Tower Vibration-Based Icing Detection on Operational Wind Turbines

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ABSTRACT

Ice accretion on wind turbines poses a significant safety risk, especially in densely populated areas. Ice built up on the blades can be thrown towards people and infrastructure and cause potential damage and harm. This risk is known and, as such, several solutions exist in today's market to detect ice accretion on the blades and timely shut down the system. The industry consensus is that icing detection systems installed directly on the blades offer more reliable detection. However, (post-) installation of hardware on the blades poses some practical limitations, impacting the overall cost and maintainability. To complement existing technology this study proposes monitoring the whirling modes, which are the natural frequencies associated with the wind turbine rotor, through a sensitive accelerometer mounted on the tower. The working principles rely on the concept that the increase of mass due to ice will lower the natural frequencies of the rotor. Observing this phenomenon from the tower implies a similar working principle as some blade mounted systems, while having a sensor installed on the tower simplifies installation and maintenance. Utilizing SHM data from tower, an ice indicator was made during standstill and operation which provided a proof of concept for this method.

INTRODUCTION

Wind turbines are a popular source of renewable energy, with large-scale projects being implemented worldwide to combat climate change. Wind energy is highly dependent on environmental conditions and with it come many challenges. A particular phenomenon encountered in cold regions is the icing on the blades of wind turbines [1]. Icing accretion on the blades affects the aerodynamic shape of blades resulting in power losses [1]. Moreover, the uneven shape of the ice-covered blades can generate noise and vibrations which contribute to fatigue and increased lifetime consumption. Icing can also impose safety risks towards nearby inhabitants as ice can be thrown towards people and infrastructure, particularly in densely populated areas. In Europe the severity and occurrence vary strongly between regions which is presented in [1]. Therefore, multiple market solutions that aim to mitigate its impact already exist.

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Given the different severity and occurrence as well as the built environment, the way icing is handled differs between countries. For instance, for Scandinavian countries such as Norway icing is a long-term issue with icing period lasting more than 30 days per year in often remote areas. As such, the main concern is the power losses associated with rotor icing rather than safety. As icing equates to loss of efficiency and therefore loss of revenue, blade heating solutions are a viable measure against icing even despite their cost of operation. On the other hand, for countries such as Belgium rotor icing is a short-term problem, and therefore the power losses are minimal. For densely populated countries with short icing periods, safety from the ice thrown is the main priority. In general very conservative ice-prevention strategies are adopted, shutting down the machine when weather conditions have an elevated risk of ice formation. The machine is only restarted when a visual (on-site) inspection confirms the absence of ice. As icing is rare, this scenario only plays out a few times every winter, making high-end icing detection or blade heating too expensive compared to the gained revenue. While conservative, the strategy is not flawless, fluke weather conditions and ill-judgement during the visual inspection may still result in the turbine operating with ice.

In this contribution, the aim is develop an ice detection solution that is more cost-effective than existing solutions on today's market. It aims to re-use the Structural Health Monitoring hardware used for other purposes, such as fatigue assessment. Simultaneously it does not rely on hardware inside the blades, or the outside of the wind turbine. Facilitating installation and maintenance of the device.

STATE-OF-THE-ART ON ICING DETECTION

The current state-of-the-art methods can be classified into two groups, nacelle-based systems, and rotor-based systems which are presented in [2]. The icing detection systems on nacelle-based systems working principle relies on assessing the meteorological conditions (such as measuring the temperature and humidity) and inferring the likelihood of rotor icing. While on the hand, the rotor-based systems deploy sensors directly on the rotor and detect icing via impedance or resonance frequency deviation. The resonance frequency method is the most common rotor-based method found in [2]. Their working principle relies on the concept that the ice mass formed on the blades will decrease the natural frequency. Thus, ice is detected by identifying a drop in the resonance frequencies. Similarly, as ice melts or falls off the blades, the mass decreases and the frequencies return to their nominal values allowing the turbine to be restarted in case of safety shutdown. In particular, monitoring the rotor modes are of interest as in theory they are the most sensitive to icing. The rotor frequency-based systems that are commercially available are Fos4ice, IDD.Blade (also known as Wölfel SHM.Blade), Bosch Rexroth blade control [2]. Since the frequencies measured are dependent on Environmental and Operating Conditions (EOC), these systems need to compensate for these variabilities. The idea is to model the EOC effects and compute the residual between the predicted resonance frequencies (given the current environmental conditions) and those observed, this residual would be evaluated to assess icing. All of the aforementioned systems install sensors as close to the tip of the rotor as possible. This could impose operation constraints as replacing the sensors is challenging, moreover concerns such as lightning and power transfer into the blade need to be resolved.

