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Evaluating the structural changes during physical testing of a full-scale 13 metre long wind turbine blade

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ABSTRACT: The structural testing of wind turbine blades is crucial to ensure their performance aligns with testing specifications and can withstand anticipated loads over their operational lifespan. The industry standard IEC 61400-23 generally recommends three main types of tests for wind turbine blades: dynamic, static, and fatigue testing. The static test assesses the wind turbine blade's structural integrity, dynamic testing examines its dynamic performance, and fatigue testing investigates the blade's durability over its expected service life. This study at the University of Galway's Large Structures Testing laboratory, examines the impacts of static and dynamic testing on a full-scale 13-meter-long wind turbine blade. From measured accelerations in dynamic testing, the first and second natural frequencies of the blade were estimated to be 2.48Hz and 7.60Hz, respectively. When the flapwise and edgewise design loads were applied to the blade during static testing, the maximum measured strain values on the suction side at 5 metres from the blade root were1220µm and 1095µm, respectively. These results validate the dynamic and static design requirements of the blade and derisk the blades related to the idealised dynamic and static loading conditions. In addition, the decision tree model from machine learning accurately predicted the strain results in the static tests by giving the coefficient of determination (R^2) value equal to 0.999. The statistical check and 10-fold validation approach also confirm the precision of the decision tree model by indicating the high R^2 results and lower value of the errors. In this context, this research underscores the importance of dynamic and static testing along with the modelling techniques in ensuring wind turbine blades meet relevant performance standards, thus contributing to the advancement and reliability of wind turbine blades.

KEYWORDS: Wind turbine blade; Testing; strain; displacement; loading.

1 INTRODUCTION

Wind energy is a renewable energy source that has become an essential aspect of energy systems in several countries and is acknowledged as a dependable and cost-effective electricity source [1, 2]. Considering the rapid surge in energy demand, the wind energy sector continuously tries to increase the required demand by installing new wind farms [3]. Wind turbines help mitigate climate change by producing clean, renewable energy, which lessens reliance on fossil fuels and moves us closer to a more sustainable energy future [4]. Wind energy is a highly promising and efficient form of clean energy due to its feasibility and cost-effectiveness [5]. In 2020, the world experienced a worldwide outbreak that impeded the expansion of wind power plants due to delays in the supply network and a lack of workers. However, still as per the recently published Global Wind Report from the Global Wind Energy Council [6], the global wind sector achieved a remarkable milestone in 2023 by installing a record-breaking 117GW of new capacity to bring the total capacity of operational wind farms to 1023 GW. This makes it the most successful year in history for the expansion of wind energy. The worldwide offshore market is projected to grow from 10.8 GW in 2023 to 37.1 GW in 2028, resulting in its proportion of new global installations rising from the current 9% to 20% by 2028. From 2024 to 2028, it is anticipated that over 42 GW of offshore wind capacity will be constructed in Europe, with the United Kingdom set to be given 44% of this capacity.[6].

Given the significant increase in the global demand for and installation of wind farms, thoroughly testing the many components of wind turbines and developing innovative modelling methodologies are necessary to guarantee their stability and endurance [7]. A lot of care needs to be taken when testing or modelling the wind turbine blades because they are an important part of the wind turbine system [8, 9]. Physical testing of lengthy and heavy blades is still regarded as a difficult and technical activity due to the additional time, effort, and state-of-the-art laboratory equipment required [10]. The IEC 61400-23 [11] international standard outlines the structural design requirements that blades must meet for testing purposes. The primary criterion for the blades, and the main subject of the current investigation, is the structural response to static loads.

This study emphasises the crucial significance of both dynamic and static testing, along with cutting-edge modelling tools, in ensuring that wind turbine blades satisfy demanding performance criteria. This study offers useful insights into the structural integrity through physical testing and use of recorded data for further machine learning modelling to predict the parameters such as strain on a full-scale 13-meter-long blade. The results indicate that both dynamic and static testing is beneficial in confirming design requirements and reducing risks associated with idealised loading conditions. Moreover, the use of machine learning methodologies, shown by the decision tree model, presents an optimistic potential for accurate prediction of strain outcomes in static tests. In summary, this study highlights the need for thorough testing and modelling methods in improving the dependability and effectiveness of wind turbine technology.

