Replies to Reviewer 2 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 your comments.

1) Abstract: The validation of the proposed FEA model should be mentioned

Ans: We will add this information in the revised manuscript. The natural frequencies of the NREL 5 MW wind turbine blade calculated using the FEM model derived in this work are compared with the frequencies predicted using BModes tool.

2) Structural Model:

a. More information (such as cross-sectional properties of the blade, number of beam elements and boundary conditions) on the modal analysis of NREL 5MW wind turbine blade should be given.

Ans: We have used the same cross-sectional properties given in [R1], if you insist to give again, we will add them in the revised manuscript.
We have discretized the 5 MW turbine blade using 100 beam elements to calculate its natural frequencies and used a fixed boundary condition at the blade root. We will mention this information in the revised manuscript.

b. For 1st edgewise mode In Fig. 5, please explain why the difference in case of 12.1rpm is much higher than the difference in case of 0rpm.

Ans: 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 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 1.

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

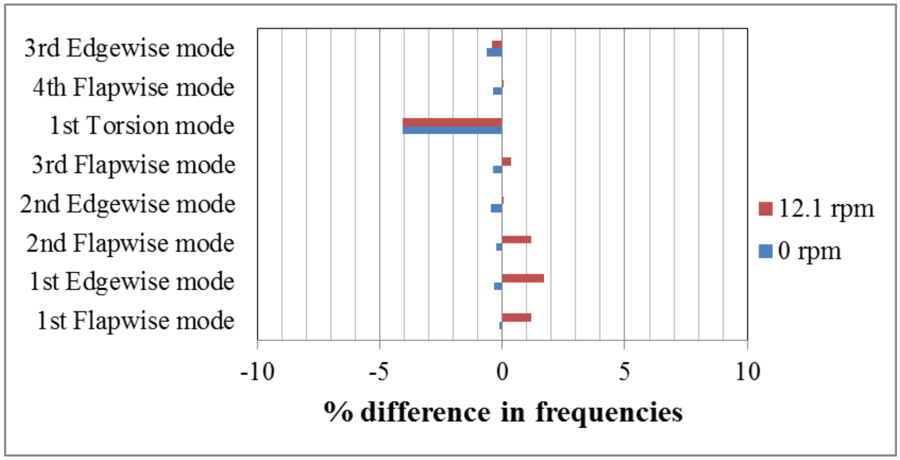

Figure 1. Error between natural frequencies predicted using the current FEM model and BModes tool

3) Artificial neural networks (ANN): A more detailed flowchart of ANN should be given. What does "W" and "b" in Figure 8

<u>Ans:</u> We will include the flowchart shown in Figure 2 in the revised manuscript outlining the ice mass prediction using ANN.

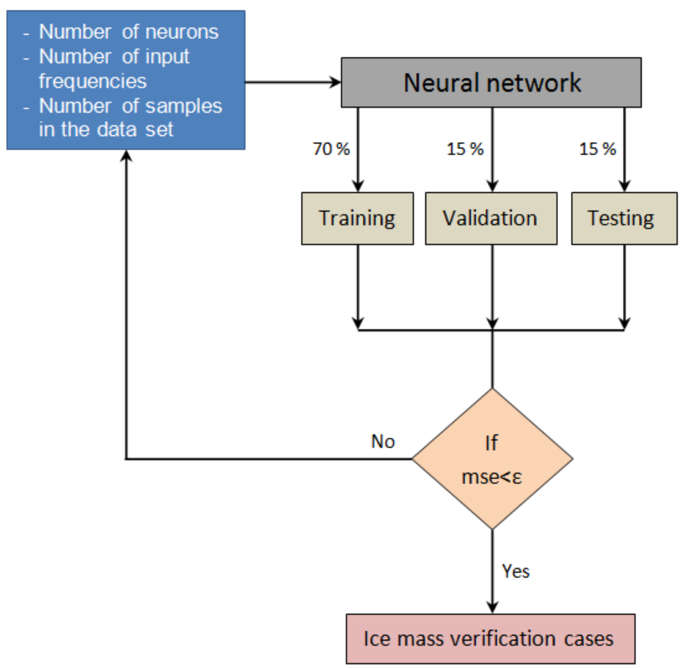

Figure 2. Flowchart for the ice mass prediction using ANN
(Note: mse is the mean square error, ε is a limit defined for convergence)

The w and b in Figure 8 of the original manuscript refer to weights and bias associated with the neurons. The weights of neurons either increase or decrease the input signals to the neuron whereas bias has the effect of increasing or lowering the net input to the neuron. These weights and bias of neurons are determined in the training process which will minimize the error between network output and the actual output. We will specify this information in the revised manuscript

4) Results & Discussions

a. How the ten ice mass validation cases were chosen?

