Replies to Reviewer 1 comments

The authors thank the reviewer for his time and effort in reviewing our paper and making valuable comments about our work. We would like to give following replies to reviewer comments.

1) . (a) The method proposed by the authors rely on the estimation of five modal frequencies of each blade during operation. The authors do not discuss how these frequencies are estimate, or what accuracy of such estimation is needed for their method to work.

Ans. The authors accept that they didn't discuss about the estimation of natural frequencies of the blade in operation, but the authors work started based on the fact that the ice detection systems available in the market detect ice based on these frequencies. Our work is only a theoretical study, so we used eigenvalue analysis of the equations of motion of a single blade to calculate its natural frequencies. However, we discuss below the estimation procedure of the ice detection systems from the information available on the web.

A. The authors would like to refer a patent from Vestas [R1] in which they proposed to use the pitch actuation system to excite the blade (different possible excitation signals are shown in Figure 1 below) and measure its vibration response using accelerometers installed at different locations on the blade.

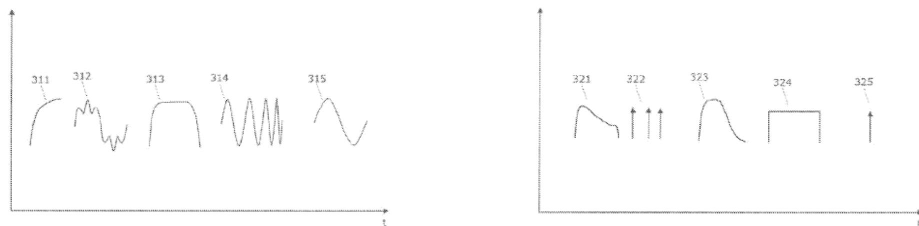
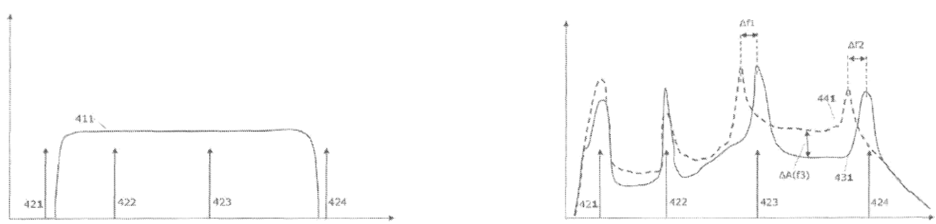


Figure 1. Different excitation signals to excite the blade [R1]

Ice is detected based on the deviations in blade natural frequencies (Refer Figure 2). They propose to use multiple sensors at different locations on the blade for measuring vibrations along one transverse axis. They discussed about an idea to estimate the location of ice: "When a number of vibration amplitudes along a given direction are known and the resonance frequency is known, the mode shape can be approximated. By comparing the determined shape of the vibration with a reference vibration mode obtained with a known location of an undesired loading, the unknown spatial location of the undesired loading can be determined or estimated". But it requires multiple sensors along the blade.



(a) (b)

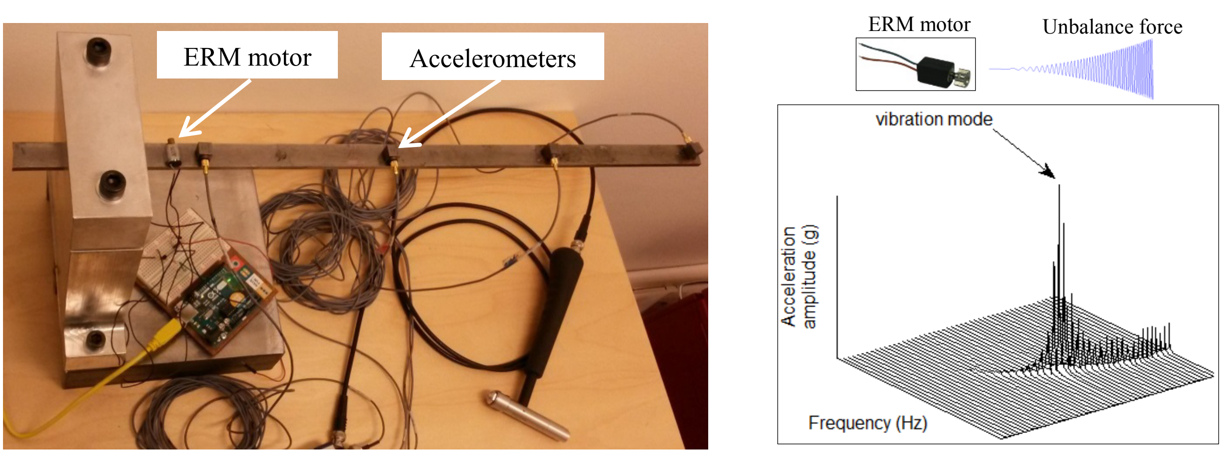
Figure 2. (a) Excitation signal, (b) Spectrum of vibration response [R1]

Vestas is offering a deicing system (called Vesats De-icing system, VDS) that consists of an Ice detection system which detects ice from the vibration measurements of a single accelerometer. The detection system stops the turbine when some conditions on the vibrations are met.

