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TRANSFORMER-BASED MODELS FOR PREDICTIVE SIMULATIONS OF VORTEX-INDUCED VIBRATIONS

Jacques Honigbaum
Fernando A. Rochinha
Federal University of Rio de Janeiro, Brazil
jacques@coppe.ufrj.br, faro@mecanica.coppe.ufrj.br

Rodolfo S. M. Freitas
Queen Mary University of London, United Kingdom
rodolfosmfreitas@gmail.com

Souleymane Zio
École Polytechnique de Ouagadougou, Burkina Faso
ziosouleymane27@gmail.com

Gabriel M. Guerra
Federal Fluminense University, Brazil
gguerra@id.uff.br

Abstract. *The impact of vortex-induced vibrations (VIV) can assume a fundamental part in the motion of submerged objects, especially those related to offshore-designed structures. Due to large displacements, vortex shedding on the wake can result in continued degradation of structural performance or even catastrophic failure; thus, accurate prediction of the structural response is needed. The structure nonlinear dynamics is coupled to the surrounding flow dynamics by a typical high-fidelity fluid-structure interaction (FSI) model required to describe vortex-induced vibrations. The latter is usually based on a Navier-Stokes formulation to be solved with computational fluid dynamics (CFD) methods with a fine mesh that must be suited to structure motion. Nevertheless, considering extensive multi-query analysis like optimization, real-time response, or uncertainty quantification, the resulting model often demands a high computational cost. High-fidelity codes based on physics-based models are frequently challenging due to these time-consuming tasks. A decent option to beat such limits is the development of surrogate models that have become well known in some areas of research because of their aptitude in being effective alternatives for high-fidelity models. As essential tools for simplifying analysis, these models can be advantageous in a wide range of industrial applications because they can make predictions at a much lower computational cost than CFD. Due to their potential to enhance the capacity of computational simulations to describe complex physical systems, data-driven machine learning (ML) models, which can combine field or experimental data with high-fidelity simulations, have gained prominence in this context. Data-driven ML predictive models that provide accurate predictions at a low cost have been the subject of several studies. Self-attention-based transformer models have recently been used to model dynamic systems, which have the potential to take the place of costly computational models. This model can accurately predict different dynamical systems, which outperforms traditional approaches used in scientific machine learning literature. As a surrogate model for VIV dynamics, we present a machine-learning strategy based on self-attention transformers in this work. We demonstrate that the surrogate model can accurately predict VIV dynamics through numerical testing. Moreover, it makes studying important aspects of commonly used wake oscillator models easier.*

Keywords: *vortex-induced vibrations, transformers, deep learning, surrogate modeling.*

1. INTRODUCTION

Vortex-induced vibrations (VIV) are crucial in the design of offshore floating structures. Because vortex shedding behind bluff bodies may cause structural degradation or failure, it is essential to accurately predict structural instability. A complete representation of the fluid-structure interaction is typically needed to describe vortex-induced vibrations. This representation includes an oscillator for the structure coupled to a flow formulation based on Computational Fluid Dynamics (CFD) methods.

The CFD approach solves the Navier-Stokes equations directly, mainly limited by high computational costs (CPU time and memory), limiting the field's advance. Such time-consuming tasks often hamper the use of high-fidelity codes constructed upon physics-based models. That becomes a more critical issue when facing many-query applications like sensitivity analysis, design, optimization, or uncertainty quantification.

To cope with these challenges, reduced-order models (ROMs), also called surrogate models, can be an interesting approach to help obtain predictions with lower computational cost than CFD and become a helpful tool with broad industrial applications. ROMs have become popular within the field of turbulent flows due to their success in being a proxy for high-fidelity models (Brunton *et al.*, 2020). ROMs allow modeling the main flow dynamics with a reduced computational cost. Furthermore, utilizing data provided by experiments and high-fidelity simulations to understand better the underlying VIV phenomenon has become a new challenge and research opportunity.

Recently, data-driven machine learning (ML) models have gained prominence due to the potential to enhance the capability of computational simulations to describe complex physical systems (Oishi and Yagawa, 2017). Several works have been dedicated to constructing predictive data-driven machine learning models able to return accurate predictions at a low cost (Zhu and Zabaras, 2018; Freitas *et al.*, 2021, 2022). Here, the focus relies on the transformer model (Vaswani *et al.*, 2017), built on self-attention, which has become the state-of-the-art machine learning approach for a large set of natural language processing (NLP) tasks. In the recent work, proposed by (Geneva and Zabaras, 2022), transformers were applied to model dynamical systems that can replace otherwise expensive computational models. Such a model has been proven to predict various dynamical systems accurately and outperforms classical methods commonly used in the scientific machine learning literature.

