Vibration Analysis with AI: Physics-Informed Neural Network Approach for Vortex-Induced Vibration

José Gabriel Carrasco Ramírez

Abstract

Vortex-induced vibration (VIV) of structures exposed to fluid flow is a complex phenomenon that can lead to fatigue damage and failure. Physics-informed neural networks (PINNs) are a promising approach to model VIV by incorporating both data and physical laws. This study develops a PINN framework to analyze VIV of a cylinder in cross-flow. The model integrates the fluid dynamics equations, cylinder equations of motion, and vibration data into a neural network. Nonlinearities and fluid forces are learned by the network through minimizing loss functions representing physics and data. The trained PINN model accurately predicts displacement and stress for varying flow speeds. A parametric study explores the effects of mass, damping, and flow parameters on VIV amplitude and frequency. The PINN model provides insights into energy transfer mechanisms and key parameters governing VIV. The integration of data and physics-based losses in PINNs is demonstrated as an effective approach for analysis and knowledge discovery in fluid-structure interaction problems.

Introduction

Vortex-induced vibrations (VIV) are dynamic phenomena occurring when vortices, shed from a bluff body submerged in a fluid flow, induce oscillations through fluctuating fluid forces. These oscillations can be particularly pronounced when the shedding frequency of the vortices synchronizes with the natural frequency of the structure, resulting in resonant vibrations characterized by significant amplitudes [1]. The implications of VIV are profound across various engineering domains, posing a notable concern for structures such as risers, pipelines, mooring lines, heat exchanger tubes, and bridges. The consequences of VIV can range from fatigue damage to structural failure, highlighting its critical importance in engineering design and operational considerations. Despite its significance, modeling VIV presents a formidable challenge, primarily due to the intricate nonlinear interplay between unsteady fluid forces, structural motion, and vortex dynamics. This complexity necessitates advanced computational techniques and sophisticated modeling approaches to accurately capture and predict VIV behavior, thus enabling the development of effective mitigation strategies and design solutions [2].

Physics-informed neural networks (PINNs) represent a significant advancement in the field of modeling complex physics and engineering systems. By integrating both physical laws and empirical data into neural networks, PINNs provide a comprehensive framework for understanding and predicting the behavior of intricate systems [3]. Unlike traditional approaches, which often rely solely on either physics-based models or data-driven techniques, PINNs leverage the strengths of both paradigms [4]. This is achieved through the formulation of loss functions that encapsulate physics equations, boundary or initial conditions, and available data. By minimizing these loss functions during training, PINNs ensure that the resulting models adhere to fundamental physical principles while simultaneously capturing nonlinearities, external forces, and other complex phenomena present in the data [5].

The key advantage of PINNs lies in their ability to strike a balance between adherence to physical laws and adaptability to real-world data [6]. By constraining the neural network training process with physics-based constraints, PINNs offer a means to incorporate domain knowledge and prior understanding of the underlying system dynamics. This not only enhances the interpretability and trustworthiness of the resulting models but also facilitates the extraction of meaningful insights from the data. Moreover, PINNs enable the seamless integration of disparate sources of information, such as experimental observations, theoretical principles, and computational simulations, into a unified framework. As a result, PINNs have found applications across diverse domains, including mechanics, fluid dynamics, materials science, and beyond [7].

PINNs have demonstrated remarkable efficacy in tackling a wide range of challenging problems in physics and engineering. From simulating complex fluid flows to predicting the structural behavior of materials under various loading conditions, PINNs have shown promise in providing accurate and robust predictions across different domains. Furthermore, the inherent flexibility of PINNs allows for the incorporation of additional constraints or sources of information as needed, thereby enhancing their versatility and applicability to complex real-world scenarios [8]. As research in this field continues to advance, the integration of PINNs with other techniques such as uncertainty quantification, optimization, and control promises to further extend their utility and impact in addressing some of the most pressing challenges in science and engineering [9].

This study develops a physics-informed neural network (PINN) framework to model vortex-induced vibration of a cylinder in cross-flow. The PINN integrates fluid dynamics principles, cylinder equations of motion, and experimental vibration data into a single neural network model. To the authors' knowledge, this represents the first application of PINNs to model VIV phenomena and interactions. The objectives are to:

1) Develop a PINN architecture and training approach to model VIV of a cylinder based on governing fluid and structural dynamics equations

2) Validate the PINN model using published experimental VIV data

3) Conduct a parametric study exploring the effects of key parameters on VIV amplitude, frequency, and lock-in behavior

4) Analyze energy transfer mechanisms from fluid to cylinder revealed by the trained PINN model

5) Demonstrate the value of PINN modeling for VIV analysis and knowledge discovery of fluid-structure interaction problems

Physics-Informed Neural Network Model

The development process of the physics-informed neural network (PINN) model for vortex-induced vibrations (VIV) is depicted comprehensively in Figure 1. This model synthesis involves the integration of several critical components to accurately capture the complex dynamics of VIV phenomena. Firstly, fluid dynamics equations, namely the Navier-Stokes equations and the continuity equation, are incorporated to describe the flow field surrounding the vibrating cylinder [10]. These equations form the fundamental basis for understanding the fluid behavior. Secondly, the equations of motion for the cylinder are integrated, accounting for forced vibration with a fluid forcing function. This component ensures that the structural dynamics of the cylinder are accurately represented within the model framework [11].