2 METHODOLOGY

2.1 *Aim and Objectives*

The overreaching aim of the presented paper is to describe the experimental, validation, and modelling approaches for a 13-metre-long wind turbine blade to assess better insights into the blade's nature. Therefore, to achieve this aim, the following aspects are summarised in the paper:

- Structural testing (static and dynamic) at the state-of-the-art Large Structures Testing laboratory of the University of Galway.
- Validate the testing results using the finite element analysis (FEA) using ABAQUS.
- Applications of machine learning tools to predict the strain values on the wind turbine blade using the static test data.
- Employ statistical checks, sensitivity analysis, and a 10-fold validation approach to evaluate the model’s legitimacy, impact of the inputs, and validity of the selected model, respectively.

Moreover, the flowchart, as shown in Figure 1, depicts the adopted step-by-step strategy for the presented study.

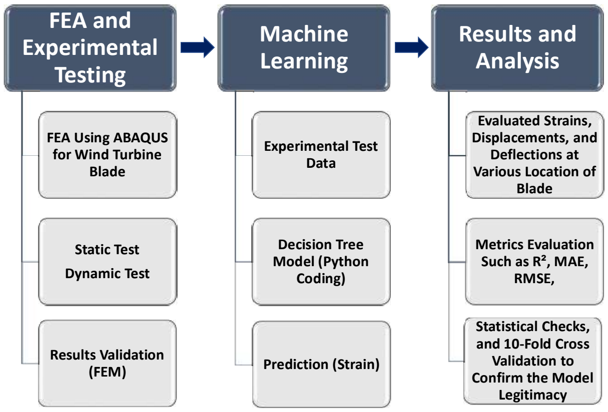

Figure 1. Flowchart for the research strategy

2.2 *Facilities for testing*

The testing of a 13m wind turbine blade at the Structures Research Laboratory was conducted in accordance with the DNVGL-ST-0376 standard [12]. The tested blade was made of a glass-fibre reinforced powder epoxy composite material and is part of a 225 kW wind turbine with a total weight of 674 kg. The computer-generated image, shown in Figure 2, reflects the facilities and tools available in the laboratory. Moreover, the facilities of the large structures testing laboratory at the University of Galway can be seen here [13].

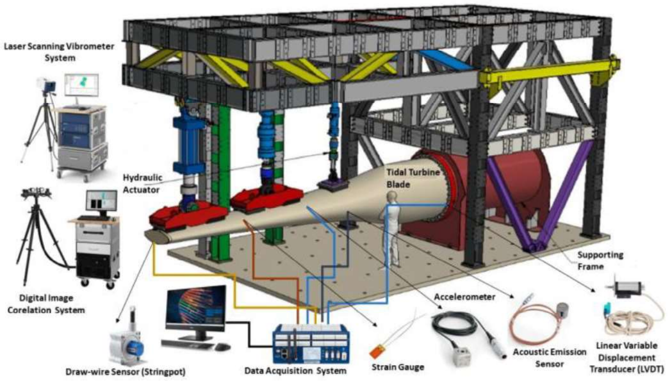

Figure 2. Capability of the structural laboratory [14]

2.3 *Dynamic Test*

The blade was subjected to dynamic testing to ascertain its natural frequencies. A series of single-axis accelerometers were strategically positioned on the suction side of the blade. An impact hammer generated vibrations in the blade, which resulted in a momentary impact on the tip of the blade. The natural frequencies were measured before and after testing. The tests were conducted without the load introduction fixtures. The positions of the accelerometers to the blade are shown in Figure 3.

