

# Response to Reviewer Comments

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We sincerely thank the reviewer for their thorough review of our manuscript titled "*Multi-task Learning Long Short-term Memory Model to Emulate Wind Turbine Blade Dynamics*" and for providing valuable feedback. The reviewer's comments have greatly contributed to improving the overall quality of this paper.

In response to the reviewer's comments, this document lists each comment in *italic text*, followed by our responses in standard text. In addition, a separate PDF file is attached, addressing the detailed comments provided by the second reviewer.

## Reviewer 1

*The article presents a method of developing LSTM models for predicting blade response using multi-stage modelling and multi-task learning with dimensionality reduction techniques. Overall, the article is well-written, presenting a novel and relevant contribution in data driven methods. There are several minor aspects of the article which could be modified to improve its quality.*

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**Q 1.1** *Article can be made more concise - Consider shortening section 2 – not necessary to explain how TurbSim works, possible to reorganise by removing section 2 entirely and including the important parts as part of section 6*

**Reply:** We thank the reviewer for this suggestion. In the revised manuscript, the content of Section 2 (Generation of stochastic wind field) has been merged with Section 6 (Data Generation: Selection of Input Variables), and only the relevant information for this study has been retained.

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**Q 1.2** *Sufficient to simply state that IEA-15MW reference turbine is used – Figure 2 and Table 1 not necessary*

**Reply:** Figure 2 and Table 1 have been removed from the manuscript to improve conciseness. For further details on the parameters of the 15 MW wind turbine, readers are directed to the original document, which has been cited in the revised manuscript.

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**Q 1.3** *In Section 1 or 5 – should include a justification on why LSTM (or RNNs in general) is used in this work, as opposed to conventional Neural Networks*

**Reply:** Thank you for your suggestion. A brief discussion has been added to Section 5, explaining the rationale for choosing LSTM over conventional neural networks. This justification has been included to provide clarity on the choice of algorithm.

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**Q 1.4** *Table 3 – Optimized value for Fully connected layer is at upper limit – why is range not expanded to ensure it is actually optimal?*

**Reply:** We thank the reviewer for their insightful suggestion. In response, we have expanded the optimisation bounds for the fully connected layer to ensure that the obtained solution is indeed optimal. The updated results, presented in the revised manuscript, show different parameter values; however, these changes did not significantly impact the model performance. Since the overall predictive accuracy and behaviour of the

model remain consistent, we have retained the original figures in the manuscript to maintain continuity with the discussion and results presented.

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**Q 1.5** *Table 5 – Between RMSE and signals shown in Figures 14 to 17, it is clear that LSTM model is accurate. However, RMSE may not necessarily be the best metric to measure model performance, as it does not take into account the variation of the signal (e.g. oop deflection has much larger magnitudes than ip deflection). Consider the use of other metrics such as Variance Accounted For or Confidence Index.*

**Reply:** We thank the reviewer for their suggestion. To better account for signal variation, we have replaced RMSE with Normalised Root Mean Square Error (NRMSE) in the revised manuscript. NRMSE normalises errors by the data range, making it more suitable for comparing signals with different magnitudes, such as oop and ip deflections. This change aligns with the reviewer’s feedback and is also consistent with the suggestions of the second reviewer.

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**Q 1.6** *Figure 10 – Unclear on what this figure represents – some additional explanation in caption may be helpful*

**Reply:** We thank the reviewer for this suggestion. To improve the clarity of Figure 10, additional details have been added to the manuscript, explaining the grouping of 2D DCT components and their significance in capturing spatial frequency information. In addition, an additional figure has been included showing a representative example of DCT components, to aid the reader in understanding how feature subsets are constructed and utilised in the model.

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**Q 1.7** *Example LSTM predictions (Figures 9,12,14 to 17) show results at  $TI=11.54$  – however, range from Table 2 shows that max  $TI$  should be 7.629*

**Reply:** The bounds provided in Table 2 correspond to the variance in wind speed  $\sigma_u$ . Since the turbulence intensity (TI) is defined as  $TI = \frac{\sigma_u}{U}$  where  $U$  represents the mean wind speed. As such, TI values for above-rated wind speeds can achieve values higher than 7.629%. These changes are reflected in the modified manuscript.