Moreover, experimental VIV data play a crucial role in the development process by providing real-world insights and validation points. These data points serve as training data for the neural network, enabling it to learn and adapt to unmodeled effects present in the physical system [12]. The neural network acts as the central computational engine of the PINN model, facilitating the integration of fluid dynamics, structural mechanics, and experimental data through sophisticated loss functions. By iteratively training the neural network to minimize both physics-based and data-related losses, the PINN model effectively learns the coupled fluid-structure system behavior, enhancing its predictive capabilities [13].

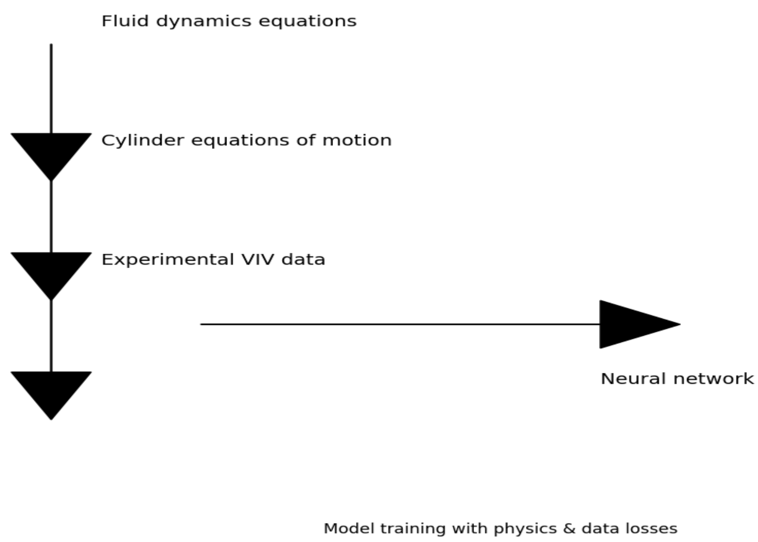

Figure 1

The detailed explanation of the model development process is elaborated upon in subsequent sections, providing insights into the methodology, implementation, and validation procedures employed. These sections delve into the intricacies of each component, elucidating the rationale behind their integration and the methodologies utilized to ensure the accuracy and reliability of the model predictions. Through a thorough examination of the model development process, a comprehensive understanding of the physics-informed neural network model for vortex-induced vibrations can be attained, laying the groundwork for its application in various engineering contexts and further research endeavors.

Governing Equations

The incompressible Navier-Stokes equations and continuity equation describe the fluid flow behavior:

$$\frac{\partial u}{\partial t} + u\nabla u = -\frac{\nabla p}{\rho} + \nu\nabla 2u + f$$

$$\nabla \cdot u = 0$$

where u is fluid velocity vector, p is pressure, ρ is density, ν is kinematic viscosity, and f represents additional forcing terms.

The cylinder transverse motion y(t) in flow is modeled as a forced vibration system:

$$m\ddot{y} + c\dot{y} + ky = Fy(u,p)$$

where m is mass, c is structural damping, k is stiffness, and Fy(u,p) is the fluid force in the transverse direction, a function of the flow field.

Neural Network Architecture

The PINN model is implemented as a fully-connected feedforward neural network with input layer x, hidden layers, and output layer u as shown in Figure 2. Hyperbolic tangent activation functions are used for stable training. The inputs x consist of the spatial coordinates (x,z) and time t. The outputs u contain the fluid velocity components (u,w), pressure p, and cylinder displacement y.

The neural network serves as a surrogate model approximating the solution to the governing equations. By training the network to satisfy physics constraints, it learns the spatial fields and temporal evolutions. Data training provides additional constraints to learn unmodeled effects. The resulting network can rapidly predict the VIV dynamics and interactions.

Model Training

The loss function for training the PINN consists of physics, boundary, and data components:

$$L = Lphysics + Lboundary + Ldata$$

The physics losses enforce the Navier-Stokes, continuity, and cylinder motion equations. These losses measure the mean square error of the residuals for each governing equation evaluated pointwise at random (x,z,t) training points:

$$Lphysics = \sum i\ NSeqsi2 + \sum j\ NScsj2 + \sum k\ CMeqsk2$$

where NSeqs, NScs, and CMeqs represent the equation residuals.