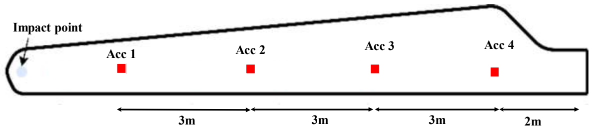

Figure 3. Positions of the accelerometers on blade

2.4 *Static Test*

In the static tests, the blade was loaded using two hydraulic actuators of a capacity of 250 kN and 750 kN at 6.49 and 10.59 meters, respectively, from the root of the blade. String pots were attached to the blade to measure vertical displacements at 6.60 m from the root (i.e. close to the 250kN actuator) and at 13 m from the root (i.e. close to the tip). Moreover, several linear and rosette strain gauges were also attached on both the pressure and suction sides of the blade at various locations to record the changes during the testing. The blade was loaded at different design loadings, such as 25%, 50%, 75%, and 100%, for flapwise and edgewise testing. The estimated design loads of flapwise testing from actuators were 5.45 KN (250 KN actuator) and 11.50 KN (750 KN actuator), respectively, from the maximum load case of all the cases. The data sets for load cases have been recorded in the data acquisition (DAQ) system for further analysis. The blade setup for flapwise and edgewise static testing in the laboratory is shown in Figure 4. Furthermore, Linear Variable Differential Transformers (LVDT) were used to monitor movement/deformation of the support frame during the test, as shown in Figure 5. In addition, the location of the strain gauges attached to the blade is shown in the Figure 6.

