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A multi-source hybrid AI approach to evaluate wind effects on structures.

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Summary

Wind is a particularly challenging natural hazard due to its complex and dynamic interaction with structures, which can lead to significant damage and occupant safety concerns. This work presents a fast and efficacious prediction methodology that integrates multi-source data to predict wind effects on structures. The multi-source can be from wind tunnel testing and various numerical models, such as RANS and LES, in numerical simulations. The approach leverages Artificial Intelligence (AI) combined with the multi-physics nature of the problem. The wind hazard is modeled with a Coopman operator, while the structure is modeled with classical FEM. Traditional numerical approaches for solving the coupled wind–structure problem are computationally expensive, especially when modeling turbulent three-dimensional flows over large domains. By combining the rapid evaluation of the fluid domain with physics-based structural domain analysis, the method ensures the efficiency and effectiveness of structural evaluation under wind loads.

Keywords: *wind engineering, Multi-source AI, Structural response, Wind effects, Hazard assessment*

1 INTRODUCTION

In civil engineering, structures are conceptualized, analyzed against wind loads, designed, and constructed based on scaled-down lab test results or, more recently, through computational models. In practice, structural engineering projects often involve unique designs, with limited or no data available during the analysis and design phases on how structures will respond to dynamic loads, such as wind forces. Additionally, the completed structure must be resilient enough to withstand various load scenarios and natural hazards over time. Therefore, accurate modeling is crucial to ensure the structure's reliability and safety. With the increasing risks posed by climate change, including more frequent and intense extreme weather events, this necessity becomes even more critical [1,2]. However, due to the bespoke, unique nature of many structures, conducting scaled-down tests can be prohibitively expensive, limiting the analysis of multiple hazard scenarios. As a result, computational methods are becoming more appealing, as prototypes can be tested more easily and cost-effectively.

The importance of wind effects on structures is of increasingly great concern [3]. Wind is an inherently complex dynamic phenomenon due to the randomness of flow and the characteristics of the atmospheric boundary layer. When interacting with the structure, complex flow-induced phenomena like vortex shedding, flutter, galloping, etc. can develop. These phenomena have resulted in catastrophic failures in the past, including the famous collapse of the Tacoma Narrows bridge in 1940 [4]. Traditionally, wind tunnels and reduced-scale testing are employed to understand the wind effects on structures. Complementary to these traditional approaches, Computational Wind Engineering (CWE) has gained attention in application to flow problems including structural wind engineering in the past 60 years [5]. Despite significant advancements, the simulation using CWE tools for the wind effects on structures still faces challenges due to the complexity of the dynamic problem at high Reynolds numbers [6, 7, 8]. Specifically, obtaining the wind loads on the structural hull is the most computationally expensive task compared to obtaining the displacements

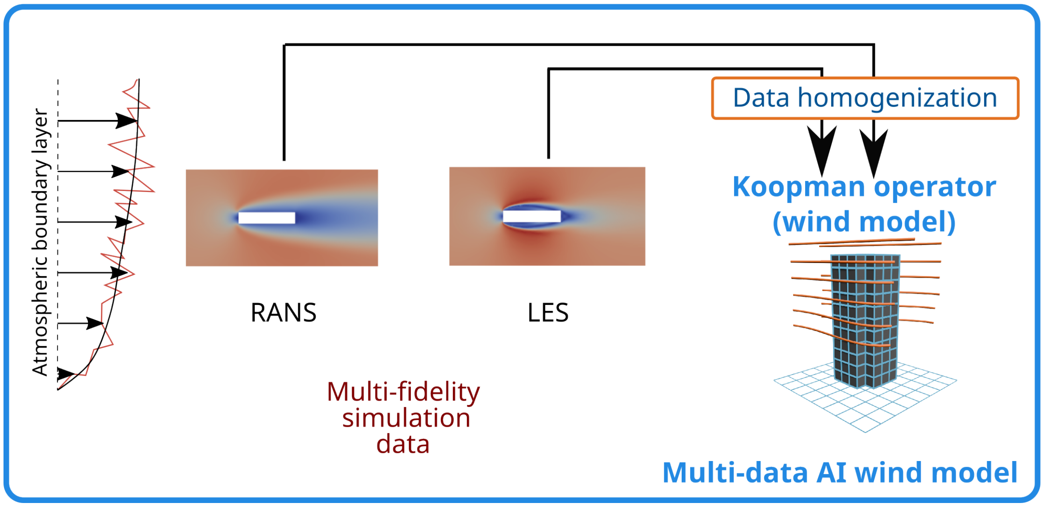

Figure 1: The overvie of the workflow adopted for multi souce wind model

of the structure. To reduce the computational cost, data-driven AI methods are very promising, provided sufficient relevant data is available [9].

