and production predictability. Reliable ice throw forecasts and/or real-time warnings are important measures with regards to the safety of both wind farm employees as well as public users of the wind farm area. The usage of real-time SCADA data can be especially important for declaring the wind farm area safe following an icing event.

II. Methodology

A. *Meso-scale model data for forecasting*

In this work, two numerical weather prediction models have been used. The first is the Weather Research and Forecasting (WRF) model with model setup as described in [1] and is denoted as "WRF" in this work. The second is the forecast system developed in the MetCoop Ensemble

Table 1 Meso-scale model information

Forecast model data	NWP model	Members	Daily runs	Period (hours)	Spatial resolution	Temporal resolution
WRF	WRF	1	4	48	4 km x 4 km	1 hour
MEPS	HARMONIE-AROME	30	4	62	2.5 km x 2.5 km	1 hour

Prediction System and is denoted as "MEPS" in this work. The MEPS system is a collaboration between the MET, SMHI and FMI and is an implementation of the HarmonEPS system for producing a 30-member ensemble realization of HARMONIE-AROME [2]. Information on both forecast model data sources is given in Table 1. Where the model terrain differs from the actual elevation of the site, temperature and moisture parameters are lifted adiabatically to improve the accuracy of the icing calculations. Furthermore, key parameters in the WRF forecasts are statistically downscaled using a short-term, high-resolution WRF hindcast dataset (spatial resolution down to 750 m x 750 m) to better represent various effects of local topography. In particular, the liquid water content is downscaled using the methodology described in [3], while the wind fields are corrected using the methodology described in [4]. In this work, only the latter is used for wind turbine sites, while both are performed for power line sites.

B. *Ice Accretion Model*

The ice accretion model applied in the present forecast system is a modified version of the time-dependent model described in [5]. The model calculates the rates at which rime ice accumulates, melts and sublimates on cylindrical objects based on input data from the ensemble forecasts – yielding continuous, hourly time series of the total ice load [kg/m]. The modifications include a replacement of the monodispersed droplet size distribution with the full Langmuir D distribution [6] and decompositions of the wind field to account for the fixed, horizontal orientation of the power line spans. The present ice accretion model has been validated in [6] and [3].

C. *Proof of concept forecasting system*

The ice accretion model has been coupled with real-time measurements to improve the accuracy and reliability of the forecast system. Although conceptually similar, the technicalities of this process are quite different for the two applications described in the present study (power lines and wind turbines). Importantly, the forecasting system described in this work is still in a pilot phase and is subject to calibration. However, the results give a useful proof of concept on how the coupling between measurement and model is to be performed in a fully operational phase.

D. *Data periods*

The current setup has a limited amount of data for validation and calibration covering from 2021-10-01 up to 2022-03-15. While some general conclusions can be made, the length of the dataset is not sufficient to perform larger statistical analyses.

III. Results and Discussion

A. *Power Lines*

The average ice load on an overhead power line span is possible to measure with relatively high accuracy. Through the Icebox project, Kjeller Vindteknikk has developed a tension load cell (see Figure 1) that can be attached directly to the insulator string of suspension towers to monitor the ice loading in real-time, called LoadTroll [7]. The tension load is subsequently converted to give the average ice load across the span in kg/m, making the data highly compatible for validation and calibration of the ice accretion model.

The tension load sensors enable the ice accretion model to be initialized with the measured ice load for each forecast iteration, helping the current iteration to avoid inheriting errors from previous iterations. This is particularly crucial to mitigate escalating errors at high-altitude sites where rime ice may accumulate for days, or even weeks, uninterrupted by melting periods. It also enables the ice accretion model to be reset following an ice shedding event, potentially avoiding false predictions of critical ice loads. Furthermore, on-site historical measurement data may be used to further optimize the forecast system through statistical corrections (e.g. reduce biases).

Figure 1 One of the load tension cells ("LoadTroll") installed in the insulator string of a 420 kV line in Norway.

As with all common weather predictions, the uncertainties related to the forecasted variables are expected to increase with lead time (e.g., the ice load two days from now is more difficult to predict than the ice load two hours from now). In the validation, the performance of the MEPS ensemble is compared to the WRF based forecasts as well as a constant forecast that assumes the measured ice load at the time of initiation to remain unchanged throughout the forecast period. The latter was included as a reference in order to investigate whether the model forecasts add value to a monitoring system based on measurements only.