The performance of the self-attention transformers model for modeling physical dynamics makes it a suitable tool for the analysis of VIV dynamics and fluid flows. This work aims to apply the self-attention transformers model for modeling VIV dynamics. Here, we demonstrate the applicability of the present approach using data provided by CFD simulations, which captures essential features of the VIV dynamics. To the authors' best knowledge, this is the first work to extend the self-attention transformers model for the surrogate modeling of fluid-structure interaction. Also, it might be expected that such an approach can be extended for the analysis of fluid flows that include many variables and DOFs (*degrees of freedom*), which is beyond the scope of the present work, and further research efforts are needed.

The remainder of this paper is organized as follows. The next section details the governing equations of the phenomenological model adopted for generating the synthetic data to train the surrogate model. Section 3 presents the numerical dataset. Section 4 presents preliminary results. The paper ends with a summary of our main findings.

2. COMPUTATIONAL FRAMEWORK

The proposed computational framework uses modern machine-learning techniques to model the dynamics of the physical systems described by an ordinary or partial differential equation. More specifically, assuming a dynamical system given by the form,

$$\frac{d\boldsymbol{\psi}}{dt} = f(\boldsymbol{\psi}, t, \mathbf{x}, \boldsymbol{\theta}) \qquad \mathbf{x} \in \Omega \subset \mathbb{R}^m \tag{1}$$

where $\boldsymbol{\psi} \in \mathbb{R}^n$ is the solution of the dynamical system of n state variables with parameters $\boldsymbol{\theta}$, in the time interval $t \in \mathcal{T} \subset \mathbb{R}^+$. The solution of this general form can characterize a vast range of physical phenomena embodying high-dimensional problems such as fluid flow and transport processes, multi-physics and multi-scale systems such as chemical kinetics and molecular dynamics, among others.

Specifically, it is assumed that the continuous solution of the system in the time interval $\mathcal{T}$ is discretized by T time steps with a time-step size Δt. Thus, the modeling of a dynamical system is posed as a time-series problem propagating from the initial state $\boldsymbol{\psi}_0$, making the modeling of the dynamical system applicable to the use of machine learning architectures.

The machine learning model has two core components, as shown in Fig. 1. The transformer model models dynamics and the embedding model for projecting physical states into a latent space. The embedding model is trained prior to the transformer. This embedding model is then frozen, and the entire dataset is projected to the hidden, latent space in which the transformer is then trained. After training, the embedding decoder reconstructs the solution from the latent space. Further details regarding the machine learning model can be found in (Geneva and Zabaras, 2022), and a brief introduction of the transformer and embedding models are given in the following subsections.

2.1 Transformer model

In the present approach, the transformer model is posed as a time integrator for the dynamical system. The model is based on NLP with the primary input a word vector embeddings of a text. Hence, considering that any dynamical problem can be posed as a sequence of vectors, the primary input of the transformer model is the embedded latent space of the dynamics, $\mathcal{Z} = (\mathbf{z}_0, \mathbf{z}_1, \cdots, \mathbf{z}_T)$, where $\mathbf{z}_j \in \mathbb{R}^e$ is the embedded state at time-step j.

The motivation for using a language modeling architecture to predict physical dynamics relies on this model designed for the sequential prediction of words in a text (Radford and Narasimhan, 2018; Wolf *et al.*, 2020). This suggests that transformer models may be viable for constructing ROMs for dynamical systems (Chen *et al.*, 2020; Geneva and Zabaras,