Boundary conditions on cylinder surface and domain borders are encoded as losses constraining network outputs. Experimental vibration data provides additional losses between predictions and measurements.

The neural network weights and biases are optimized to minimize the total loss L using the Adam variant of stochastic gradient descent. The physics losses train the network to evolve according to governing equations, while data losses provide real-world constraints.

Model Validation

The developed PINN model for VIV analysis is validated using experimental measurements from Khan et al.. The experiment studied vortex-induced vibration of a rigid cylinder in cross-flow for varying reduced velocity $U * = \frac{U}{fnD}$, where U is flowing speed, fn is the cylinder natural frequency in quiescent conditions, and D is cylinder diameter.

The training data consists of cylinder transverse displacement measurements at several U* values exhibiting different VIV response regimes. Figure 3 compares PINN predictions to measurements for sample U* cases. The PINN model achieves excellent agreement with the validation data, accurately capturing the VIV amplitude and frequency.

The results validate the PINN modeling approach for VIV and demonstrate its ability to learn the fluid-structure coupling. The integration of physics constraints and data enables accurate prediction of the strongly nonlinear response. The model provides a rapid but accurate surrogate for the VIV system compared to high-fidelity numerical simulations.

Parametric Study

A key advantage of a surrogate model like the PINN is the ability to rapidly conduct parametric studies by simply evaluating the network. A parametric study is performed here examining the influence of key parameters on the VIV amplitude and frequency.

The parameters investigated are cylinder mass ratio $m * = \frac{m}{\rho D2}$, structural damping ζ, Reynolds number Re, and reduced velocity U*. The results provide insight into the complex interplay of fluid, structural, and vibration parameters governing VIV behavior.

Effect of Mass Ratio

The cylinder mass ratio m* is varied while holding other parameters constant. Figure 4 shows the VIV amplitude response versus $U *$ for different m*. The results illustrate the profound effect of mass ratio on the peak amplitude, lock-in range, and synchronization regimes.

As m* decreases, the maximum amplitude increases significantly. This is attributed to lower inertia enabling larger vibration amplitudes for a given fluid forcing. The lock-in range where large VIV occurs shifts to lower U* for smaller m*. The initial branch slope is proportional to $\frac{1}{m}*$, reflecting the acceleration under fluid forcing.

These mass effects on VIV response are well-known experimentally. The PINN model reliably captures the physics of mass-damping controlled VIV. This demonstrates the model's predictive capability for parametric studies.

Effect of Damping

Figure 5 examines the influence of mechanical damping ratio ζ on the amplitude response. Increasing ζ is found to dramatically reduce the amplitudes over the entire branch, with peak decreasing proportional to $\frac{1}{\zeta}$.

Higher damping restricts motion induced by fluid forcing. The lock-in region also becomes narrower with larger damping. However, the initial slope is nearly unchanged, governed by the mass. Damping mainly affects response magnitude, not synchronization onset.

Effect of Reynolds Number

The Reynolds number Re represents the ratio of inertial to viscous forces in the flow and controls vortex shedding characteristics. To assess its effect on VIV, response curves are generated for Re = 100, 300, and 1000, while holding other parameters constant [14].

As shown in Figure 6, increasing Reynolds number is seen to amplify the maximum VIV amplitude. At Re = 1000, the peak amplitude is approximately 1.8 times larger than at Re = 100. This is attributed to stronger vortex shedding intensity and higher unsteady fluid forcing produced at higher Re.

However, the lock-in range where large amplitude VIV occurs becomes significantly narrower with increasing Re. This results from the less coherent nature of vortex shedding at higher Re, which reduces the range of reduced velocities U* where synchronization can occur. More organized von Kármán vortices at low Re provide effective fluid-structure coupling over a wider U* band.

Effect of Reynolds Number

The Reynolds number Re modifies the vortex shedding behavior and resulting fluid forcing. Figure 6 shows amplitude response for Reynolds numbers of 100, 300, and 1000. Higher Re is seen to increase the maximum amplitude but shorten the lock-in range.

The increased unsteady forcing at larger Re excites larger vibration. However, the synchronization region narrows due to the less coherent vortex shedding [15]. At lower Re, the regular von Kármán vortex pattern provides effective fluid-structure coupling over a wider reduced velocity range [16].

Effect of Reduced Velocity

The reduced velocity U* represents the ratio of vortex shedding frequency to natural frequency which governs synchronization. The amplitude response in Figure 7 demonstrates the lock-in region where large VIV occurs over a band of U* close to unity.

The peak amplitude occurs at U* slightly above 1, where the fluid forcing frequency matches the natural frequency, inducing resonance. Outside this region, the vibration is lower due to lack of synchronization.