Figure 2 and Figure 3 show mean absolute errors (MAE) and biases of the icing forecasts at four different sites, respectively. As expected, the MAE of all forecasts increase with lead time at all four sites. The MEPS ensemble outperforms WRF at two of the four sites (Sima-Dagali and Sima-Samnanger), while the performances are quite similar at Moskog-Høyanger. At Salten-Svartisen, however, the MEPS

ensemble systematically overestimates the measured ice loads significantly. This is partly due to the complexity of the local topography surrounding the site, which is likely better represented by the downscaled WRF forecast. The general model performance is otherwise considered to be quite good, although slightly conservative.

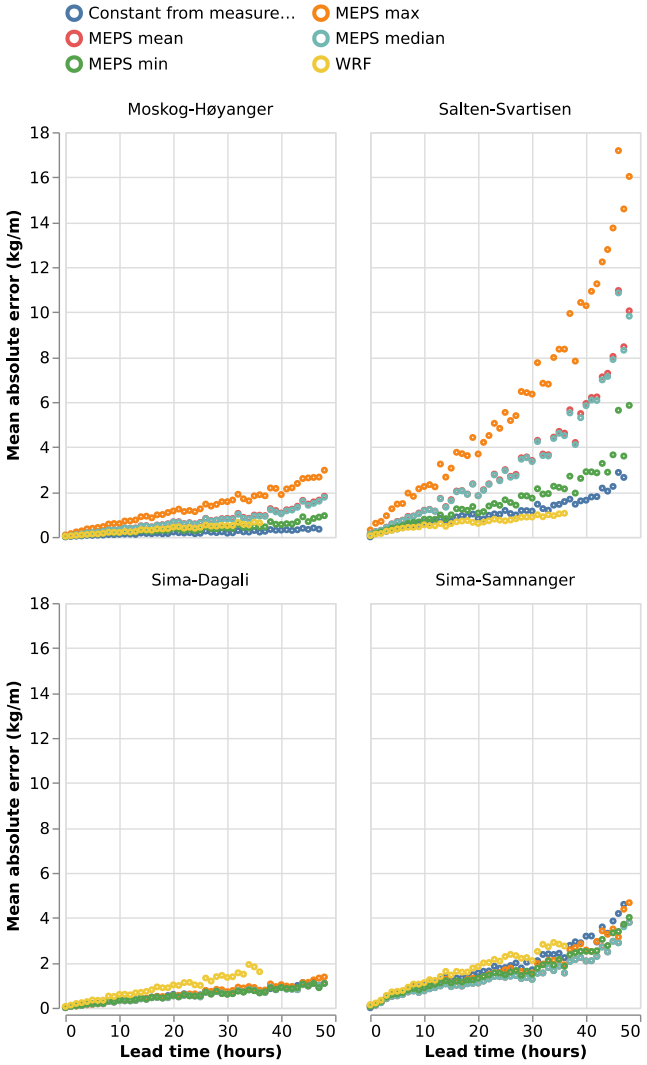

Figure 2 Mean absolute error versus lead time.

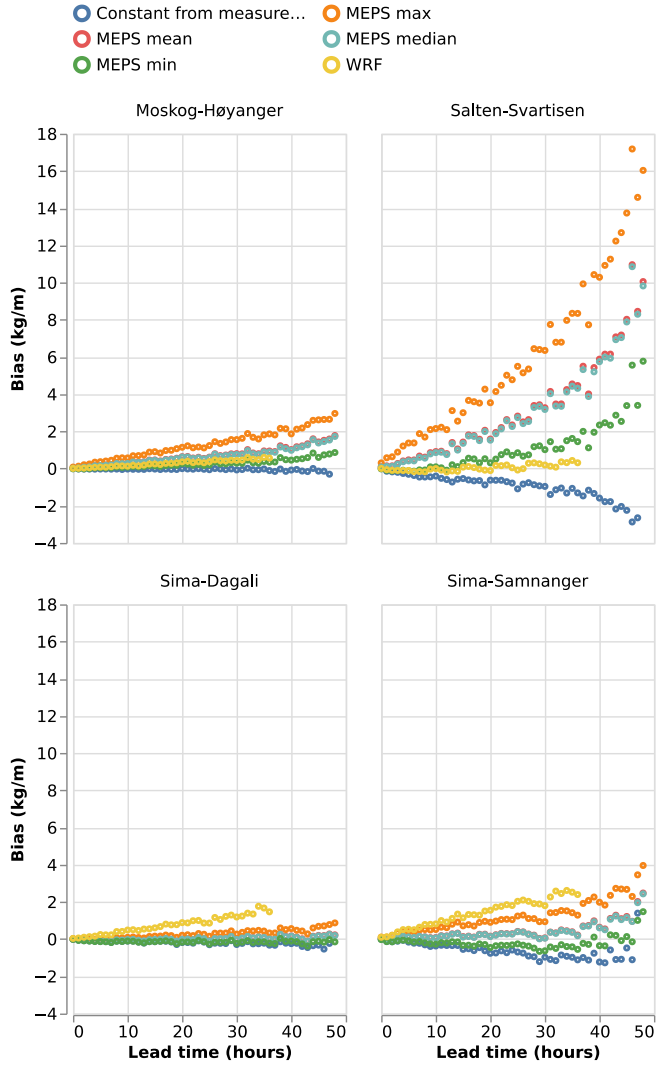

Figure 3 Mean bias error versus lead time.