As an alternative, this paper purposed building on the work of [3], by investigating both feasibility of monitoring the whirling modes from the tower and the ability of detecting icing using those rotor modes during operation and standstill. This offers a cost-effective method to detect icing by lowering the complexity and maintainability of sensors. However, when rotor modes are observed from the tower they show rotor speed dependency, hence often refer to as “whirling modes”. With the forward whirling mode increases with rotorspeed, while the backward whirling modes decreases. According to [4] simulation results, with only 2% additional mass the whirling modes frequencies can drop up to 5%. . Moreover, the method is coupled with machine learning techniques to compensate for natural variabilities in the measurements. Like the aforementioned frequency monitoring systems, the EOC variability is modelled and then removed allowing the assessment to focus on structural changes.

METHODOLOGY

This study was implemented on data obtained from an operational wind turbine in the Amel wind farm which is located in Liège, Belgium. The data provided by OWI-lab contained the Model Parameter Estimation (MPE) which is collected through a SHM sensor installed in the tower of the wind turbine along with the turbine SCADA parameters (such as pitch, rotor speed, etc.). The MPE is obtained through Operational Model analysis where the structure is assumed to be excited by white noise (natural vibrations) and the output is recorded. Using this process parameters such as frequency and damping are estimated which then can be used for structural health monitoring applications, more about the process can be found in [5]. The time period recorded is from the 7th of December 2020 until the 30th of March 2021. Moreover, meteorological data was obtained through the Royal Meteorological institute of Belgium. In Figure 1 the frequencies measured are plotted against the rotor speed to produce a so-called Campbell diagram. The Campbell diagram is a relevant plot as it shows the different types of modes captured by the SHM system. The different of modes captured can be summarized as:

- Rotor harmonics: multiples of the rotor speed frequencies 1p, 3p, 6p, 9p (black dashed lines).
- Structural modes: mostly dependent on mass and stiffness of the structure such as the first side-side natural frequency (SS1), independent of the rotor speed (black bold line)
- Whirling modes: rotor modes which are dependent on mass, stiffness of the rotor and the rotor speed (orange lines).

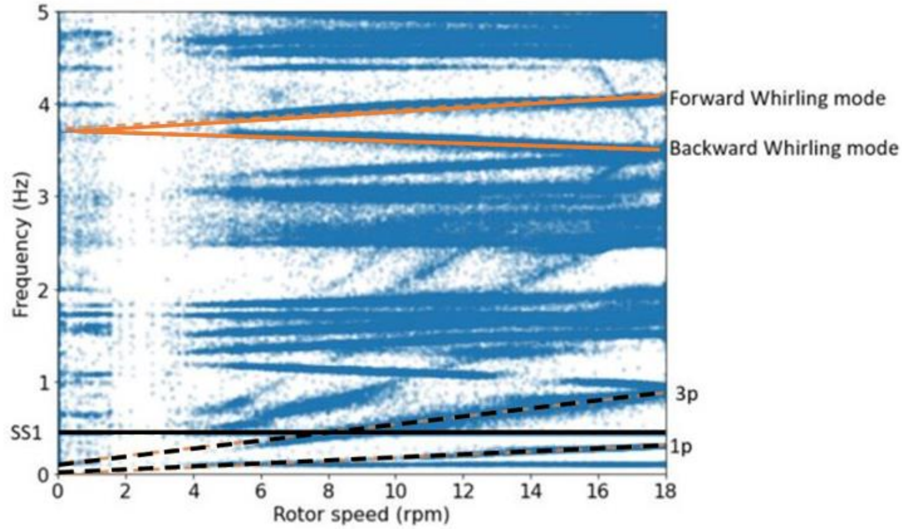

Figure 1 Campbell diagram in the side-side direction, showing the observed resonance frequencies with the SHM system.

