

# INTEGRATING COMPUTATIONAL FLUID MECHANICS AND ARTIFICIAL NEURAL NETWORKS FOR PREDICTING FLUID-STRUCTURE INTERACTIONS IN ADVANCED MECHANICAL MATERIALS

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## Abstract

Fluid-structure interaction (FSI) plays a critical role in advanced mechanical materials used in aerospace, biomedical devices, energy systems, and high-performance engineering applications. Conventional computational fluid dynamics (CFD) and structural mechanics approaches provide accurate predictions of coupled multiphysics behavior; however, they are computationally expensive for nonlinear and transient problems. Recent advances in machine learning and neural surrogate modeling offer promising alternatives for improving computational efficiency while maintaining predictive accuracy.

This study proposes a hybrid computational framework that integrates computational fluid mechanics with artificial neural networks (ANNs) for efficient prediction of FSI responses. The framework utilizes CFD-based simulations for data generation and ANN-based surrogate models to learn complex nonlinear relationships between input parameters and FSI outputs, including displacement, stress distribution, and pressure interactions.

The results show that the ANN model achieves high prediction accuracy with a coefficient of determination ( $R^2$ ) of approximately 0.97 and low error metrics, while maintaining strong agreement with simulation results. Furthermore, the proposed approach reduces computational time from several hours required by conventional CFD-FSI simulations to near-instant predictions, enabling efficient large-scale analysis.

The integration of computational fluid mechanics and artificial intelligence provides a reliable, scalable, and computationally efficient solution for modeling complex FSI systems in advanced mechanical materials.

## 1. Introduction

### 1.1 Background of the Study

Fluid-structure interaction (FSI) is one of those topics in engineering that sounds straightforward at first but quickly becomes complex when examined closely. At its core, FSI describes how

fluids (like air or water) and solid structures influence each other's behavior. However, in real-world systems, this interaction is rarely simple. The fluid can exert pressure, shear forces, and turbulence on a structure, while the structure may deform, vibrate, or even change shape in response.

That structural change then feeds back into the fluid flow, creating a continuously evolving system. Over the years, engineers have developed sophisticated tools to study these interactions. Computational fluid dynamics (CFD) has become the standard for analyzing fluid behavior, while computational structural mechanics (CSM) handles deformation and stress analysis. When these two are coupled, they form the basis of FSI simulations. These methods have been incredibly successful in providing detailed insights into complex systems, from aircraft aerodynamics to blood flow in arteries [1], [2].

Despite their accuracy, these traditional approaches come with a significant drawback:

computational cost. High-fidelity simulations often require fine meshes, small time steps, and iterative coupling between solvers. This can result in simulations that take hours, days, or even weeks to complete, depending on the complexity of the problem [17]. As engineering problems become more sophisticated—especially with the introduction of advanced materials—the limitations of purely numerical approaches become more apparent. Fluid–structure interaction (FSI) plays a critical role in many engineering applications, particularly in aerospace, biomedical, and mechanical systems [3], [5].