The constant forecast is outperformed by at least one model for all sites except Moskog-Høyanger, where the former performs best in terms of both MAE and bias. This was found to be partly due to rather frequent shedding events (i.e. ice falling off of the conductor) not accounted for by the models. Figure 4 exemplifies how shedding events may impact the performance of the model forecasts in terms of MAE and bias. The measured ice load drops from ~14 kg/m to ~1 kg/m between hour six and seven (upper panel), causing the constant forecast to outperform both models for the remainder of the forecast period. The forecast iteration initiated after the shedding event (lower panel) successfully predicts the ice growth to continue, but both the MEPS median and WRF forecasts are still outperformed by the constant forecast following a second, partial shedding event. We would argue that even though the long-term statistics suggest that a constant forecast (or no forecast) outperforms the models in terms of MAE and bias, the models can provide useful information about imminent ice growth.

Although the model forecasts will tend to be conservative at sites with frequent shedding events, ice shedding is highly stochastic in nature and is by no means guaranteed to occur. Therefore, it is recommended that the forecast system issues alarms whenever the predicted ice load exceeds a user specified threshold regardless of the probability of ice shedding. The current system issues alarms via SMS and e-mail to the grid operator when 1) the forecasted ice load exceeds the design load and 2) the measured ice load exceeds 60 % of the design load.

The potential for calibration and re-tuning of the current forecast system is high. When more data is available, systematic biases (such as for Salten-Svartisen) can be mitigated e.g. by using neighbouring grid points, adjusting the adiabatic lifting of the model data or different statistical corrections (e.g. machine learning).

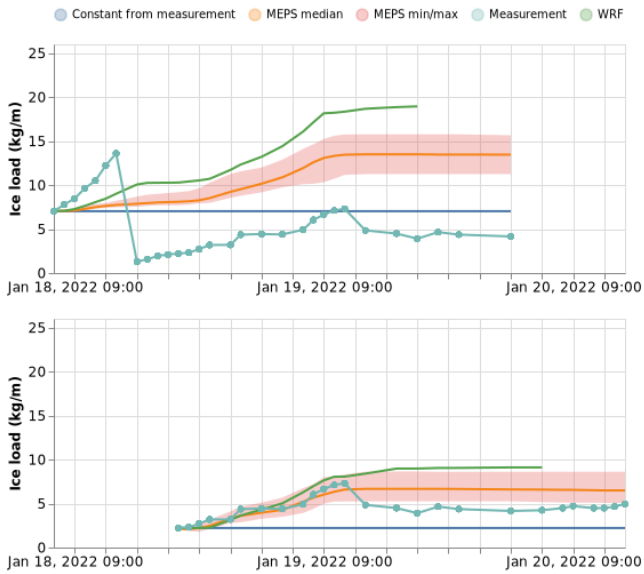

Figure 4 Ice load forecasts for a shedding event on the Sima-Samnanger site. The upper figure shows the forecasted ice load before a shedding event while the lower figure shows the forecasted ice load after the same shedding event.

B. Wind turbines

Icing forecasts for wind turbines can be applied both for production loss estimates and ice risk. Here, communication of potential ice risk to the public is the main motivation. Validity and good communication of the extent of the forecasts are essential for successful impact [8]. However, communication of potential ice risk from wind turbines is challenging. Wet snow and rime ice may accrete on the turbine tower, hub and blades and may shed at any time. Additionally, dry snow may drift and stockpile on various places on the hub and tower depending on the design of the turbine. This snow may also melt due to the heat generated from the radiator and/or turbine generator and form icicles [9]. In addition to ample icing scenarios, there are limited number of ice detection devices. While there are some wind turbines with either cameras or icing sensors, these are quite sparsely populated. Hence, direct measurements of ice load for wind turbines comparable what is done for power lines in the previous subsection is currently not feasible.