B. Icing is detected using the vibration signatures in the detection systems: BladeControl [R2], fos4XIcedetection [R3], IDD.Blade [R4] which are already in use in some of the wind turbines installed in cold climates. These systems use accelerometer on the blade to measure vibration signals and ice is detected based on the reduction in blade natural frequencies [R5] from the vibration spectrums. Some more details about these systems are available in [R3, R4].

The BladeControl system requires a minimum wind speed of 2 m/s for ice detection. Edgewise vibration spectrum is analyzed when the turbine is running and flapwise vibration spectrum is analyzed when turbine is at standstill for ice detection. No further information about their detection technique is known to the author's knowledge. From these details, it is certain that blade natural frequencies are excited by ambient excitation (wind turbulence or wind shear). Using some special algorithms, they detect the presence of ice on the blade (cannot identify the location and quantity of ice). They only classify the state of icing on the blade as ice-free, non-critical and critical based on the amount of reduction in blade natural frequencies.

C. Authors proposal: The above two approaches either use an external system (pitch actuation system) or ambient excitation to excite blade vibration modes. The authors propose an idea to excite blade vibration modes using an eccentric rotating mass (ERM) driven by a small DC motor whose speed can be controlled to excite the appropriate vibration modes (low damped modes). The unbalance force generated by the rotating mass is in synchronous with the rotational speed of the motor. We can vary the rotational frequency of the motor to excite the blade vibration modes with corresponding forcing frequency. It is possible to excite higher modes of the blade. Spectral analysis of the vibration response measured on the blade using accelerometer enables to estimate natural frequencies of the blade. This is just an idea similar to the electromechanical actuator proposed in [R6] for the structural health monitoring of the blades. We have tried this idea on a small experimental set-up (simple cantilever beam) as shown in the below Figure 3.



(a) (b)

Figure 3. (a) Experimental set-up, (b) Flapwise vibration response

From the above discussion, it is clear that blade frequencies can be excited either by external system or ambient excitation, and it is also possible to detect them from the vibration measurements using accelerometers on the rotating blade.

(b) The flapwise blade modes are highly damped by the aerodynamic forces and they cannot be estimate from methods like stochastic subspace identification methods. Edgewise blade modes are low damped, but here the problem is identify the modal frequencies for the individual blade.

Ans: We agree with your comment on the damped flapwise modes. First of all, it is possible to detect ice mass using first few edgewise modes alone in the neural network model proposed in this work. These modes are lightly damped (as you also agree) and it is possible to estimate these frequencies by exciting blade using pitch actuation systems (as described in [R1]). Second, the first flapwise mode is the most damped mode, higher modes are comparatively less damped (Figure 23 in [R7], Figure 6 in [R8]). So it is possible to identify a combination of flapwise and edgewise modes specific to a blade that can be practically excited and identified in the vibration measurements, which can be later used for ice mass detection. The detection technique becomes robust when multiple modes (can be edgewise or flapwise or combination of both) are used. With the idea of blade excitation using external systems, it is possible to excite even higher modes of the blade. The main objective of this paper is to demonstrate the idea of ice detection using the blade frequencies.

(c) For a three-bladed turbine, the blade vibrations are coupled in symmetric and forward and backward whirling modes.

Your comment is true if the accelerometer is installed on the static structure like a tower or nacelle. As accelerometers are installed on the rotating blade, the frequencies estimated from their vibration spectrum correspond to their natural frequencies (similar to the eigenvalue analysis of the equations of motion derived in a rotating frame of reference in the paper). The blade experiences different wind velocities in rotation and makes the system matrices time periodic. Time-periodic systems will have periodic modeshapes consisting frequencies as harmonics of the rotational speeds leading to multiple resonances for a single mode [R9]. We have shown Fourier transform of the vibration response of the blade simulated using FAST in Figure 4 considering a turbulent wind profile on the turbine rotor. The vibrations degrees of freedom are not transformed into multi-blade coordinates in the time domain analysis of the equations of motion. Turbulent wind excites the blade vibration modes in these figures.