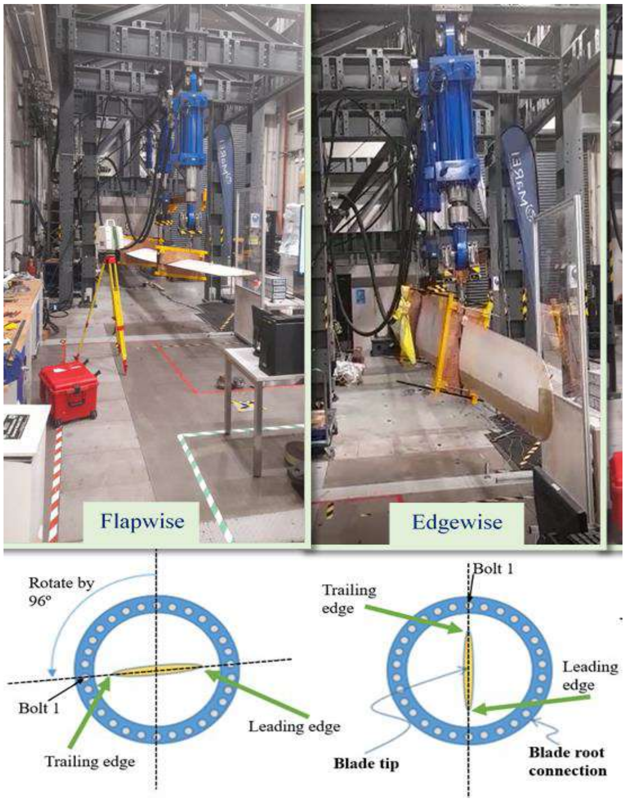

Figure 4. Blade setup for flapwise and edgewise testing in the laboratory

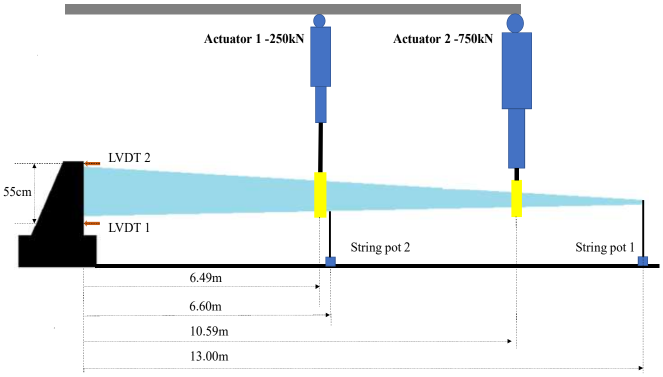

Figure 5. Location of the actuators, string ports, and LVDT's

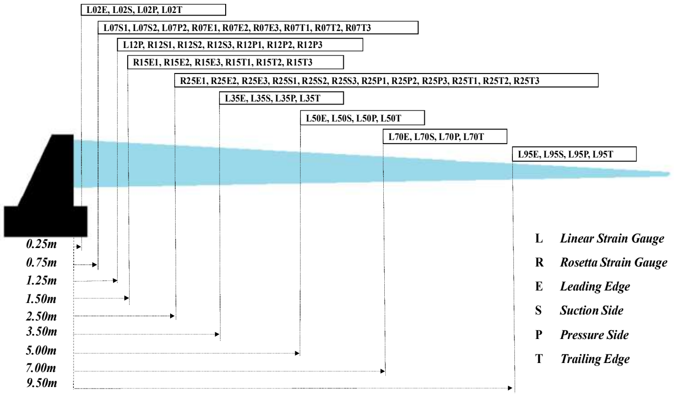

Figure 6. Location of the attached strain gauges

2.5 *ABAQUS Model*

The static test was simulated using the ABAQUS finite element (FE) program. The blade's geometry, presented as a STEP file, was meshed using ABAQUS CAE, which acted as the pre-and post-processor for ABAQUS. The blade model was created using structural shell elements (S4). Each shell element was furnished with stratified shell sections consisting of numerous layers, with three integration points per layer. Figure 7 depicts the ABAQUS finite element model that was specifically designed for the investigation of flapwise loads. The load introduction mechanism used in the tests was recreated in the simulation utilising stiff connections.

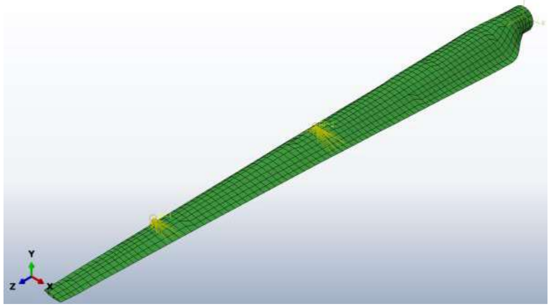

Figure 7. FE model generated using Abaqus 2023 version

2.6 *Data description for machine learning*

Machine learning involves using algorithms and statistical models that allow computers to carry out activities by themselves without the need for explicit programming. The data on which these models are trained allows them to learn from it, recognise patterns, and then make predictions or judgments based on the given information. In the presented study, the 1749 data points used for the machine learning modelling was taken from the static test (100% load case only) of the blade. The data set was initially arranged adequately for the modelling. The load applications from the two actuators and displacement results were considered to predict the strain values at the different locations of the blade. Python coding was used in the Anaconda Navigator (spyder) software to run the decision tree models for prediction purposes. The model performance was evaluated using metrics such as coefficient of determination (R^2), mean absolute error (MAE), and Root Mean Square Error (RMSE). The 10-fold cross-validation approach validated the model while predicting the strain values. Moreover, sensitivity analysis was also done to evaluate the impact of the variables considered for the modelling. This, in combination with traditional methods of analysis, allows researchers and engineers to make well-informed choices regarding the selection, optimisation, and design of materials, ultimately creating innovative selections with improved capabilities and durability.

3 RESULTS AND DISCUSSION

3.1 *Experimental test results*

The load calculation for the static testing for both flapwise and edgewise has been done using finite element analysis (FEA) from the ABAQUS model. The dynamic test gives the natural frequency of 2.48 Hz and 7.60 Hz, respectively, of the blade as depicted in Figure 8. The summary of the recorded data for both flapwise and edgewise static testing from installed instrumentation is shown in Table 1 and Table 2, respectively. However, the maximum strain was noted on the pressure side at a distance of 5 metres from the root during the flapwise static testing. In comparison, maximum strain values during edgewise testing were reported on the pressure side at a distance of 2 metres from the blade's root. The reason for getting the high strain away from the root is due to the geometric shape and thickness of the blade. The thickness at the support level and the influence of the steel insert during the testing can increase the strength of this part of the blade. Moreover, the summary of the recorded data for flapwise and edgewise static testing from installed instrumentation is shown in Figure 9 and Figure 10, respectively.