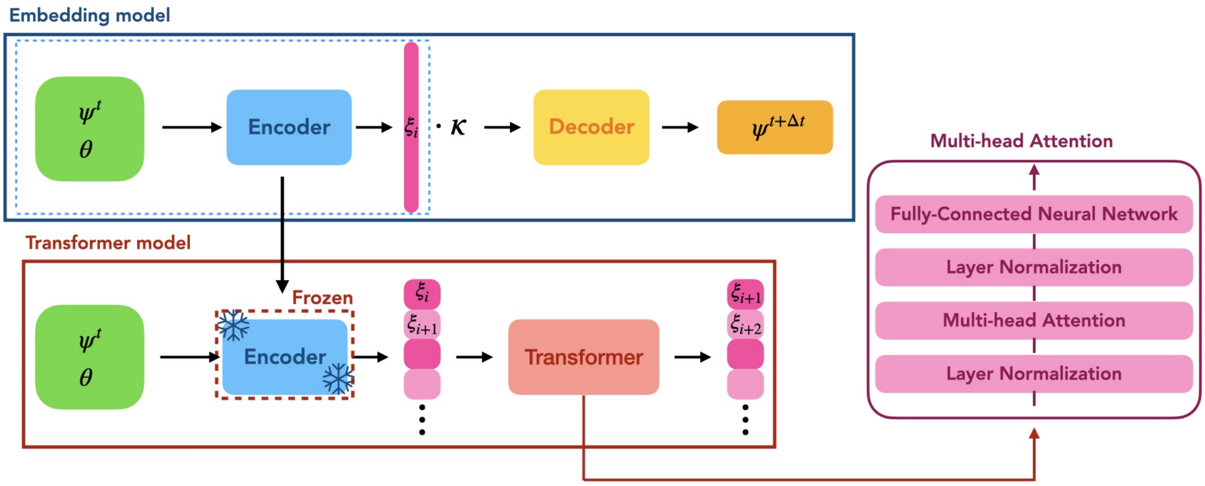

Figure 1: Transformers for modeling physical systems.

2022). Considering a dataset with time-series of the embedded dynamical system $\mathcal{D} = \{\mathbf{z}^i\}_{i=1}^{D}$, the transformer model is trained using the standard time-series Markov model log-likelihood,

$$L_z = \sum_{i}^{D}\sum_{j}^{T} -\log p(\mathbf{z}_j^i|\mathbf{z}_{j-k}^i, \dots, \mathbf{z}_{j-1}^i, \boldsymbol{\eta}) \tag{2}$$

where $\boldsymbol{\eta}$ are the transformer's parameters, like fully-connected neural networks. Here, the likelihood is assumed as a standard Gaussian between the target latent space and the transformer prediction, resulting in a L_2 loss. It is worth remembering that for problems suffering from the curse of dimensionality, training the transformer with a low-dimensional latent space significantly reduces the training costs.

2.2 Embedding model

The second component of the computational framework is the embedding model for projecting physical states into a latent space, $\mathcal{F} : \mathbb{R}^n \rightarrow \mathbb{R}^e$ and $\mathcal{G} : \mathbb{R}^e \rightarrow \mathbb{R}^n$. The Koopman dynamics methodology is used in the present approach to develop the embedding model. The Koopman theory assumes that any dynamical system can be described as an infinite dimensional linear operator acting on an infinite set of state observable functions, $g(\boldsymbol{\psi}_j)$,

$$Kg(\boldsymbol{\psi}_j) \triangleq g \circ \mathbb{F}(\boldsymbol{\psi}_j) \tag{3}$$

where $\mathbb{F}$ is the dynamic map from one time-step to the next and K is the infinite-dimensional linear operator referred to as the Koopman operator (Koopman, 1931). Thus, the states can be evolved in time through repeated application of the Koopman operator,

$$g(\boldsymbol{\psi}_{j+1}) = Kg(\boldsymbol{\psi}_j),\;\; g(\boldsymbol{\psi}_{j+2}) = K^2 g(\boldsymbol{\psi}_j),\;\; g(\boldsymbol{\psi}_{j+3}) = K^3 g(\boldsymbol{\psi}_j),\; \dots \tag{4}$$

where K^p represents a p-fold composition, i.e., $K^3(g) = K(K(K(g)))$. In the present approach, a data-driven machine learning model is used for learning the Koopman operator. More specifically, the Koopman operator assumes the form of a learnable banded matrix that is learned with the embedding model. Given a dataset with time-series of the dynamical system $\mathcal{D}_\psi = \{\boldsymbol{\psi}^i\}_{i=1}^{D}$, the embedding model is training using the loss function given by,

$$L_E = \sum_{i}^{D}\sum_{j}^{T} MSE(\boldsymbol{\psi}_j^i, \mathcal{G} \circ \mathcal{F}) + MSE(\boldsymbol{\psi}_j^i, \mathcal{G} \circ K^j \mathcal{F}(\boldsymbol{\psi}_0^i)) + \|K\|_2^2. \tag{5}$$

The embedding loss function consists of three components. The first is reconstruction loss, which ensures a consistent mapping to and from the latent space. The second component is the Koopman dynamics loss, which enforces $\mathbf{z}_j$ to follow linear dynamics. Finally, the last term is a L_2-regularization of the Koopman parameters, which helps the model discover the underlying dynamical modes and avoid overfitting.