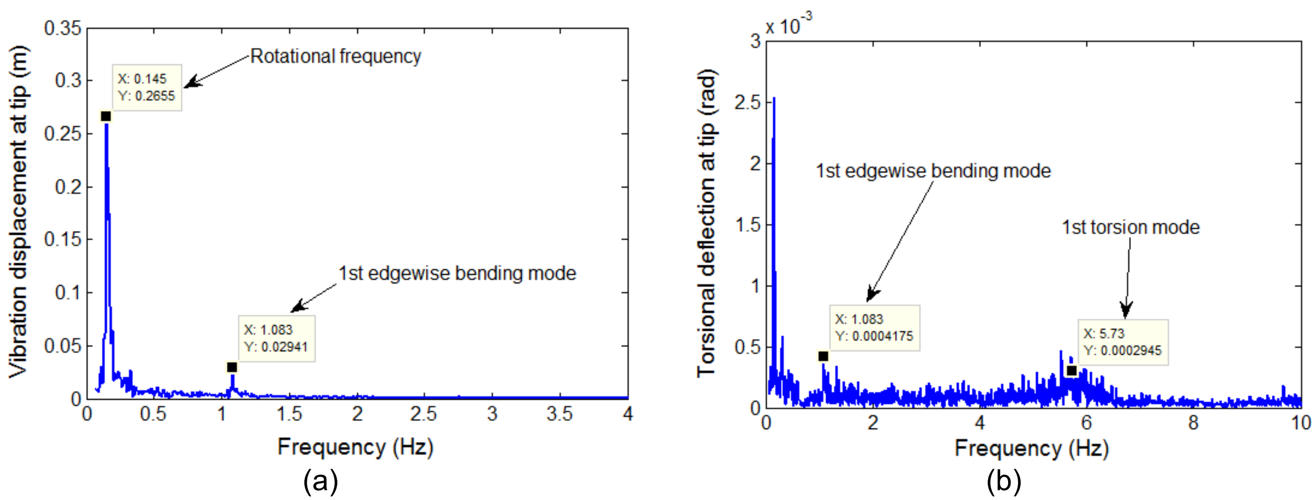


Figure 4. Blade tip vibration response (a) edgewise deflection, (b) torsional deflection

2) (a) The authors seem to have decided to use neural network to transform five inputs to three outputs describing the distribution of the ice masses, which is not justified.

The accuracy and consistency of ice mass detection are influenced by the number of natural frequencies used in the detection algorithm. It is possible to detect some ice mass combinations in the three zones with just two or three natural frequencies of the blade, but they fail to differentiate multiple possibilities of ice masses in these three zones. When multiple frequencies are considered as input to the neural network, it establishes a valid function between inputs and outputs of the network and eliminates uncertainty associated with multiple possibilities (in contrast to local minima and global minima in the least squares method) of ice mass combinations that have a similar reduction in blade natural frequencies.

(b) Why not use a simple least square method, or even simpler a linear transformation from three blade frequencies like the first three edgewise blade frequencies to the ice masses in the three spanwise positions on the blade.

We can fit a function between inputs and outputs of a process, for example, outputs of a process can be approximated using a polynomial function defined in terms of the input variables and least square method can be used to find the coefficients of the polynomial terms such that the difference between function output and actual output are minimized. If we want to use such method for the current problem, we should know the nature of the function, like, what order of the polynomial function to use, whether the output variable depends on the interaction between input variables or not. That means the function needs to be defined explicitly. This need is relaxed if we use neural networks which can approximate underlying complex nonlinear functions by changing network parameters like number of neurons, hidden layers and the activation functions used in the neurons. Once these parameters are specified, the backpropagation algorithm uses least square method to minimize the difference between network outputs and the actual outputs by adjusting the network weights. Both methods described above uses the least square method for function approximation.

The relation between inputs and outputs of the current problem is not linear, so we cannot use the linear transformation technique you are suggesting. The main objective of the paper is to show how ice mass accumulation along the blade can be identified. When the nonlinear relation between inputs and outputs is not known, the neural network is having a definite advantage for function approximation in comparison to other conventional methods that use the least square method.

Replies to your detailed comments

As the reviewer marked detailed comments in the original manuscript file, we assigned numbers to those comments in the order as they appear and we give following replies to those comments.

1. *The authors must make it clear that they do not provide a method of estimating the natural frequencies of an operating wind blade, which is the hardest part of detecting ice. The uncertainty of such estimation may exceed the accuracy needed for the proposed method to work.*
   Ans: We will change the title of the paper to reflect the work done in this paper is a theoretical study that calculates natural frequencies of the blade from the eigenvalue analysis of the equations of motion which is derived in the rotating frame of reference.

2. *Language*
   Ans: Will be corrected in the revised manuscript.

3. *Language*
   Ans: Will be corrected in the revised manuscript.

4. *Language*
   Ans: Will be corrected in the revised manuscript.

5. *Language*

Ans: Will be corrected in the revised manuscript.

6. *Can this statement be quantified? What is the probability that the ice is detected and at the right location by the system for different types of ice building?*
Ans: It is difficult to quantify the error in the proposed method, as ice accumulation on the blade is a random phenomenon that depends on various parameters. Ice mass is a continuous variable that varies along the length of the blade, but we reduced it to three mass variables assuming they are distributed with a constant linear mass density as shown below in the Figure 5. This reduction comes with a penalty in the ice mass estimation and its accuracy depends on the actual ice mass distribution on the blade. The estimation will be poor if the actual mass distribution is very different from the constant mass distribution used to train the ANN. As the ice mass distribution is a random variable, we cannot quantify the prediction accuracy.