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**Q 1.8** *Example LSTM predictions (Figures 9,12,14 to 17) only show  $U = 13.65\text{m/s}$  upwards and  $TI=6.19$  to 11.54 – may be interesting to see predictions at lower speeds or higher  $TI$  (if possible)*

**Reply:** We thank the reviewer for their suggestion. While the manuscript focuses on the operational range of the turbine, we have generated an additional figure showing LSTM predictions at higher turbulence intensities (TI) to address the reviewer’s interest. This figure is provided as supplementary material for the reviewer’s consideration. We believe this demonstrates the model’s capability under extended conditions without altering the main results presented in the manuscript.

## Reviewer 2

*The article presents a method to a) a simple dynamic model of wind turbine b) unsteady wind order reduction and c) developing a LSTM model to predict the blade deformations from the wind time series reduced space. Although this work is interesting, and clearly, the authors put a lot of effort into it, it needs more work to be publishable. I commented on the article extensively and in detail, which you can find in the supplement. These are my general comments:*

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**Q 2.1** *The structure of the paper can be improved. It doesn’t necessarily follow the chronological order. I think there needs to be a clearer separation between methodology and results. For example, Fig 4 can be in section 8.1.2, and the explanation about DCT needs to move the part where you explain DCT.*

**Reply:** We thank the reviewer for their valuable feedback on improving the structure of the paper. While we agree with the need for a clearer separation between methodology and results, we have chosen to retain Figure 4 in its current location to maintain the logical flow of the discussion. The figure is closely tied to