3. NUMERICAL DATASET

The data for the training process was generated using a two-dimensional vortex-induced vibrations problem for an elastically mounted circular cylinder. This cylinder can oscillate in x- and y-direction only limited by a linear spring with damping. Solving this type of model requires addressing three problems. First, the Navier-Stokes equations for the 2D incompressible laminar flow on a rectangular channel that surrounds the elastically supported cylinder, second, the displacements of this cylinder are computed, and finally, the deformation of the mesh in the fluid region is solved to account for the displacement of the cylinder that is deforming the region through which fluid can flow. To solve this fluid-structure interaction modelling, we have used *COMSOL Multiphysics® V4.4*. The computational domain of this problem is shown in Fig. 2, where a circular cylinder with diameter D = 0.0016 m is located at the origin. The size of the domain is [40Dx60D].

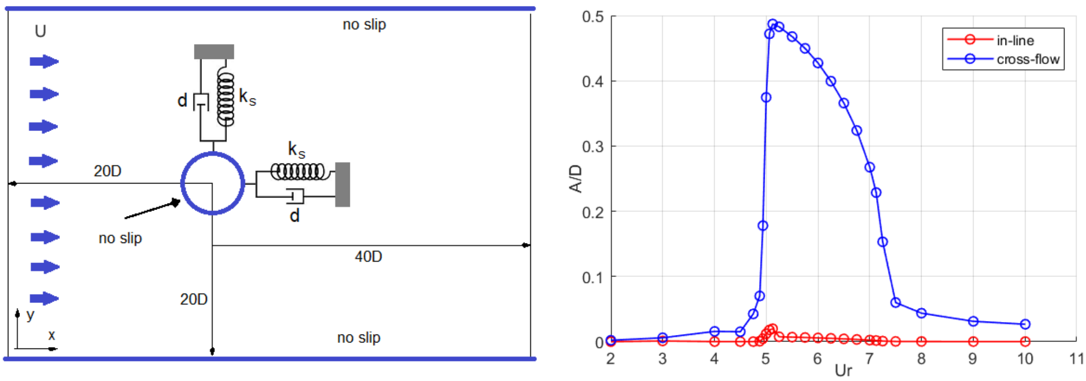

Figure 2: a) Setup of the simulation, b) Reduced amplitude distribution at reduced velocity for inline x and cross-flow y oscillating cylinder predicted by fluid-structure interaction model.

A non-slip boundary condition was applied for the top and bottom walls with pressure equal to zero at the outlet and velocity defined at the inlet. The discretization was done considering 32182 triangular elements sufficient to resolve the flow in a laminar regime. The Reynolds number defined as $Re = UD/\nu$, with inlet flow velocity is U = 0.0656 m/s in x-direction and the kinematic viscosity ν =1.05×10$^{-6}m^2/s$, results in $Re = 100$. To obtain results in the range of lock-in for the training process, spring constants varying between k_s = [593.0, -,23.7] N/m, were used to obtain a range of frequencies varying between f_n=[20.49, -,4.09] Hz and therefore the reduced velocity $U_r = \frac{U}{f_n D}$ varying in the range U_r = [2.00, -,10.00]. Finally the mass of cylinder is m = 0.03575 kg, the damping coefficient is d = 0.004 Ns/m and the mass ratio $m_r = 10$. The fluid density is set to $\rho_f = 1778.05kg/m^3$. All parameters in this model were similar to those adopted in CFD model presented in Alletto (2022).

4. RESULTS AND DISCUSSIONS

In the present section, we demonstrate the performance of the proposed methodology. Here, we are interested in learning the solutions of different operation conditions given by the reduced velocity u_r. However, the methodology can be extended for more critical issues, such as faces many-query applications like sensitivity analysis, design, optimization, and uncertainty quantification.