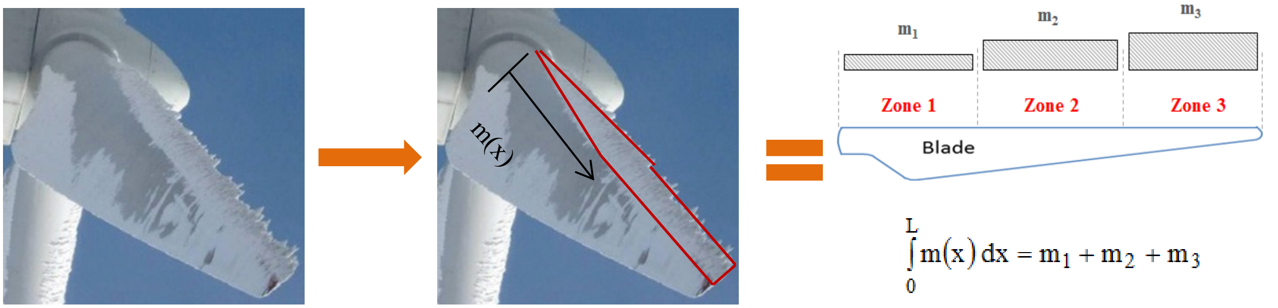


Figure 5. Approximation of the continuous ice mass variable in terms of three mass variables

7. *Language*
Ans: Will be corrected in the revised manuscript.

8. I do not understand this sentence “they predicted a bigger change in relative mean value of the dynamic response quantities for iced blades.”
Ans: The authors in that reference investigated the effects of atmospheric ice accumulation on the aerodynamic performance and structural response of wind turbines and they predicted that the relative change in mean value is bigger than the change in standard deviation for most of the response quantities (rotor speed, torque, power, thrust and structural loads) of the iced blade. This information will be added in the revised manuscript.

9. language, missing an "and"?
Ans: Will be corrected in the revised manuscript.

10. I disagree. Ice mass will increase the mass imbalance and therefore the 1P (1/rev) excitation from the rotor rotation but it is the modal frequencies and the rotor speed that determines the risk of resonance.
Ans: Our statement says “Ice mass on the blade reduces its natural frequencies and raises the risks of resonance”. It is true that resonance occurs when the excitation frequency (multiple of rotor speed like 3P) matches with the natural frequency of the blade. If we assume the rotor is rotating with the same speed with ice on the blade, the excitation frequency remains constant. As ice accumulation on the blade reduces its natural frequencies, the risk associated with resonances increase as we don’t know how much ice is going to accumulate on the blade.

11. Language
Ans: Will be corrected in the revised manuscript.

12. “dynamic magnification factors” - From what input to what output?
Ans: Dynamic magnification factors in that reference refers to the ratio of the dynamic deflection to static deflection.

13. I do not agree to these conclusions: First, there is mismatch between the figure labels and the caption. According to the caption the frequencies are normalized by the standstill frequency of the uniform blade but the red curve starting at 1 is labeled "Shape 2". It is surely just a typo, but there is also a fundamental problem with the Campbell diagram of blade

frequencies versus rotor speed. How do the authors explain that the centrifugal effect is stiffening for Shape 3 at high rotor speeds? Which nonlinear effect are we looking at? I have looked in the original EWEA PhD seminar paper. First problem here is that Figure 1 of this manuscript is not part of the original paper.
Ans: You are correct, there is a mismatch in the labels used in the Figure, it was our mistake. We will correct this in the revised manuscript.

We presented our work at the EAWE PhD seminar 2015 which only published our one page abstract, but we also submitted a full paper later, which is not made available to public. We are sorry that we didn't realize this until you have asked. As the paper is not available online, we have added the material referred in that paper below.

The equation of motion (EOM) governing linear in-plane bending vibrations of a rotating beam is given in Eq. (1).

$$(\rho A)\ddot{q} + (EI)q'' - \Omega^2(\rho A)q - \Omega^2\left(\rho A\left\{r(l_b - x) + \frac{1}{2}\left(l_b^2 - x^2\right)\right\}(q')\right)' = 0 \quad (1)$$

where $\rho A, EI$ are the mass density per unit length and section stiffnesses of the beam; Ω is the angular rotational frequency; q is the in-plane bending vibrations of the beam; $\ddot{q}, q', q''$ refers to second order temporal, first and second order spatial partial differentiations of the vibrations q; r is the distance between the rotational axis of the beam and its root; x is the distance of any section of the blade from root; l_b is the length of the beam. The third term in Equation (1) corresponds to spin softening and fourth term correspond to centrifugal stiffening. The above equation is reduced to a single degree of freedom model by assuming the vibration response in terms of an admissible function, i.e., $q(x,t) = \psi(x)\, p(t)$, where ψ(x) is a function that satisfies the boundary conditions of the beam and it is differentiable twice.