To develop an ice indicator for wind turbines, it is essential to focus on frequencies that are sensitive towards icing such as the whirling modes. However, there is a significant difference between the operating conditions of a turbine during parked and operation. For instance, during parked conditions, the rotor speed influences disappear on those modes, hence these modes depend solely on environmental factors. In contrast, during operation, the harmonic and the rotor speed effect come into play. Since the behavior of the rotor modes differ depending on the operating state, a single model is not sufficient to detect icing in these two states. Therefore, the data was divided accordingly so an ice indicator can be built for each parked and operational conditions. The environmental variabilities on both data must be compensated so that the study would be limited to structural changes such as ice forming on the blade. The final stage of making an ice indicator is anomaly detection. Rotor icing is considered as anomaly since it is not present in the data during nominal conditions. Hence, to detect icing is to detect points that lie outside the normal distribution of the normalized data. The ice indicator used in this study is the Mahalanobis distance which is given by the following equation (1).

$$D^2 = (x - \hat{x})^T \times C^{-1} \times (x - \hat{x}) \quad (1)$$

With D being the Mahalanobis distance, $(x - \hat{x})$ is the variation of the modes from their mean and C is the covariance matrix [6].The Mahalanobis distance is a statistical measure used to assess the similarity/dissimilarity between points in a multivariate dataset. It considers the correlation between variables via the covariance matrix, which makes it a useful tool to identify outliers. In theory, ice build-up will affect multiple modes, and hence a high Mahalanobis distance will be computed as anomalies will be found across different modes. The Mahalanobis distance squared follows a chi-square distribution, and a typical practice is to select the threshold for outliers as being between the 95th and 99th percentile of the distribution.

PARKED CONDITIONS

The parked data is obtained by focusing on data with low rotor speed (rpm<1). The emphasis was on measurement points with sufficient wind speed (above 3m/s) to excite the natural frequencies captured. Furthermore, to ensure that physical modes are captured, the analysis was limited to frequencies below 6 Hz and damping values below 10%. The modes were then tracked by specifying a certain threshold away from the frequency of interest, typically 5%. Overall, 12 modes were tracked for each the Fore-aft and Side-Side.

During standstill, the whirling modes will appear at slightly different frequency compared to operation case especially with the effect of rotor speed disappearing. Hence, the emphasis was on using the tracked standstill modes that are close to the whirling modes frequency band (1.25 Hz and 3.8 Hz) for the ice indicator. Structural modes are less sensitive to icing; hence they could reduce the performance of the ice indicator. Thus, they are not used to calculate the Mahalanobis distance. As data was sufficiently small to apply any advanced normalizing techniques, the correlation matrix, a linear correlation between influencing parameters (i.e. SCADA and temperature) and the frequencies, was used to check the influence of EOC on modes. Overall, it was established that the correlation with EOC was weak and the Mahalanobis distance can be applied directly without any further normalization process. The ice indicator using the Mahalanobis distance during parked conditions is shown in Figure 2.

As shown in Figure 2, a period stood out (27th of January) with few points crossing the assigned threshold. The outliers found were the points with the lowest frequency during this period. Observing the behavior of the modes in this period, it was found the frequencies were increasing back to nominal values. This was seen across both structural modes and the standstill rotor modes. Moreover, this occurred during low temperatures which is suited for icing conditions. The frequency might be returning to the nominal values after the ice started to melt or fall off the rotor. This behavior is important to detect as the operation can be resumed once the frequencies are back to nominal values. This period can be investigated during operating conditions to infer what might have occurred leading up to parked conditions. What is expected to be seen is that the frequencies decreased leading up to shut down due to the addition mass of ice forming on the blades.

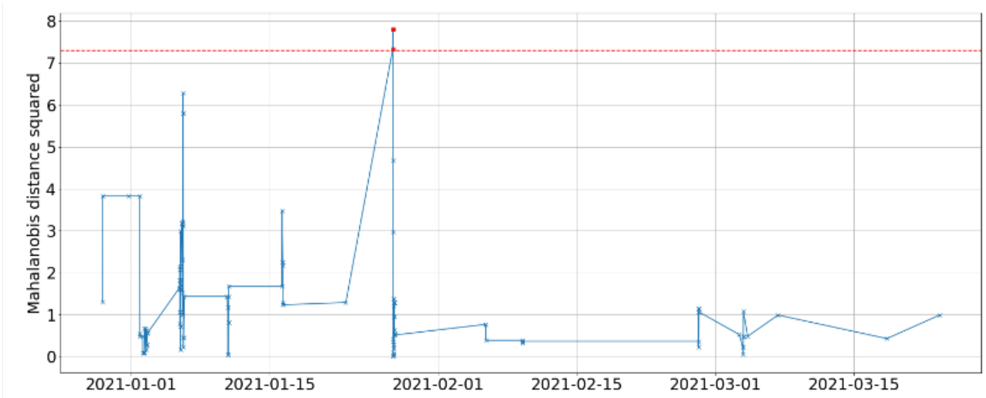

Figure 2 Ice indicator built using the Mahalanobis distance during standstill (Red dash line) threshold set using 97.5th percentile of the distribution (Red dots) outliers.