Ans: In reality, ice mass is not concentrated in one location along the blade, it is a continuous variable that varies randomly along the blade length. We approximated this continuous variation in terms of three masses that are distributed with constant linear mass densities as shown in the Figure 3 below. This is the simplest approximation we can make and generated a data set of natural frequencies considering different masses to train a neural network.

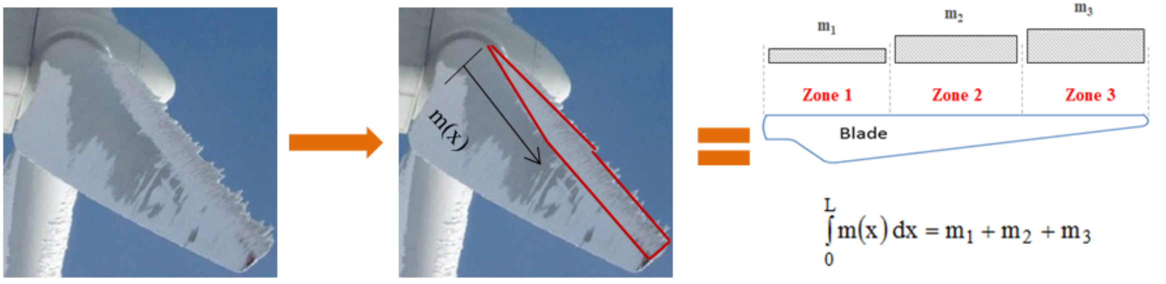

Figure 3. Approximation of the continuous ice mass variable in terms of three mass variables

The trained neural network should detect initiation of the icing at the earliest so that necessary action like deicing can be taken to avoid any shutdown of the turbine. To know the effectiveness of the prediction model we chose first 6 ice mass validation cases where 50 kg and 100 kg of ice masses considered exclusively in each zone. The network is trained with masses that are distributed considering constant linear mass densities along the length of the zones defined on the blade. The last 4 ice mass validation cases are chosen such that their mass distribution is different from the way it is considered to train the network. There exist many possibilities to define such mass distributions in the ice mass validation cases, we chose these mass distributions randomly and used to test the estimation capability of the network model.

b. How long does it take to finish one case study using ANN model? Is it computationally efficient?

Ans: The training starts with random weights initially, which are modified iteratively to minimize the error between actual output and the network output. The time taken for training depends on many parameters like the data set size, number of neurons and usually changes with the complexity of the relation between inputs and outputs. It took less than 10 minutes for training the network shown in Figure 8 of the original manuscript where the training data set consists of 9261 samples. In the case of data set consisting 17576 samples, it took less than 20 min for training the network. These computations are carried out on a personal laptop (configuration: Intel i7 processor @2.10 GHz, 8 GB RAM). The network training takes only 1/4th of time required for generating the above data sets from the eigenvalue analysis of the equations of motion of the blade (FEM model considering 100 elements with 6 DOF per node).

c. Please justify the choice of values of the No. of neurons and training data size in Table 3? If we use higher values of these parameters, will we get more accurate results?

Ans: There are no specific rules to follow while choosing the number of neurons and training data size. We have chosen these values randomly. Any values for these network parameters are acceptable as long as the mean square error between the network output and actual output is negligible. If we are able to achieve an acceptable error value for a network generated with lower values of the model parameters, generating a new network with higher values of these parameters offers no significant improvement in the estimation accuracy of the output. If we change any of these parameters, we get a new network model, i.e., new set of weights for the neurons. When we used different network models for prediction in Table 4, predicted values did not change significantly from one another. We didn't do any systematic study to find the minimum values for the network model parameters which can identify the ice masses with the same order of accuracy obtained in Table 4 because both the eigenvalue analysis for the training data set generation and the network training were not taking much computational effort.