Here, the CFD simulations are performed by varying the reduced velocity inside the lock-in condition, a local synchronization between the vortex shedding and cross-flow structural vibration frequencies, in which large amplitude oscillations occur, leading to failures in offshore structures. The dataset consists of a time series of the dynamical system described by a cross-flow displacement variable y and the normalized lift coefficient q (wake variable). In particular, the training and testing data sets containing 8 and 4 time series at a time-step size of $\Delta\tau = 0.25$, respectively. Specifically, the reduced velocity (control variable) of training data is $u_r = [5.43, 5.72, 6.27, 6.52, 6.79, 7.41, 8.05, 8.15]$, and $u_r = [5.82, 6.04, 7.09, 7.96]$ for the testing set, used for cross-validation purposes. The training dataset has a time series of 1000 time steps containing the solution during unsteady and steady states, providing the system's whole dynamics. The cross-validation dataset contains 1600 time steps to evaluate the trained transformer model and extrapolate the model in time.

Figures 3 and 4 show randomly selected test samples for which only the initial state is provided, and the machine learning model predicts 1600 time steps forward. So, the transformer model can predict the cross-flow displacement accurately.

Additionally, we test the ability of the proposed transformer model to predict the amplitude and frequency of vibration as a function of reduced velocity for the cross-flow direction. The transformer model can yield highly accurate predictions, as shown in Figs. 5. For the sake of clarity, the root-mean-squared error (RMSE) between the amplitude of vibration predicted by the transformer model and computed by the CFD simulations is $RMSE = 3.4 \times 10^{-3}$.

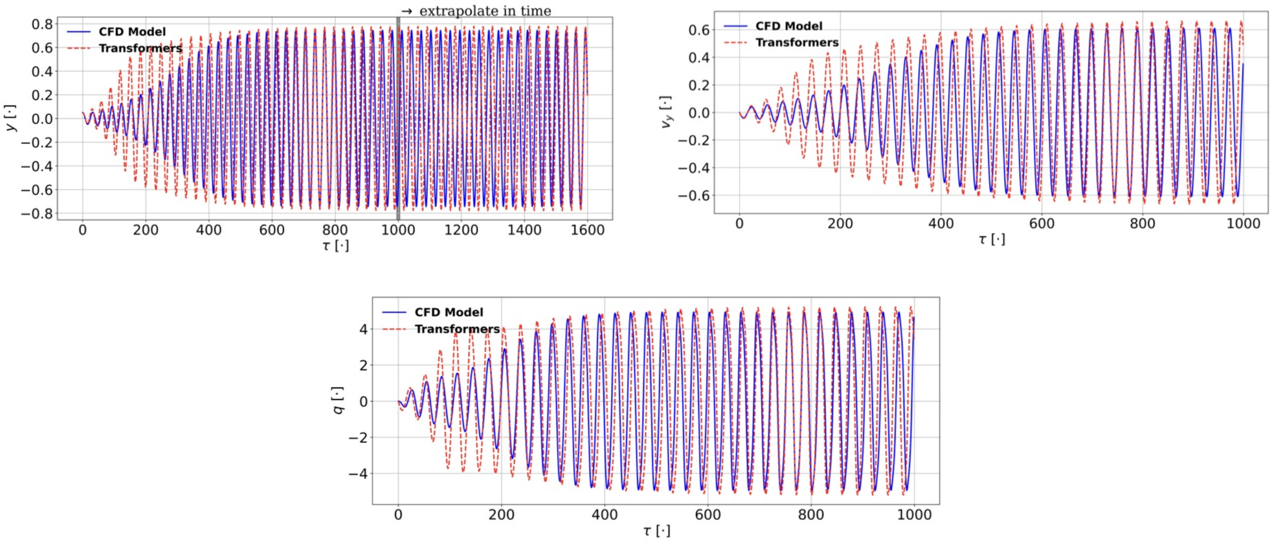

Figure 3: Displacement in the cross-flow y direction predicted by the transformer model and provided by the CFD for a randomly selected reduced velocity in the test dataset. Reduced velocity, $u_r = 5.82$.