OPERATING CONDITONS

In operation state, the objective is to detect ice accretion on the blades, and hence a frequency decrease so a safety shutdown can be performed. However, to make an ice indicator similar to parked conditions, the whirling modes must be tracked first. However, during operation, the whirling is also dependent on the rotor speed and a simple fixed boundaries tracking is not sufficient to capture those modes. In [7] , it is assumed that the whirling modes vary linearly with the rotor speed at a rate of 1p via the following equations:

$$f_{bw,fw} = f_w \mp rpm/60 \tag{2}$$

In practice, the variation of the whirling modes is not a linear behavior as other influencing factors can come to play such as the EOC effects. Nonetheless, using those equations it is possible to isolate the frequency of interest. Fitting the bi-linear model found in equation (2), frequencies within 5% tolerance away from the model are captured. Even though the linear assumption is not ideal, the whirling modes are still captured sufficiently. The data now can undergo a normalization process.

To normalize the data, random forest regressors are used to predict the influence of the EOC. Some parameters required normalization before feeding it to the algorithm such as the yaw angle. The yaw angle varies from 0 to 360 degrees; however, without normalization the algorithm would not consider 360 and 0 as successive angles. To deal with this, the cosine and sine of the yaw angle are used instead. Moreover, some feature engineering was introduced to link some parameters to each other. Feature engineering is the process of feeding a nondimensional parameter that links different features to each other to aid the algorithm in learning the relationship between the different features more efficiently. In the case of wind turbines, the feature engineering parameters that are used are the capacity factor and the tip speed ratio. TABLE I summarizes the input and output of the algorithm used to normalized the data. The flap wise modes are associated with the direction perpendicular to airflow, while the edge wise modes are parallel to airflow.

TABLE I RANDOM FOREST REGRESSOR INPUTS AND OUTPUTS

Features (Symbol, unit)	**Feature Engineering (unitless)**	**Variables to predict (unit)**
• Yaw ($\emptyset, °$) • Pitch ($\beta, °$) • Wind speed (v, m/s) • Rotational speed ($\omega, rad/s$) • Temperature (T,℃) • Power (P, W) • Density ($\rho, kg/m^3$)	• Tip speed ratio $\text{TSR} = \frac{Radius \times \omega}{v}$ • Capacity factor $C_p = \frac{P}{0.5 \times v^3 \times \rho \times A}$ • $\sin \emptyset, \cos \emptyset$	• Edgewise whirling modes (Hz) • Flap-wise whirling modes (Hz)

The data was split into three datasets: training, validation, and testing, with a corresponding size of 61%, 14% and 25%, respectively. The training was carried out during February and March. The validation dataset was used to tune the model before using it on testing dataset. The testing dataset was the month of January as it is a period with lowest temperatures, and hence has the highest chance of icing occurring within it. Moreover, it is of interest to investigate the period found in the pervious section, 27th of January, to analysis what occurred leading up to shut down. Subtracting the model from the measurements and evaluating the residual using the Mahalanobis distance, the ice indicator found in Figure 3 is constructed. At the beginning of January, the Mahalanobis distance gradually increased until it reached the assigned threshold with a clear bump observed in Figure 3. Zooming in on the (1) and (2), a frequency drop occurred during the night of (1) which then propagated into the (2). Moreover, during (2) the normalized frequency was below the nominal values throughout the day with the alarm triggered during the morning and during the evening. This might indicate a light icing period as the frequencies decreased; Nonetheless, no shutdown occurred during those periods.

On the other hand, the (3) was a very clear outlier period with a very high Mahalanobis distance. Looking at (3), it could be seen that the frequency was gradually decreasing until a shutdown occurred. This coincides with the parked condition results where the frequencies were recovering after the shutdown during the 27th of January. What can be inferred is that ice builds up on the blades leading up to a shut down by the operator. Then as was found in pervious section (PARKED CONDITIONS), once the turbine was shut down, ice started falling off or melting down of the blades leading to reduction of mass and increase of frequency. Thus, this demonstrates that it is feasible to detect icing using measurements from the tower in both operating states.