$$m\ddot{p} + \left[k + \Omega^2(m_c - m)\right] p = 0$$
$$\omega_n = \sqrt{\frac{k}{m} + \Omega^2\left(\frac{m_c}{m} - 1\right)} \quad (2)$$

where m, k are the modal mass and stiffness values, m_c is the centrifugal stiffening value. The blade natural frequency (ω_n) is a non-linear function of Ω. The natural frequency increases with increasing Ω if m_c is greater than m and it decreases with increasing Ω if m_c is less than m. These values for the three mass distributions considered on a cantilever beam in Figure 1 of the original manuscript are given in the below Table.

	k/m	m_c/m
Shape 1	173.35	1.3112
Shape 2	297.56	1.5984
Shape 3	112.92	1.1513

From the above table it is clear that, the rate of change in the natural frequency of the beam with rotational frequency is higher for shape 2 and it is lower for the shape 3. When this ratio is less than 1, the effective stiffness reduces quadratically with Ω, so the natural frequency reduces non-linearly with Ω.

These values will be accurate if the considered functions ψ(x) closely matches with the modeshapes of the beam or by considering more such functions in the approximation. At higher Ω, the vibration response depends on multiple vibration modes, so a finite element model can be used to model the vibration behavior accurately at higher Ω. The Figure 1 in the original manuscript is obtained from the eigenvalue analysis of the equations of motion obtained from finite element method. At higher Ω, the natural frequency of shape 3 is decreasing, which indicates that the exact value of m_c/m is less than 1 and this variation is non-linear which is evident from Eq. (2).

14. Language: one can not simulate natural frequencies. They are the results of an eigenvalue problem that one can solve numerically. Of course you may use system identification methods to estimate the modal frequencies of a system from simulations but then you are still not simulating the frequencies themselves.
Ans: That sentence will be corrected in the revised manuscript.

15. Language
Ans: That sentence will be corrected in the revised manuscript.

16. This definition of the pitch axis is not valid for any real wind turbine blade. The authors should turn the statement around and say that the aerodynamic center in the quarter chord is assumed to lie on the pitch axis, which is the axis around which the blade is pitching.
Ans: This assumption is taken from the [R10] (refer to 2nd section, 3rd paragraph, line 2). However, we will state that this is an assumption in the derivation and that sentence will be modified in the revised manuscript as "The line joining quarter chord points of the aerofoil sections is assumed to lie on the pitch axis of the blade and it coincides with the X axis of the rotating coordinate system".

17. The author must state what sign convention that is used for the DOFs and for the coordinate axes Y and Z. I can see from Figure 4 that those axes and the DOFs are not rotated with the blade pitch, but where is the wind coming from?
Ans: The rotating coordinate system OXYZ is fixed at the hub center, which is used to derive the governing equations of the blade vibrations. This coordinate system is only having rotational motion about the hub axis. The right part of the Figure 4 in the original manuscript consists of the projection of a blade cross-section on to the Y-Z plane. Blade displacements in the axial (u), edgewise (v), flapwise (w) directions are defined at the point of intersection between pitch axis and blade cross section in the directions of X,Y,Z axis in Figure 4 in the original manuscript are considered as vibrations DOF. These DOF are defined with respect to the coordinate system fixed at the blade cross-section, which is the reason why the coordinate system is not rotating with blade pitch or torsional vibrations. The wind direction will be indicated in the figure in the revised manuscript.

18. Assuming small torsional rotations, phi.
Ans: This information will be added in the revised manuscript.

19. I do not understand the second term of this rotational velocity vector. Why does the torsional rotation about the pitch axis lead to a component of the rotor rotation about the Y-axis? Why are you including the rotor rotation in this vector that you are using to derive the kinetic energy of the polar moment of inertia of the blade section given by J_p?
Ans: We accept that the inclusion of the second term was wrong in that equation. When the rotating coordinate system is used to derive the equations, there will not be a relative motion between coordinate system and the blade due to blade rotation. This term should be considered only if the coordinate system used to derive equations of motion is stationary with respect to the blade, but in our case it is not. When this term is excluded in the rotational velocity vector, the sixth term of the 4th equation in Appendix now becomes $J_P \ddot{\varphi}$ instead of $J_P\left(\ddot{\varphi}-\Omega^2\varphi\right)$. The wrong inclusion of the second term in Equation (3) of the original manuscript introduced a reduction in torsional stiffness ($-J_P \Omega^2 \varphi$) which can be seen in the Table 1 of the original manuscript where the torsional frequency of rotating blade is slightly less than that of the non-rotating blade, which is wrong. The new frequencies are recalculated.

20. This rotational kinetic energy term does not make sense to me.
Ans: You are correct, rotational kinetic energy is correct when the second term in Equation (3) is removed.