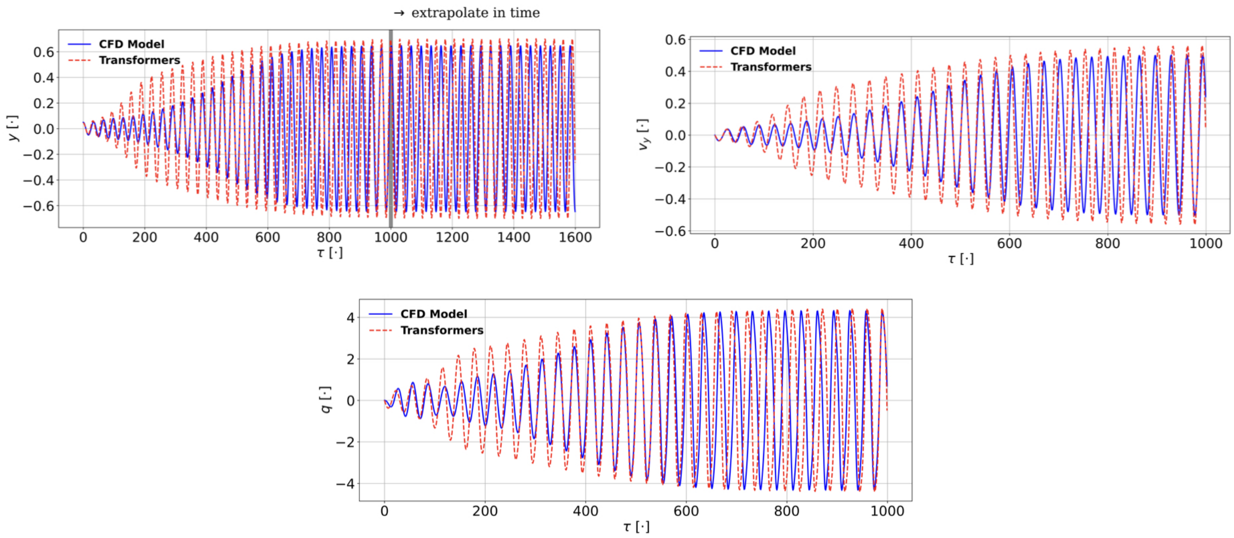

Figure 4: Displacement in the cross-flow y direction predicted by the transformer model and provided by the CFD for a randomly selected reduced velocity in the test dataset. Reduced velocity, $u_r = 6.04$.

5. CONCLUSIONS

The present study addresses the construction of reduced-order models of physics-based computational models. Here, the attention goes to using the self-attention transformers model for modeling VIV dynamics. The applicability of the proposed approach was tested using data provided by the CFD model, which captures features of the VIV dynamics. More specifically, a numerical experiment was proposed in which the reduced velocity was assumed following independent and identically distributed probabilistic functions. Such an approach has been revealed to yield highly accurate predictions for different dynamic conditions.

Furthermore, we place our contribution in the emerging area of physics-aware machine learning, where the final model, in many different ways, blends two main components: availability of experimental data and/or often expensive computational models, data-driven machine learning techniques. Such a combination allows an understanding of the

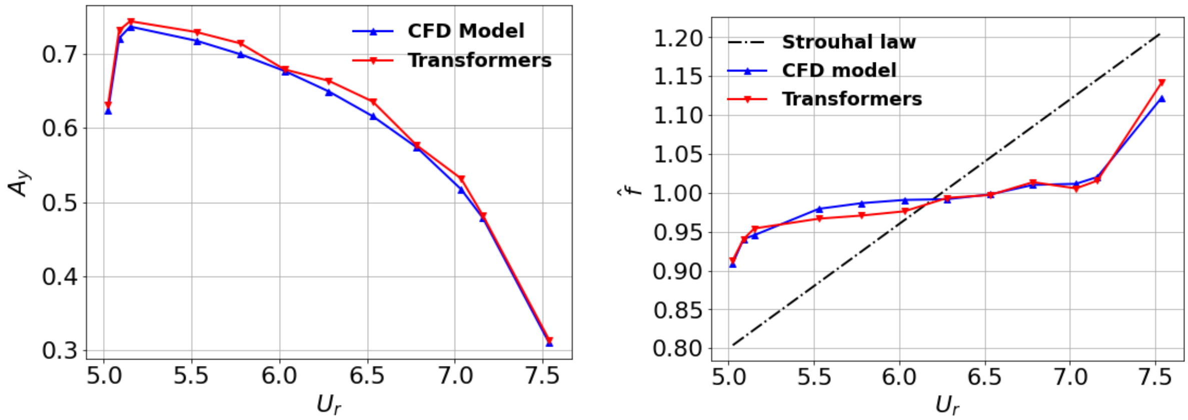

Figure 5: Amplitude dependence on the reduced velocity and Frequency dependence on the reduced velocity.

underlying physics of dynamics systems at a relatively low cost. Also, it offers a broad spectrum of opportunities to extend fluid flow analysis that includes many variables and degrees of freedom.

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