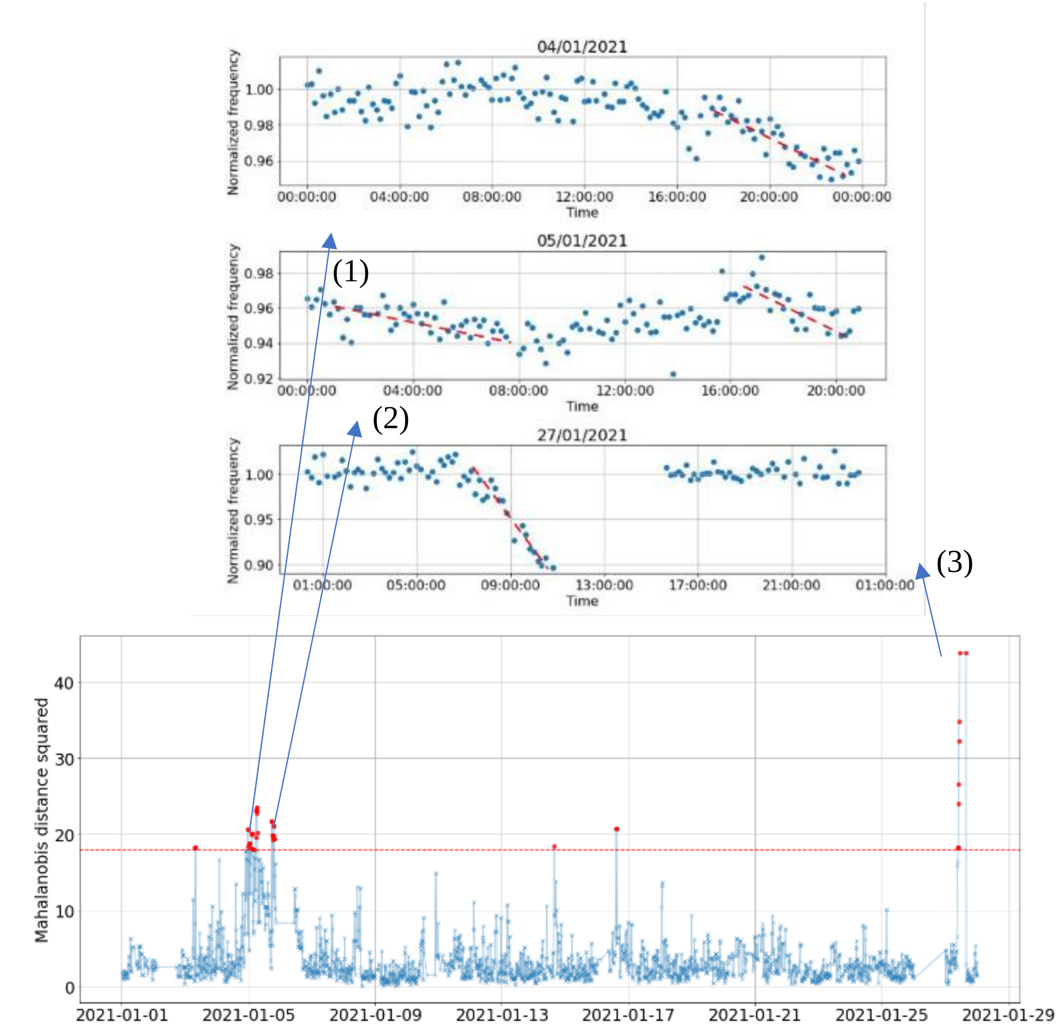

Figure 3 (Upper) Normalized frequency of points that crossed the threshold (Red) outlier zone (Lower) Ice indicator built using the Mahalanobis distance (Red dash line) threshold set using 99.9th percentile of the distribution (Red dots) outliers. (1) 04/01/2021 (2) 05/01/2021 (3) 27/01/2021.

CONCLUSION

The research has demonstrated the use of rotor modes observed from the tower to detect icing. This technique offers a cost-effective solution due to its installation and the ease of sensor replacement compared to similar technologies which rely on sensors installed in the rotor. This could potentially provide an economical solution to reduce the risk of ice thrown towards inhabitants in densely populated areas with low icing occurrence. This method showed its ability to detect icing during both parked and operating conditions. The ice indicator was realized through normalizing the EOC effects and evaluating the residual via computing the Mahalanobis distance. Future research is investigating the feasibility of using the same trained model across multiple turbines.

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