21. The first term of this spanwise force is the centrifugal force due to the mass from the section at the coordinate x to the tip, right? Where is the integration over the varying "linear mass density" gone? Or are you assuming that it is constant?
Ans: Yes, the first term corresponds to the centrifugal force. As the wind turbine blade's linear mass density ρA is not a constant value, it is integrated over the blade length in the Equation (6) where the potential energy due to these forces is calculated.

22. Around which axis?
Ans: Polar mass moment of inertia is defined along the pitch axis of the blade and this information will be included in the revised manuscript.

23. Which forces are that? Aerodynamic?

Ans: Generalized forces can be any external forces, in the case of wind turbines, they are aerodynamic forces. We included these generalized forces for the sake of completeness in the derivation, we didn't consider any aerodynamic forces in this study as we used homogeneous part of the equation of motion for the eigenvalue analysis.

24. The authors should present the element type and DOFs of their FEM model. And they should insert an "a" here.
Ans: Wind turbine blade is discretized using one dimensional beam elements as shown in the Figure 6. The beam elements consist of two nodes with 6 degrees of freedom: u_i, v_i, w_i, φ_i, α_i, β_i, where i represent the i^{th} node, u_i, v_i, w_i are the blade axial, in-plane and out-of plane vibrations, φ_i refers to the blade torsional vibrations, α_i, β_i are the slopes of the beam bending displacement curves. This information will be included in the revised manuscript.

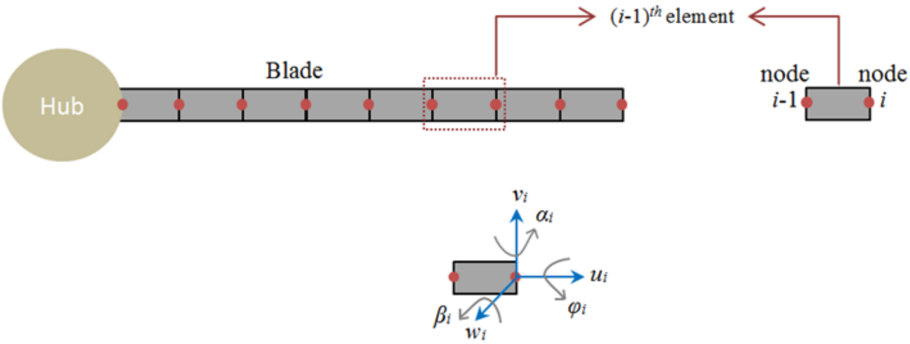


Figure 6. Finite element model of the wind turbine blade

25. The authors have an error on the first edgewise frequency for the rotating blade. It seems that the geometrical softening effect of the centrifugal forces on inplane blade deflections is not included, however, the edgewise equation in the appendix includes this negative stiffness term proportional to the squared rotor speed.
Ans: We have included the geometrical softening effect in the derivation of equations of motion which you can find in the equations in the Appendix of the original manuscript. We tried to find the source of error for this frequency in our FEM model and we found following two issues in our code.
1). We used wrong limits in the code for the axial force integration along the blade from h to $h+L$ instead of 0 to L, where, h is the hub radius and L is the blade length.
2). Number of elements used to discretize the blade in BModes and the current FEM model are different, we increased them till we got converged results from both tools.

After these corrections in the code, we compared blade frequencies in the below table and shown the % error in the frequencies in Figure 7.

Vibration mode	At 0 rpm		At 12.1 rpm	
	BModes	FEM code	BModes	FEM code
1st Flapwise mode	0.677	0.677	0.729	0.738
1st Edgewise mode	1.089	1.086	1.098	1.117
2nd Flapwise mode	1.957	1.952	2.016	2.040
2nd Edgewise mode	4.024	4.006	4.047	4.048
3rd Flapwise mode	4.540	4.523	4.591	4.607
1st Torsion mode	5.824	5.587	5.829	5.591
4th Flapwise mode	8.067	8.035	8.120	8.126
3rd Edgewise mode	9.464	9.402	9.487	9.446