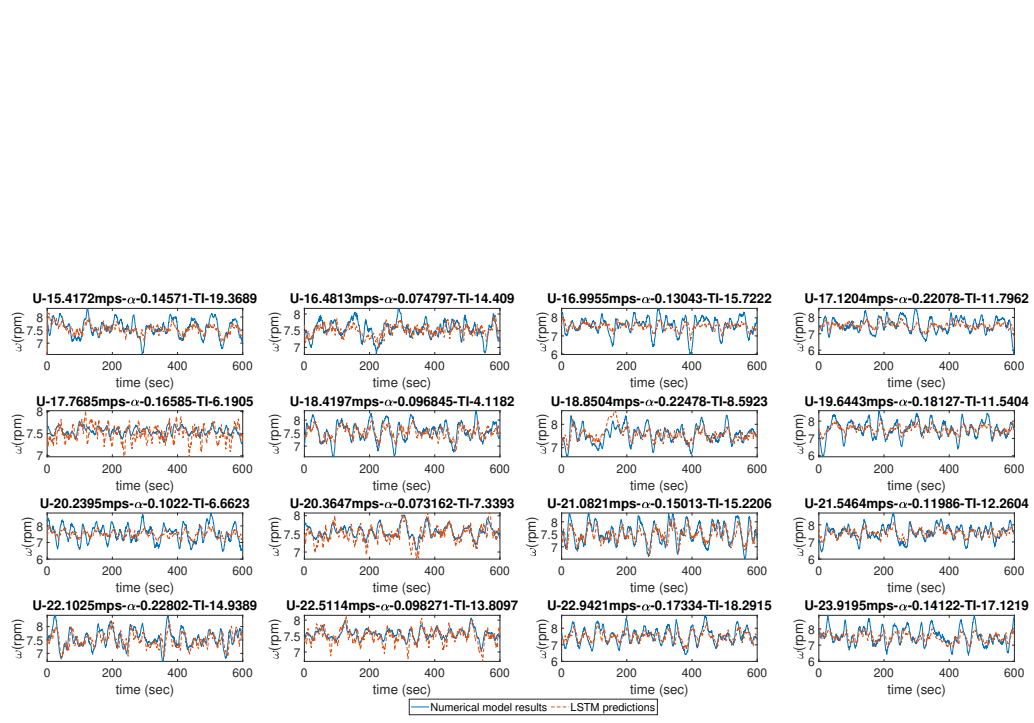


Figure 1: Rotor speed predictions at higher turbulence intensity

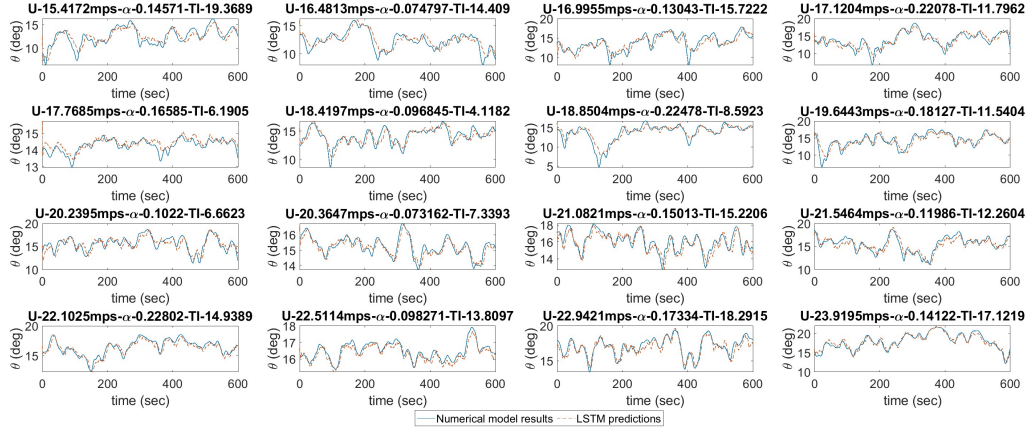


Figure 2: Blade pitch angle predictions at higher turbulence intensity

the methodological explanation of the 2D Discrete Cosine Transform (DCT), and relocating it to the results section could disrupt the reader’s understanding of the process. However, we have revised the manuscript to consolidate the DCT explanation within the methodology section and removed redundant information to enhance clarity and readability. We believe these changes address the reviewer’s concerns while preserving the coherence of the paper.

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**Q 2.2** *The article is well-written, but it could be more concise. Some sentences are long and written in passive voice, making them hard to follow.*

**Reply:** We thank the reviewer for their constructive feedback on improving the readability of the manuscript. In response, we thoroughly reviewed the text and revised it to reduce sentence length and convert passive voice to active voice whenever possible. We have also removed redundant information not relevant to this study to make the article more concise. We believe that these edits improve the overall readability of the manuscript.

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**Q 2.3** *The quality of the figures can be improved. Figures with time series data are small and not legible. The flowcharts can have a better graphical quality.*

**Reply:** We thank the reviewer for their feedback regarding the quality of the figures. We have revised the manuscript to improve the resolution and legibility of the time series figures wherever possible. However, for some figures, the quality is constrained by the nature of the data and the original source, making further enhancements challenging.

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**Q 2.4** *It is necessary to show how the LSTM results match OpenFAST and how much data is lost when reconstructing your wind time series from the reduced space (PCA or DCT).*

**Reply:** We thank the reviewer for their comment. The primary aim of this study is not to reconstruct wind time series using PCA or DCT but to use these methods as feature extraction techniques for the LSTM algorithm. The selection of principal components and discrete cosine transforms is guided by their relevance to the quantity of interest and the requirements of the machine learning algorithm, rather than reconstruction accuracy. As such, the focus is on leveraging these transformations to enhance the LSTM’s predictive performance, not on minimizing reconstruction loss. Therefore, analysing the reconstruction error is beyond the scope of this study. Also, since the LSTM model is trained using the data from numerical model as the ground truth, direct comparison of LSTM model with OpenFast is not presented in the article. A more detailed response to this query is also included in the attached document.

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**Q 2.5** *The DCT part needs to be explained better. What do you do with your time when you are going through DCT? Section 8.1.2 makes this a bit clearer, but it needs to be explained earlier.*

**Reply:** We thank the reviewer for their comment regarding the explanation of the DCT method. At each time step, the wind field, modeled as a 25x25 grid, is decomposed into a selected number of DCT components. This process captures both spatial and temporal variations in the wind field, as the DCT is applied sequentially across time steps. The resulting components serve as feature inputs to the LSTM model, enabling it to learn the underlying dynamics of the wind turbine blade response. To address the reviewer’s concern, we have enhanced the explanation of the DCT process earlier in the manuscript, ensuring a clearer and more comprehensive description of its role in the methodology. Additional details are also provided in the attached document for further clarification.