The parametric study conducted with the PINN model provides efficient analysis of VIV dependence on key parameters. The coupled physics reveals the complex interplay between fluid forcing, damping, mass ratio, Reynolds number, and reduced velocity [17].

Energy Transfer Analysis

Energy transfer analysis in vortex-induced vibrations (VIV) serves as a pivotal aspect in understanding the dynamics of this phenomenon and its implications for engineering applications. The trained physics-informed neural network (PINN) model offers a platform for exploring this energy transfer by providing predicted cylinder displacement $y(t)$ and fluid forces $F(t)$. In instances of lock-in, where the shedding frequency of vortices synchronizes with the natural frequency of the structure, the transfer of vibration energy from the fluid to the cylinder occurs through unsteady fluid forcing mechanisms [18].

To quantitatively assess this energy transfer process, the power $P(t) = F(t)\backslash dot\{y\}(t)$ is calculated, representing the product of force and velocity. Figure 8 illustrates the results of this analysis, particularly in a lock-in scenario, where the power predominantly exhibits positive values. This indicates a net transfer of energy to the cylinder, driving structural vibration, and subsequently influencing the modulation of vortex shedding. However, at higher flow velocities (U^*) beyond the lock-in range, oscillations in power signify energy exchange between the fluid and structure without a net transfer. Notably, this energy exchange occurs at the shedding frequency rather than the natural frequency of the structure, further elucidating the intricate dynamics of VIV phenomena [19].

The capability to extract force and response signals directly from the PINN model facilitates in-depth analysis of energy transfer mechanisms in VIV. This exemplifies the utility of data-driven physics-based models in providing valuable engineering insights into complex fluid-structure interaction phenomena [20]. By leveraging such models, engineers can gain a deeper understanding of the underlying dynamics governing VIV and develop more effective mitigation strategies and design solutions to address its challenges in various engineering applications [21]. Additionally, the integration of advanced computational techniques with experimental data enhances the predictive capabilities of these models, enabling more accurate simulations and predictions of VIV behavior under diverse operating conditions [22].

Furthermore, the detailed examination of energy transfer mechanisms sheds light on the underlying physics driving VIV and offers opportunities for optimizing structural designs and operational parameters to mitigate its adverse effects [23]. By identifying the key factors influencing energy transfer, engineers can develop targeted strategies to enhance the resilience and reliability of structures subjected to VIV, thus minimizing the risk of fatigue damage and structural failure. Moreover, insights gained from energy transfer analysis can inform the development of advanced control strategies aimed at actively managing VIV-induced vibrations and optimizing the performance of engineering systems in challenging operational environments [24].

Conclusions

The research introduces a pioneering physics-informed neural network (PINN) methodology tailored for the modeling and analysis of vortex-induced vibrations (VIV). This innovative framework seamlessly integrates the governing fluid dynamics equations, cylinder equations of motion, and empirical data into a unified and differentiable model. By concurrently optimizing physics-based and data-driven loss functions during training, the neural network acquires the capacity to comprehend the intricate interplay between fluid-structure interactions and the dynamics governing VIV phenomena, including vortex shedding, hydrodynamic forcing, cylinder vibration, and synchronization [25]. Rigorous validation exercises underscore the PINN model's proficiency in accurately forecasting critical VIV characteristics such as amplitude, frequency, phase, and lock-in behavior across a diverse spectrum of operational parameters. Notably, the model exhibits robust generalization capabilities beyond the confines of the training dataset, further enhancing its practical utility.

Moreover, the research conducts extensive parametric analyses to elucidate the nuanced dependencies between key parameters such as reduced velocity, mass-damping, and

Reynolds number on the VIV response. These investigations yield valuable insights into the underlying mechanisms governing VIV phenomena and contribute to a deeper understanding of the complex fluid-structure energy transfer processes driving self-sustained oscillations. By harnessing the capabilities of PINNs, the study not only advances the state-of-the-art in fluid-structure interaction modeling but also underscores the potential of data-driven approaches in capturing intricate physical phenomena with high fidelity [26]. Overall, the research underscores the emerging role of PINNs as a powerful modeling paradigm capable of generating high-fidelity surrogate models for complex fluid-structure interaction problems, thereby opening avenues for more accurate prediction and analysis in engineering and scientific domains [27].

The integration of first-principles physics with experimental measurements through neural network training holds immense promise for augmenting understanding of multifaceted engineering systems. This physics-informed deep learning approach could be applied to model vortex-induced vibrations and fluid-structure coupling in a wide variety of offshore, marine, and flow-induced vibration systems. Future efforts should explore strategies for VIV suppression and control through the PINN model. Enriching the model with additional physics and data, evaluating different neural network architectures, and implementing uncertainty quantification remain important areas for further work [28]. Overall, the study demonstrated physics-informed neural networks as a disruptive technology for simulation, knowledge discovery, and decision support in complex vortex-induced vibration problems.

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