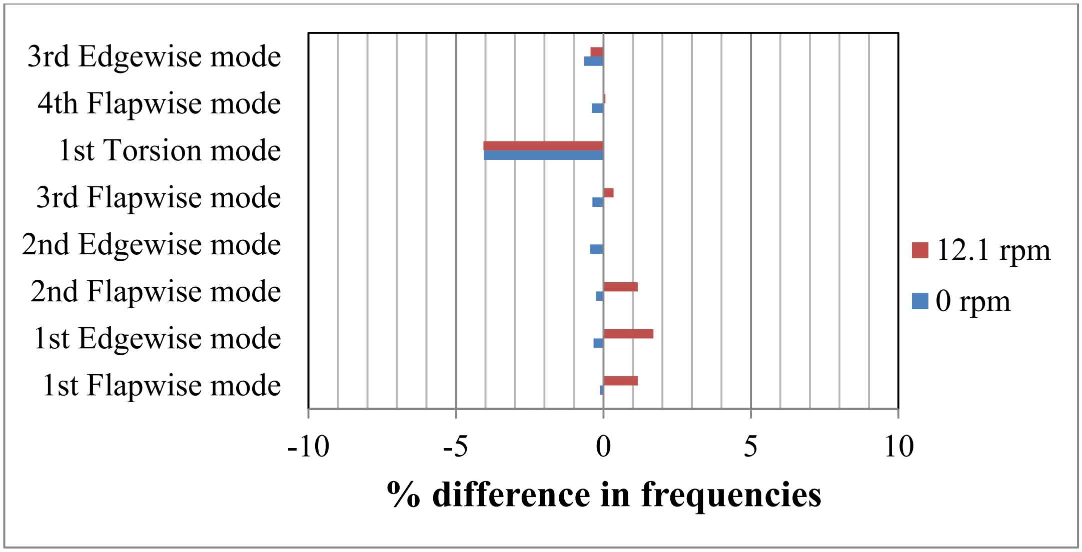


Figure 7. Error between natural frequencies predicted using the current FEM model and BModes tool

26. Are the authors only consider a single ice mass distribution?
Ans: No, we estimated the ice mass distribution as defined by GL limit just to set the limits for maximum ice mass values to be considered on the blade for the generation of a training data set. Ice mass accumulation on the blade depends on many parameters that vary stochastically in space and time, which results in a non-uniform ice mass distribution. In this study, we considered different ice mass values between zero and the maximum ice value (defined by GL limit) in each zone. These ice masses are distributed with a constant linear mass density (mass per unit length) as shown in Figure 4 of this document. The training data set comprises of different combinations of ice masses in the three zones and corresponding blade natural frequencies calculated from the eigenvalue analysis.

27. is?
Ans: Sentence will be corrected in the revised manuscript.

28. This particular part is the core of the work. I am not sure that I understand at this point how a neural network can predict the location but I assume that it is because they use the frequency shifts of several modes, and not just one mode. If this assumption is correct then I suggest that the author make it much clearer to reader at this point. I also suggest that they explain why they need a neural network and not just a least square fit.
Ans: We calculated frequency shifts of several modes considering different ice masses along the blade and trained the neural network with this data. This will be mentioned explicitly in the revised manuscript. In order to use a least squares fit between inputs and outputs, a function needs to be defined explicitly which is an unknown for the current problem. In this situation, ANN is more suitable because it doesn't require such function definition between inputs and outputs. This will be mentioned in the revised manuscript.

29. Very clear and nice introduction to the field. Thanks.
Ans: Thanks for your comment.

30. What is the difference between validation and testing here? Later, it seems that there is only a training set and a validation set of 10 cases. I may be have misunderstood this comment here.
Ans: In this study, we considered (n+1) mass values ($0, m_1, m_2, \ldots, m_{GL}$, where m_{GL} is the maximum ice mass in each zone defined by GL limit) in each zone, which will generate (n+1)^3 possible combinations of ice masses in three zones. The blade natural frequencies are calculated considering these ice masses where each ice mass is distributed with a constant linear mass density along the length of the zones defined on the blade. This data set comprising ice masses and corresponding blade natural frequencies is divided into three sets: 70% for training, 15% for validation and 15% for testing the neural network model. The training set is used for computing the gradient (rate of change in frequencies with variation of weights used in the neural network) and updating the network weights and biases. The error on the

validation set is monitored during the training process. The validation error normally decreases during the initial phase of training, as does the training set error. However, when the network begins to overfit the data, the error on the validation set typically begins to rise. The network weights and biases are saved at the minimum of the validation set error. The test set error is not used during training, but it is used to measure the network accuracy independently. The mean square error between network output and actual output should be low in all three sets of the data (training, validation and testing). If the error is not acceptable, the neural network is not able to fit a valid model for the data set. This happened in our case, when we used three natural frequencies of the blade as input to the network. When we increased the number of frequencies in the input to the network, it was able to find a valid model for all the three sets of the data.

In order to find the minimum ice mass that can be detected by the trained network and to know how good the prediction would be for the cases of ice mass distributed differently from the way assumed to generate the training data, few ice mass cases as shown in Figure 10 of the original manuscript are considered. The blade natural frequencies are calculated considering these ice masses on the blade and given as input to the trained neural network.

31. What is the unit of this error? Error of the output? Normalized?
Ans: The mean square error (mse) is the mean of the square of the error between the output of neural network model and the actual output. As ice mass is the network output in the current case, the units of this error is kg^2. It will be mentioned in the revised manuscript.

32. How large was the training set? Basically, what is the number n?
Ans: In the section IV, we used n=20 which generated a dataset of size (n+1)^3 i.e., 9261 samples. We have not done any systematic study to find the optimum parameters required to generate a valid model. There is no hard rule to choose the model parameters like number of neurons and number of hidden layers in the network, the training data set size. These parameters need to be changed until unless a valid model with acceptable mean square error is fitted to the data set. This information will be mentioned in the revised manuscript.