Here, we explore with data-driven surrogate modeling for dynamical systems based on the so-called Koopman operator framework [10, 11, 12, 13, 14]. It allows researchers to develop computationally efficient, data-inexpensive surrogate models. A key advantage of the Koopman operator is that it is based on well-understood dynamical system theory. Originally formulated by B.O. Koopman [15, 16], the Koopman operator acts on complex-valued functions of the state of the dynamical system, advancing them forward in time by composition with the system's flow map. Because this composition is linear, the action of the Koopman operator for arbitrary, even nonlinear, flow maps is always linear [17] - even for complicated systems like turbulent flow [10, 18]. Due to their theoretical underpinning and linearity, operator-based machine learning methods open doors to robust scientific and physics-informed machine learning, leading to more interpretable predictions and models.

Section 2 outlines the details of the workflow proposed. Section 3 details the numerical examples explored, and the section 4 presents the results and conclusions from the study.

2 METHODOLOGY

The details of the proposed workflow are described in this section. The methodology focuses on creating an efficient and robust approach for training AI using multiple data sources of hazard scenarios. For a typical wind scenario, the approach will integrate data from multiple sources and fidelities, including numerical simulations using Computational Wind Engineering (CWE) techniques like Reynolds-Averaged Navier-Stokes (RANS) simulations, Large Eddy Simulations (LES) in Figure 1. It is also planned to include wind tunnel experiments, and real-world observational data . A key feature of the approach is its flexibility and generalizability, ensuring that it remains functional and effective even in the absence of one or more data sources. This will require strategies to balance the influence of high-fidelity but computationally expensive models (e.g., LES) with lower-fidelity but computationally efficient models (e.g., RANS), alongside pos-

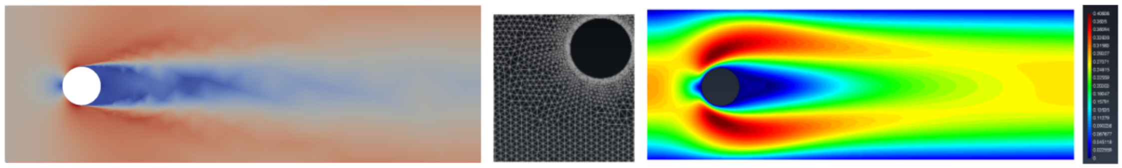

Figure 2: Details of the mesh adopted (middle) and the RANS (left), LES (right) solution of the cylinder in flow example

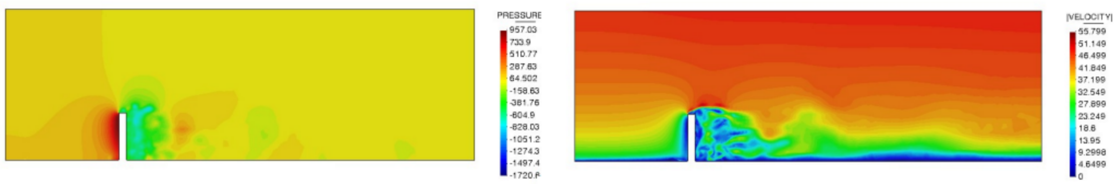

Figure 3: Details of the pressure and velocity for the CAARC example using LES

sibly available wind tunnel and real-world multi-scale measurement data. A key challenge here is the homogenization of the data from different sources, as each of them is associated with inherent characteristics and shortcomings. The main tool towards this goal will be data-driven approximations of the Koopman operator. The operator has been used for modeling and control of fluid flow before.

3 NUMERICAL STUDY

This section presents the two examples used for the multi-data AI approach for wind load estimation. This section presents the details of the for two numerical examples, namely a Flow around a Cylinder and a CAARC 2D example. In both examples, a large eddy simulation and a steady-state incompressible RANS solution (with the $k - \omega - SST$ turbulence model and wall functions) are obtained. The LES solution is also used for the same QoIs. Figures 2,3 show the mesh used and the RANS and LES solutions of the two numerical examples.

4 CONCLUSION

The proposed multi source surrogate model for wind using multi source AI is a promising way to estimate the wind loads on structures. This work is a first step in this direction and hence, exploratory in nature and aims to harness the potential of the multi source data in the surrogate. The RANS solutions are cheaprer and hence easily obtained. However they may not be able to capture the flow phenomenon fully. By combining from multiple sources with multiple fidelities, the method is able to capture the physics at less computational cost. This will be demonstrated in the study. This is a promising direction for computational wind engineering.

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