Table 1. Summary of the obtained results with the different load cases from the flapwise static testing

Parameters		25% Load case	50% Load case	75% Load case	100% Load case
250 kN Actuator	Load (kN)	1.74	2.87	4.46	5.86
	displacement (mm)	36.28	69.66	101.58	133.10
750 kN Actuator	Load (kN)	3.21	6.22	9.01	11.87
	displacement (mm)	124.21	247.69	347.40	431.50
Measured maximum displacement-String Pot 1 (mm)		196.43	319.17	472.44	612.52
Measured maximum displacement-String Pot 2 (mm)		40.13	63.18	92.26	119.24
Vertical maximum displacement-String Pot 2 (mm)		40.12	63.18	92.26	119.24

Table 2. Summary of the obtained results with the different load cases from the edgewise static testing

Parameters		25% Load Case	50% Load Case	75% Load Case	100% Load Case
250 kN Actuator	Load (kN)	2.29	4.84	6.78	9.13
	displacement (mm)	32.21	69.86	84.64	100.88
750 kN Actuator	Load (kN)	1.78	2.84	4.05	5.48
	displacement (mm)	37.87	93.01	116.11	138.30
Measured maximum displacement-String Pot 1 (mm)		45.65	118.80	148.17	181.46
Measured maximum displacement-String Pot 2 (mm)		23.60	56.39	67.87	79.87
Vertical maximum displacement-String Pot 2 (mm)		23.53	56.29	67.72	79.66

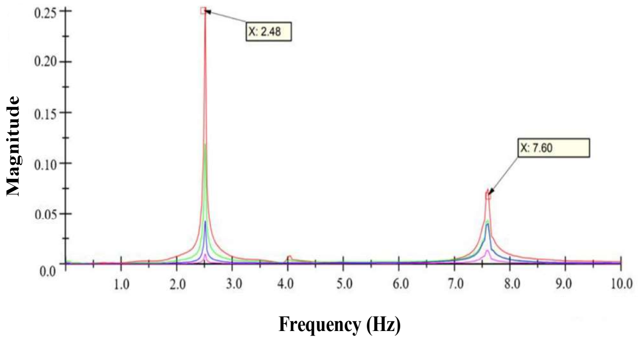

Figure 8. Average FFT spectrum of the flapwise natural frequency testing

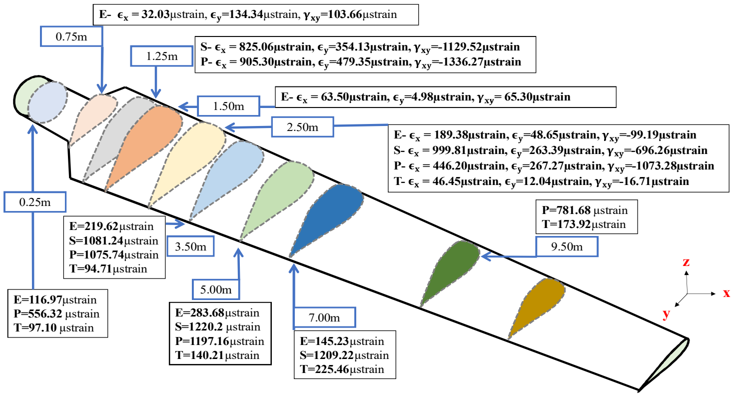

Figure 9. Summary of the strain results at various locations of the blade for flapwise static testing