33. Unit?
Ans: It will be mentioned in the Figure axis label in the revised manuscript.

34. The text here is very hard to follow; in the previous section the method was described without the subdivisions mentioned. I suggest that the authors includes a method section where this text is extended to become easier understandable.
Ans: In the section IV, a neural network model with 10 neurons in 1 hidden layer is generated and trained with a data set of size 9162 samples (consists of 5 natural frequencies of the blade as input and three ice masses as output). These parameters have been chosen randomly as there exists no hard rule. These parameters were able to fit a valid model between inputs and outputs which was confirmed from the mean square error of the network model.

In the section V, we considered 10 different ice mass distributions on the blade and calculated corresponding blade natural frequencies. These mass distributions are selected in such a way to identify the minimum ice mass that can be detected and also to assess the performance of the network model for ice mass distribution different from that used to generate the training data. Blade natural frequencies for these 10 ice mass distributions are given as input to test the accuracy of estimation of ANN models that are generated with different parameters (number of neurons, data set size, number of frequencies in the input).

We will modify this section to make it clear above points in the revised manuscript.

35. I can't find the reference to this table in the text.
Ans: The Table 4 is refereed in the text in Line 7 on page 12 of the original manuscript.

36. What are the units here?
Ans: These values correspond to the bar plot in the Figure 11, they are the % error values between ice masses predicted and actual ice mass values used in the validation cases 7 to 10. We will only show the figure and remove this table to avoid confusion.

37. Are you estimating the frequencies from simulations or eigenvalue analysis?
Ans: We are calculating the natural frequencies from the eigenvalue analysis of the equations of motion. That sentence will be corrected in the revised manuscript.

38. Simulations like in time integration of the equations of motion?
Ans: No, we only used eigenvalue analysis of the equations of motion to find natural frequencies of the blade with different ice masses.

39. Well, how are you getting the frequencies of the blade when it is operating?
Ans: The objective of this paper is only to investigate the use of neural networks to identify ice masses from the natural frequencies of the blade. We know that it is difficult to find multiple vibration modal frequencies of the blade when it is excited only by the turbulent wind. There is a need for some external mechanical excitation like the use of the pitch actuation system or an electromechanical actuator used in [R6] or a small DC motor with eccentric rotating mass (ERM) suggested by the authors. These can excite multiple vibration modes of the blade which can be identified from the vibrations measured on the blade using accelerometers. Our study is only a theoretical study which uses natural frequencies of the blade calculated from the eigenvalue analysis. The interest to perceive the idea of using these external excitation systems is increasing for the structural health monitoring of the blades. The authors are actually designing a small experimental set-up to study the rotating blade vibrations with external excitation using an ERM motor.

REFERENCES:

R1. Lauritsen, S.M. and Miranda, E.C.L., 2013, "Wind turbine system for detection of blade icing", US Patent App. 13/807,465, https://www.google.com/patents/US20130195657.

R2. Brenner, D., 2016, "Determination of the actual ice mass on wind turbine blades", Winterwind 2016, Feb 9-10, Åre, Sweden.

R3. Cattin, R. et al., 2016, "Evaluation of ice detection systems for wind turbines", Final Report, VGB Research Project No. 392, https://www.vgb.org/vgbmultimedia/392_Final+report-p-10476.pdf.

R4. Kraemer, P., Friedmann, H. and Ebert, C., 2015, "Vibration-based ice detection of rotor blades in wind turbines-The industrial realization of an SHM-system", Structural health monitoring 2015, doi: 10.12783/SHM2015/352.

R5. "Blade condition monitoring system BLADEcontrol – brochure", https://dc-corp.resource.bosch.com/media/general_use/industries_2/renewable_energies_6/windenergy/products_2/rotor_blade_condition_monitoring_systems_/BLADEcontrol_AE.pdf.

R6. Tcherniak, D. and Mølgaard, L. L., 2015, "Vibration-based SHM System: Application to Wind Turbine Blades", J. Phys.: Conf. Ser. **628,** 012072, doi: http://dx.doi.org/10.1088/1742-6596/628/1/012072.

R7. Hansen, M. H., 2007, "Aeroelastic instability problems for wind turbines", Wind Energy,10, 551–577.

R8. Gantasala, G., Luneno, J.-C, and Aidanpää, J.-O., 2016, "Influence of icing on the modal behavior of wind turbine blades, Energies, 9, 862, doi:10.3390/en9110862.

R9. Skjoldan, P.F. and Hansen, M.H., "On the similarity of the Coleman and Lyapunov-Floquet transformations for modal analysis of bladed rotor structures", Journal of Sound and Vibration, 2009, 327, 424-439.

R10. Jonkman, J., Butterfield, V., Musial, W. and Scott, G., 2009, "Definition of a 5-MW Reference Wind Turbine for Offshore System Development", National Renewable Energy laboratory, Technical report, NREL/TP-500-38060.