

# Leveraging experimental and field measurement campaigns across Machine Learning, CFD and satellite imagery in wind engineering applications

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## SUMMARY

High-quality data are of utmost importance for training Machine Learning (ML) models and validating CFD or any other computational model in wind engineering. This presentation reviews three different application cases where wind tunnel and field measurement data are key pieces in ML models of the power performance of a wind-excited energy harvesters, the validation of CFD simulations of the fluid-structure interaction of a 3:2 rectangular prism in turbulent flow and the assessment of the accuracy of wind fields extracted for Synthetic Aperture Radar (SAR) satellite imagery. The delineation between experimental and computational approaches in wind engineering is fading, while current challenges demand multidisciplinary teams covering the full range of available methodologies.

**Keywords:** CFD, wind tunnel, field measurements, Machine Learning, satellites, 3:2 rectangular prism.

## 1. INTRODUCTION

Computational approaches in wind engineering are increasing their scope and reach across multiple applications. Computational fluid dynamics (CFD) simulations are nowadays well established, and they can provide reliable results in complex scenarios such as fluid-structure interaction problems considering incoming turbulent flow. In recent years, data-based methods such as Machine Learning (ML) are providing new insights in wind engineering. Both approaches, which are computational in nature, require a strong linkage with physical reality to render reliable results. The pivotal importance of validation in CFD modeling cannot be overstated. The comparison of the outputs of CFD models with equivalent experimental data constitutes the definitive assessment of the ability of that computational model to capture the fundamental physical process at play in a given problem. In AI applications, data is the cornerstone of the whole modeling process as predictive capability of a data-based model is directly related with the quality of the data used for training.

In this work three examples of the connection between experimental data - wind tunnel and field measurements - and computational models are reviewed. The examples address three very different applications: (i) ML models for the power performance of an energy harvester trained with field measurements, (ii) wind tunnel campaign for analysing the aerodynamic and aeroelastic response of a bluff body under turbulent incoming flow, and (iii) assessment of the accuracy of offshore wind speeds obtained from satellite imagery based on weather station measurements close to the coast. The three examples show the critical importance of high-quality field measurements and experimental testing to develop and validate computational models.

## 2. MACHINE LEARNING MODEL OF THE PERFORMANCE OF A WIND-EXCITED ENERGY HARVESTER

Wind-excited energy harvesters have been extensively studied over the years based on wind tunnel testing and to a lesser extent using CFD simulations. However, the performance of these devices in real conditions has been largely overlooked, hindering their uptake in industrial applications. Modeling the long-term power output of a real scale prototype deployed in the urban environment depending on the real wind conditions is a challenge due to the complexity and variability of the incoming flow and the aeroelastic excitation of the oscillator over a long period of time. To this end, a continuous 1-month sampling campaign was conducted to gather simultaneously the 10-minute mean wind characteristics and power output of the prototype featuring a ratio 3:2 rectangular prism at the tip to train three different Machine Learning models (Poozesh et al., 2025). The three ML models (Decision Tree Regression, Random Forest and Gradient Boosting Regression Trees) provided similar accuracy, with  $R^2$  values of 0,921, 0,944 and 0,937, respectively (Poozesh et al., 2025), as illustrated in figure 1.

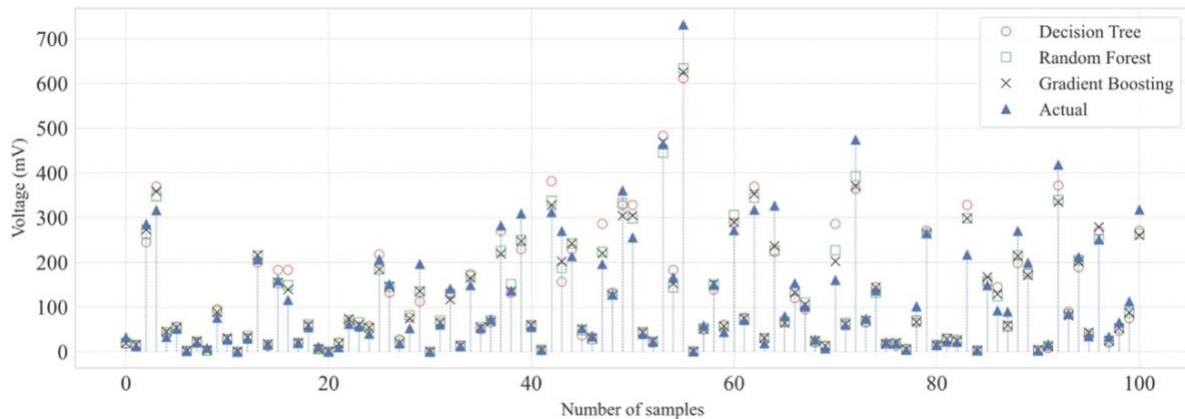


Figure 1: Comparison between predicted and measured output voltage for the three ML models considered. Figure reproduced from Poozesh et al. (2025), licensed under CC BY-NC 4.0

## 3. ERIES-SSTURBBO: WIND TUNNEL TESTING OF A 3:2 RECTANGULAR PRISM UNDER TURBULENT FLOW

One of the key research topics in wind engineering is the effect caused by free stream turbulence in the wind-induced excitation of structures, and more specifically, the influence of the length scale. Under the umbrella of the ERIES EU project that provides transnational access to advances research infrastructure, the aerodynamic and aeroelastic responses of a ratio 3:2 rectangular prism

has been studied at the Giovanni Solari Wind Tunnel of the University of Genoa (Alvarez et al., 2025). The tests considered smooth flow, but also rod-induced (small-scale) and grid-induced (large-scale) free stream turbulent flow with different turbulent intensities. The test campaign primarily clarified the impact of the turbulence intensities and length scale but also generated a rich database for validation and accuracy assessment of CFD models addressing specifically different levels of turbulence intensity and turbulence length scales. In figure 2, one of the outputs of the experimental campaign is provided as an example. The charts show the time series and power spectrum of the heave oscillation of the 3:2 rectangular prism in smooth flow undergoing galloping excitation.