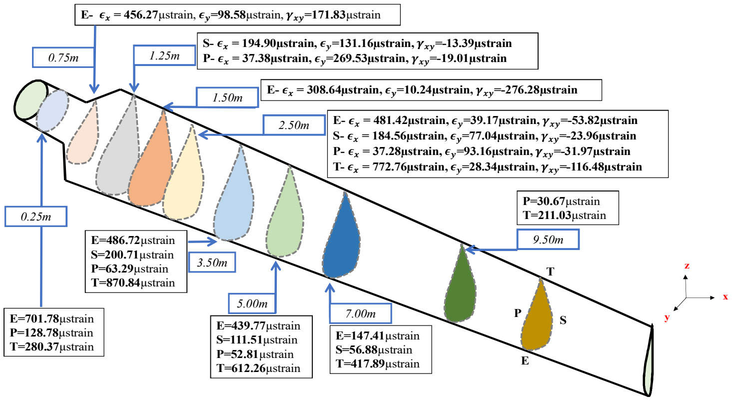

Figure 10. Summary of the strain results at various locations of the blade for edgewise static testing

3.2 Model validation

A comparative analysis of the ABAQUS model results has been made to investigate the validity of the experimental results of the wind turbine blade. Comparing the natural frequency results with the results of the ABAQUS model gives the 2.75 Hz and 8.47 Hz, indicating a difference of 10.88% and 11.44%, which is considered an acceptable agreement between predicted and measured results of the natural frequency. The displacement measured at the tip of the blade in the physical test was 612.52 mm, while it was predicted to be 531.80 mm from the FEA. A difference of 13.13% of the discrepancy is reported for displacement results. The cause of this difference may be attributed to a slight gap in the root support, which allowed for more movement of the blade in the physical test compared to the fixed boundary condition assumed in the FEA model. Moreover, the difference between the strain results from the physical test and FEA ranges between 15% and 30%, which is not a satisfactory difference between the results for both displacement and strain. It's possible that this disparity is the result of movement or rotation that occurred at the root support position while the physical testing was being done.

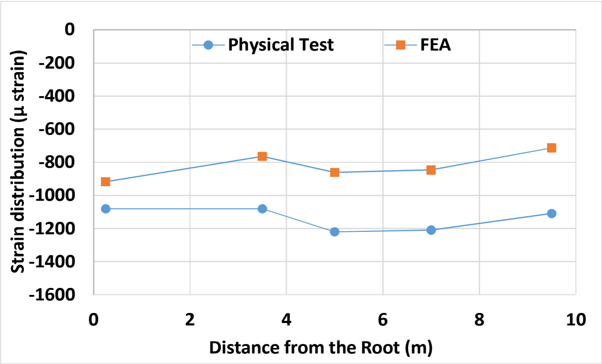

Figure 11. Comparison between the predicted (FEA) and measured (physical test) strain distribution along the spar caps on the suction side of the blade when subjected to 100% load case

3.3 Machine learning results

The machine learning models show a strong relationship between the experimental results of the strain values from the blade test and predicted results. As shown in Figure 12, the decision tree model accurately predicts the strain values at the location of 5 meters from the blade's root by indicating that R^2 equals 0.999. The 10-fold cross-validation approach also confirms the model's legitimacy by giving the lower values of the errors and a higher value of the R^2. The mean values of MAE (3.79 μm), RMSE (8.10 μm), and R^2 (0.997) from the 10-fold validation approach confirm an accurate prediction of the model. The statistical analysis of the validation process can be seen in Figure 13. Moreover, from the sensitivity analysis, the impact of the displacement variable at the location of the 250 kN actuator was 41.5% towards the prediction of strain results, while load B (250 kN) was the second highest contributor while predicting the output, as shown in Figure 14. It has been noted that the time had almost negligible influence on the required outcome. The highest influence of displacement B (at 250 KN), and load B (250 KN) is because of their location. Both the position of this load application and the displacement that was recorded (6.6 metres) are placed in close proximity to the location of the predicted strain, which is located 5 metres away from the root.