Rime ice forming on the blades can be measured indirectly using parameters such as production and blade rotation speed. Rime ice accumulates on the leading edge of the blades and disrupt the aerodynamic structure causing a lowering of the power produced at a certain wind speed. Kjeller Vindteknikk has developed an ice detection routine using SCADA data from wind farms. The routine is based on power curve and rpm curve deviation with minor additions and is called IceSignal. The wind turbine ice detection is limited to detection of ice on the blades only and to the best of our knowledge, only rime icing, though wet snow can form on the inner 1/3 of the blade. Furthermore, IceSignal is currently limited to an analog signal for each turbine. However, the number of turbines which yield an icing signal can provide information about the extent of the icing and is likely correlated with the severity of the event. In contrast to power lines, shedding of ice from wind turbine blades occurs quite frequently due to the force from the rotation of the blades and melting from blade heating systems, hence the timing and icing intensity of the forecast is more important than the actual ice load.

The IceSignal will either indicate icing, no icing or give no signal. No signal is provided if the indirect measurement parameters are unavailable, or the wind speed is too low for the turbine blades to rotate. From our experience, if there is only one icing signal from a single turbine in a wind farm, it is likely that the power curve deviation is caused by something other than icing. If, during wintertime, more than one in a cluster of turbines located at the highest altitude of the wind farm signal icing, it is a good indication that there is rime ice present on the blades. Hence, this requirement is used as the baseline for detection of rime icing in the wind farm. A similar approach can be used for icing forecasts. For ice risk, reducing false negatives to a minimum is key for public trustworthiness. Based on this, if any of the icing forecasts produced by the WRF member or of the 30 MEPS members, yield a rime ice load, that is the baseline for icing or not. Naturally, this low baseline produces a significant number of false positives, which can be tuned by either require more members to yield an ice load or raise the requirement to a set ice load or ice accretion value.

Coupling of IceSignal with icing forecasts needs to satisfy the following conditions; (1) increase the true positive rate to 1, where the IceSignal baseline itself is the positive condition and (2) limit increase in the number of false positives. The first condition can be met if once the IceSignal baseline indicate icing and there is no icing present in the forecast, the forecast is initialized with an ice load value. The second condition is dependent on two parameters; the number of ensemble members being initialized with an ice load and the ice load value. In Figure 5 an example is shown of a missed icing event for all ensemble members. In this example, the IceSignal from more than one turbine indicate icing while there is no icing in any of the ensemble members. The blue lines indicate the forecasted icing where the IceSignal triggers an initialization of 0, 0.2, 0.4, 0.6, 0.8 and 1.0 kg/m on a standard cylinder for all ensemble members. Melting or sublimation conditions in several of the members causes the fraction of members indicating icing to reduce quickly for an ice load of 0.2 kg/m, while an ice load of 1.0 kg/m ensure an ice load larger than 0 for most of the members.

Based on the experience from a few icing events such as the one in Figure 5, initialization of all ensemble members with an ice load of 0.5 kg/m was performed for four wind farms in Norway and Sweden for the period 2022-10-01 to 2022-01-30 and compared with running operationally without IceSignal calibration. Here, the most recent forecast is compared with a 9 hour delay from forecast start to the forecast being available due to computation time for both MEPS and WRF to be available. True positive and false positive rates were calculated for the four wind farm sites with and without IceSignal calibration and the results are shown as a receiver operating characteristics diagram in Figure 6.

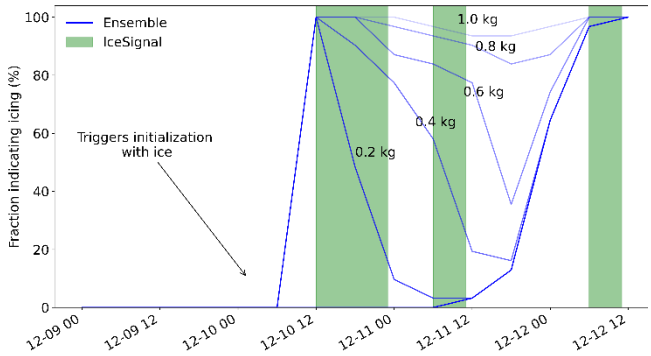

Figure 5 An example situation showing the sensitivity of initializing all ensemble members with a given ice load. The green regions indicate periods where ice is detected with IceSignal. The blue lines indicate the percentage of ensemble members that have an ice load larger than zero. The blue lines "No init", "0.2 kg", "0.4 kg", "0.6 kg", "0.8 kg" and "1.0 kg" indicate the initialization in kg/m on a standard cylinder for all ensemble members.