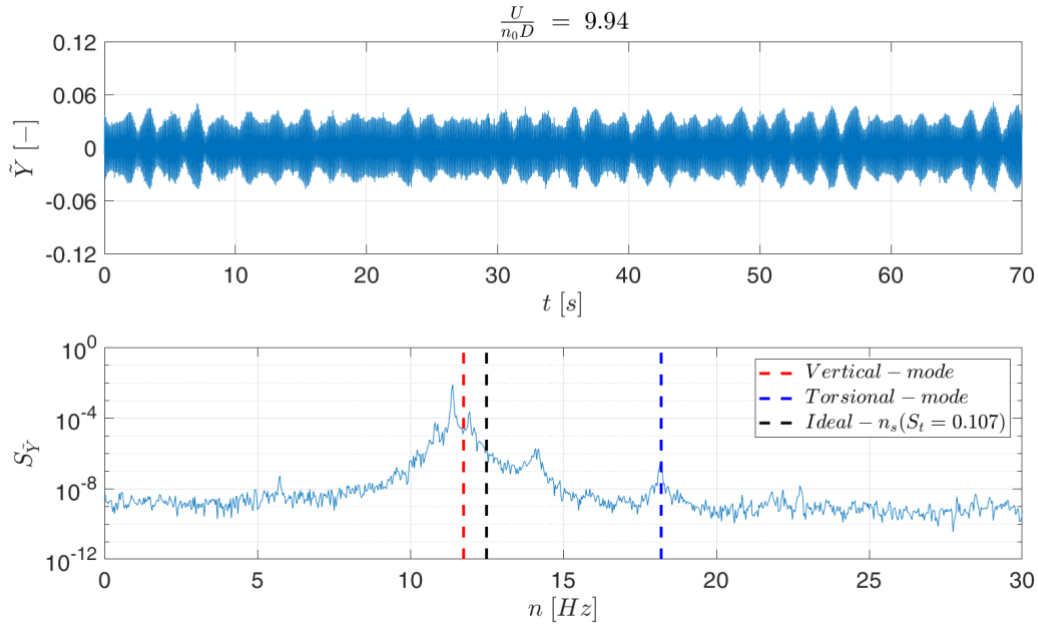


Figure 2: Timeseries and power spectrum of the heave oscillation of a 3:2 rectangular prism in smooth flow.

#### 4. OFFSHORE WIND SPEED IN THE SOUTHWESTERN COAST OF ICELAND: SATELLITE IMAGERY VS WEATHER STATIONS DATA

Earth observation techniques, such as images taken using Synthetic Aperture Radar (SAR) instruments, permit assessing the instantaneous wind magnitude over the sea (Chang et al., 2015). The application of the CMOD5 model (Hersbach, 2003) renders the 10-minute mean wind velocity and direction. Wind measures based on satellite imagery may be affected by errors and uncertainties such as the ones associated with the proximity to the coast or the impact of the actual sea state when the image is taken. Images taken from the Copernicus Sentinel-1 mission have been post-processed in coastal areas around Southwestern Iceland to obtain the 10-minute mean wind speed. Aiming at ascertaining the accuracy of satellite-based results, the data were compared with 10-minute wind speeds provided by a relatively large set of onshore weather stations close to the coast. Similarly, additional inputs from steady state CFD simulations were considered. It was found that the wind speed inferred from satellite imagery was in good qualitative agreement with the records of the network of weather stations located at the Reykjanes Peninsula (Alvarez et al., 2025).

**Table 1:** 10-minute wind speeds evaluated from SAR satellite images of nearshore locations for the 6<sup>th</sup> of February 2021, at 19:06:39 UTC time.

Nearshore point no.	Longitude [°]	Latitude [°]	SAR Mean Wind Speed [m/s]	CMOD5 Mean Wind Speed [m/s]	CMOD5 Mean Wind Dir. [°]
1	-22.7500	63.9167	6.5	6.3	52.5
2	-22.7500	64.0000	9.3	8.4	154.0
3	-22.5000	64.0000	9.1	7.1	71.7
4	-22.7500	64.0833	8.8	7.8	76.2
5	-22.5000	64.0833	8.7	7.8	75.2
6	-22.2500	64.0833	10.2	7.9	76.0
7	-22.7500	64.1667	10.0	8.1	113.4
8	-22.5000	64.1667	9.5	8.5	63.1
9	-22.2500	64.1667	11.2	10.7	57.3
10	-22.0000	64.1667	9.4	9.2	85.7

## 5. CONCLUSIONS

The range of applications presented herein, where wind tunnel and field measurements are tightly connected with ML models, CFD simulations and satellite imagery, illustrates that the boundary separating real data and computational modeling is becoming increasingly blurred if not disappearing altogether. The high complexity inherent to the actual gaps in knowledge calls for a holistic strategy in which multiple approaches and different methods are applied concurrently to unravel the intricate interaction between flow and structural response. Evidently, the reliability and usefulness of computational methods rely on high-quality experimental data and field measurements for training, benchmarking and validation. Therefore, multidisciplinary teams bringing together expertise in different fields will become the rule, with these trends intensifying as AI and quantum computation further penetrates applied research.

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