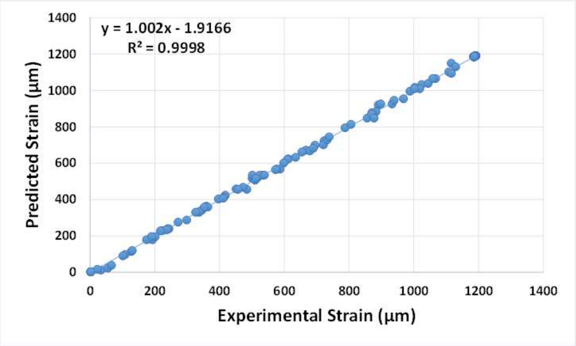

Figure 12. Relation between the experimental strain results and DT model predicted results

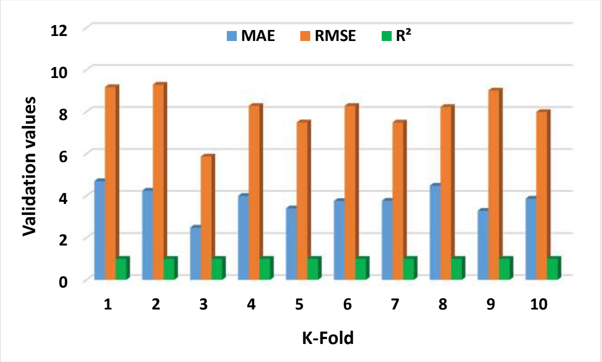

Figure 13. Statistical results from k-fold cross-validation

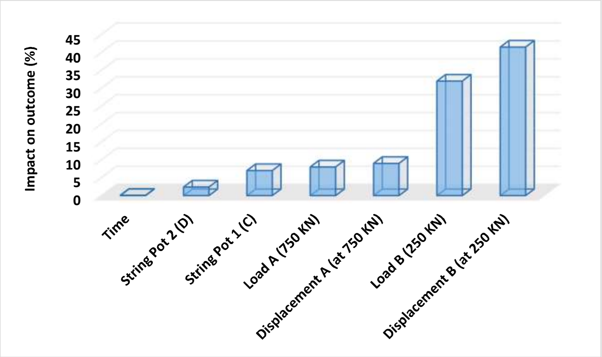

Figure 14. Impact of the parameters towards the model outcome

4 CONCLUSION

This paper describes the comparative study of the experimental testing on the 13-metre long wind turbine blade and machine learning modelling on the test data. The blade was tested, followed by the standard DNVGL-ST-0376 guidelines. It has been concluded from the testing that the blade withstands all the employed loading successfully, even 100% of the design loading, and no damage was detected to the blade material. However, the amount of tension and compression at different locations and the displacement during the testing have been recorded via installed instrumentation, and analysis has been presented in this paper. The maximum strain value of 1220 µm was recorded at 100% of the design load during the static (flapwise) test at a distance of 5 metres from the blade root on the pressure side of the blade. Moreover, the machine learning decision tree model successfully predicts the strain values using Python coding, indicating the pathway for these tools to introduce them for material testing to predict the various parameters such as strain. It was noted from the sensitivity analysis that the applied load from 250 kN and the displacement data at the same location contribute the most (32% and 41.5%, respectively) towards the prediction of strain results from the model.

The comparative study of the adopted methodology not only ensures the structural integrity of wind turbine blades but also offers a pathway to streamline material testing processes, ultimately reducing project efforts, time, and costs in the renewable energy sector. By optimizing these processes, the study contributes to the increased reliability and efficiency of renewable energy systems, thereby supporting the transition to cleaner energy sources. This advancement aligns with several United Nations Sustainable Development Goals (SDGs), including SDG 7 (Affordable and Clean Energy) by making wind energy more accessible and cost-effective, SDG 9 (Industry, Innovation, and Infrastructure) through the promotion of sustainable industrialization and innovation, and SDG 13 (Climate Action) by reducing the carbon footprint associated with energy production. Moreover, the reduction in material waste and improved testing efficiency support SDG 12 (Responsible Consumption and Production), highlighting the importance of sustainable practices in industrial processes.

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