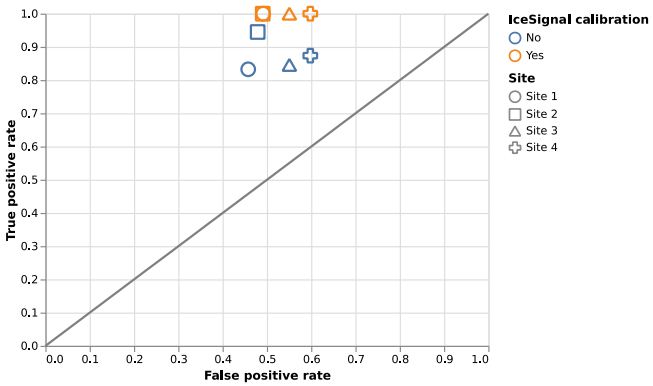

Figure 6 Receiver operating characteristics for four wind farm sites in Norway and Sweden.

The true positive rate with IceSignal calibration is at 1 for all sites as expected, since the IceSignal itself defines what is true positive. There will likely be icing events not caught by the IceSignal, which is out of the scope of this work. Promisingly, the increase in false positive rate is very low, ranging from 0 for sites 3 and 4 to 0.034 for Site 1. The low increase in false positive rate indicates that the 0.5 kg/m do not lead to ice being prolonged in the model after the icing event. Overall, the area under the curve is increased with IceSignal calibration indicating an increased accuracy. If the scaling with IceSignal method is to be applied for icing related production loss forecasting, the limiting of false positive rate is more crucial. For this purpose, the IceSignal can be seen as the "truth", since it is the effect of the ice on the power curve that is of interest. Optimization of production loss forecasting has not been within the scope of this work but could be done with tuning of the baseline forecast against previous observed icing losses.

IV. Conclusions

In this work ensemble icing forecasts combined with real-time measurements have been demonstrated as a proof of concept for two applications; power lines and wind turbines. Initialization of ice load from the LoadTroll sensor enables a higher accuracy of the icing forecast and enables a statistical evaluation of both the MEPS and WRF forecasts with regards to lead time. The validation results indicate that the overall model performance is good, although there is a potential for calibration and re-tuning. The model forecasts add value to the monitoring system by alerting about imminent, potentially critical ice loads ahead in time.

Whether there is icing or not on the turbine blades can be measured indirectly with IceSignal and calibrate model forecasts by initializing with an ice load. An initialization of 0.5 kg/m on all ensemble members ensures that the forecast have zero false negatives while limited increase in false positives, resulting in an increase in the area under the curve for the receiver operating characteristics. Overall, coupling ensemble icing forecasts with real-time measurements is a powerful method which significantly increases the accuracy of the forecasting system.

Acknowledgment

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References

[1] Ø. Byrkjedal, J. Hansson and H. van der Velde, "Development of operational forecasting for icing and wind power at cold climate sites," in *IWAIS 2015–16th International Workshop on Atmospheric Icing of Structures*, 2015.

[2] I.-L. Frogner, U. Andrae, J. Bojarova, A. Callado, P. Escribà, H. Feddersen, A. Hally, J. Kauhanen, R. Randriamampianina, A. Singleton and others, "HarmonEPS—the HARMONIE ensemble prediction system," *Weather and Forecasting*, vol. 34, p. 1909–1937, 2019.

[3] B. E. Nygaard, K. Ingvaldsen and Ø. Welgaard, "Development of Ice Load Maps for Structural Design," in *IWAIS 2022–19th International Workshop on Atmospheric Icing of Structures*, Montreal, 2022.

[4] S. Liléo, E. Berge, O. Undheim, R. Klinkert and R. E. Bredesen, "Long-term correction of wind measurements. State-of-the-art, guidlines and future work.," *Elforsk report*, no. 13:18, 2013.

[5] ISO/TC98/SC3/WG6, Atmospheric icing of structures, International Standard, 2000.

[6] K. Ingvaldsen, B. E. Nygaard, Ø. Byrkjedal and E. C. Iversen, "Validation of Modelled In-cloud Ice Accretion on Overhead Power Lines at Exposed High Altitude Sites in Norway," in *IWAIS 2019–18th International Workshop on Atmospheric Icing of Structures*, Reykjavik, 2019.

[7] B. E. Nygaard, F. K. Nyhammer, Ø. Welgaard, B. L. J. Adum and I. Gutman, "Development of sensors for real-time monitoring of ice loads on overhead lines," in *CIGRE*, Paris, 2020.

[8] J. Jeuring and A. Sivle, "Recommendations for communicating risk of ice throw/fall in Norwegian wind parks," 2021.

[9] A. M. Nodeland, R. E. Bredesen and Ø. Byrkjedal, "Risk of ice throw from wind turbines validated with data from field measurements using drones," in *IWAIS 2022–19th International Workshop on Atmospheric Icing of Structures*, Montreal, 2022.