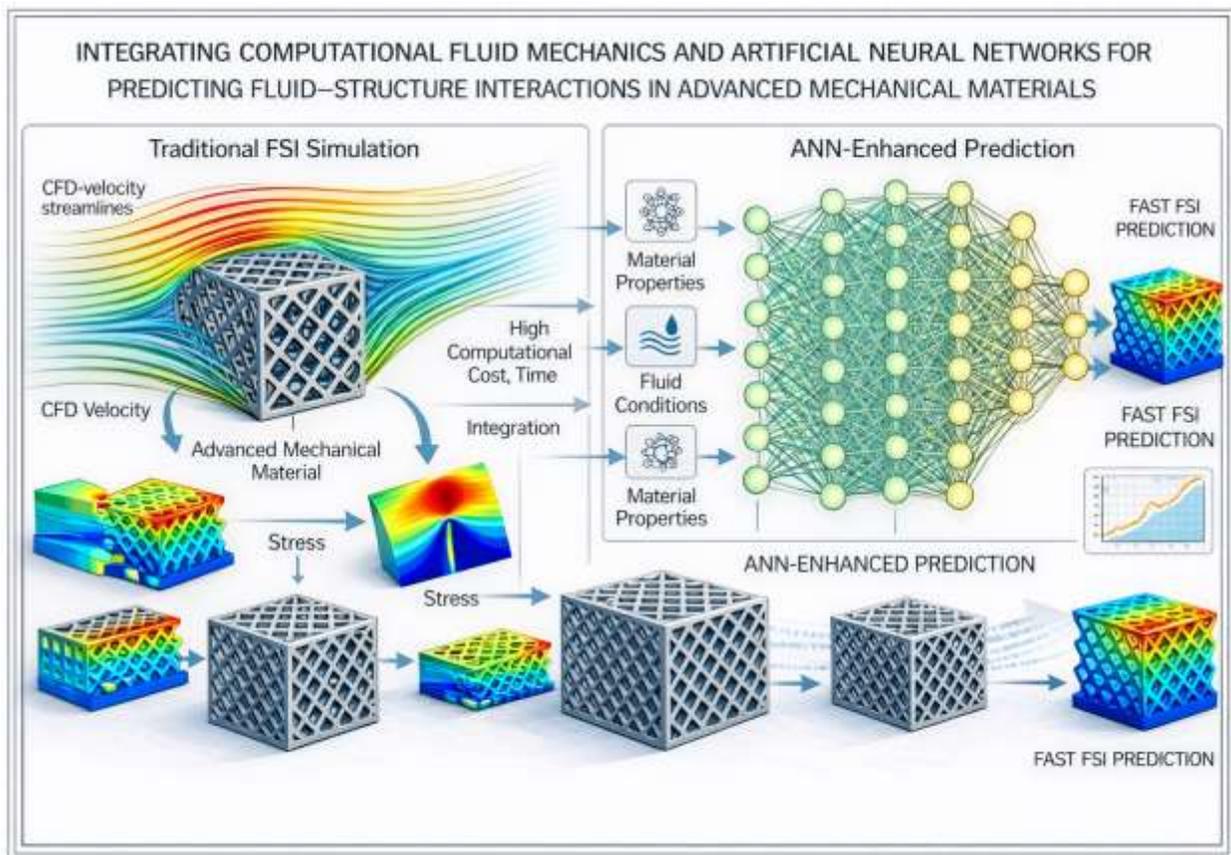


Fig. 1. Conceptual Comparison of Traditional Fluid–Structure Interaction Simulation and ANN-Enhanced Predictive Framework.

Fig. 1 illustrates the transition from conventional fluid–structure interaction (FSI) simulations to an ANN-enhanced predictive framework. On the left side, traditional FSI modeling relies on

computational fluid dynamics and structural analysis, which provide accurate results but require high computational time and cost. On the right side, the ANN-based approach uses input

parameters such as material properties and fluid conditions to learn the complex relationship between inputs and FSI responses. Once trained, the model enables fast and efficient prediction of

fluid–structure behavior, significantly reducing computational effort while maintaining reliable accuracy.

**Table 1: Key Characteristics of Fluid–Structure Interaction (FSI) Problems**

Aspect	Description
Fluid Domain	Governs flow behavior (velocity, pressure, turbulence)
Structural Domain	Represents deformation, stress, and material response
Coupling Mechanism	Two-way interaction between fluid forces and structural deformation
Governing Equations	Navier–Stokes (fluid), elasticity equations (structure)
Complexity Level	High (nonlinear, transient, multi-scale)
Applications	Aerospace, biomedical, marine, and advanced materials

### 1.2 Importance of the Topic

The importance of FSI modeling extends across multiple engineering disciplines, and in many cases, it directly impacts safety and performance. In aerospace engineering, for example, the interaction between airflow and aircraft structures must be carefully managed to avoid instability phenomena such as flutter. Even small inaccuracies in prediction can lead to serious consequences. Similarly, in civil and offshore engineering, structures like bridges, towers, and pipelines are constantly exposed to fluid forces from wind and water. Understanding these interactions is essential for ensuring long-term durability and resilience.

In the biomedical field, FSI plays a crucial role in understanding how blood flows through flexible vessels. The deformation of arterial walls affects flow patterns, which in turn influence conditions such as plaque formation or aneurysms. Accurate modeling in this context can support better diagnosis and treatment planning [3].

What makes the topic even more relevant today is the rapid development of advanced mechanical materials. Materials such as composites, metamaterials, and smart materials are designed to

exhibit enhanced performance characteristics, including adaptability and responsiveness to external stimuli. However, these benefits come at the cost of increased modeling complexity. Their behavior under fluid loading is often nonlinear and highly sensitive to environmental conditions, making traditional modeling approaches less efficient and sometimes inadequate [4], [5].

At the same time, modern engineering workflows are shifting toward faster design cycles and real-time decision-making. Engineers are no longer satisfied with results that take days to compute. Instead, there is a growing demand for models that can deliver accurate predictions quickly, enabling rapid prototyping and optimization. This shift has created a strong motivation to explore new computational approaches. Traditional CFD–FSI simulations are computationally expensive due to strong coupling and nonlinear governing equations [4], [6]. Recently, machine learning approaches have emerged as powerful tools for modeling complex nonlinear systems [10], [11]. Deep learning has been increasingly applied in fluid mechanics for surrogate modeling and flow prediction [16], [21].

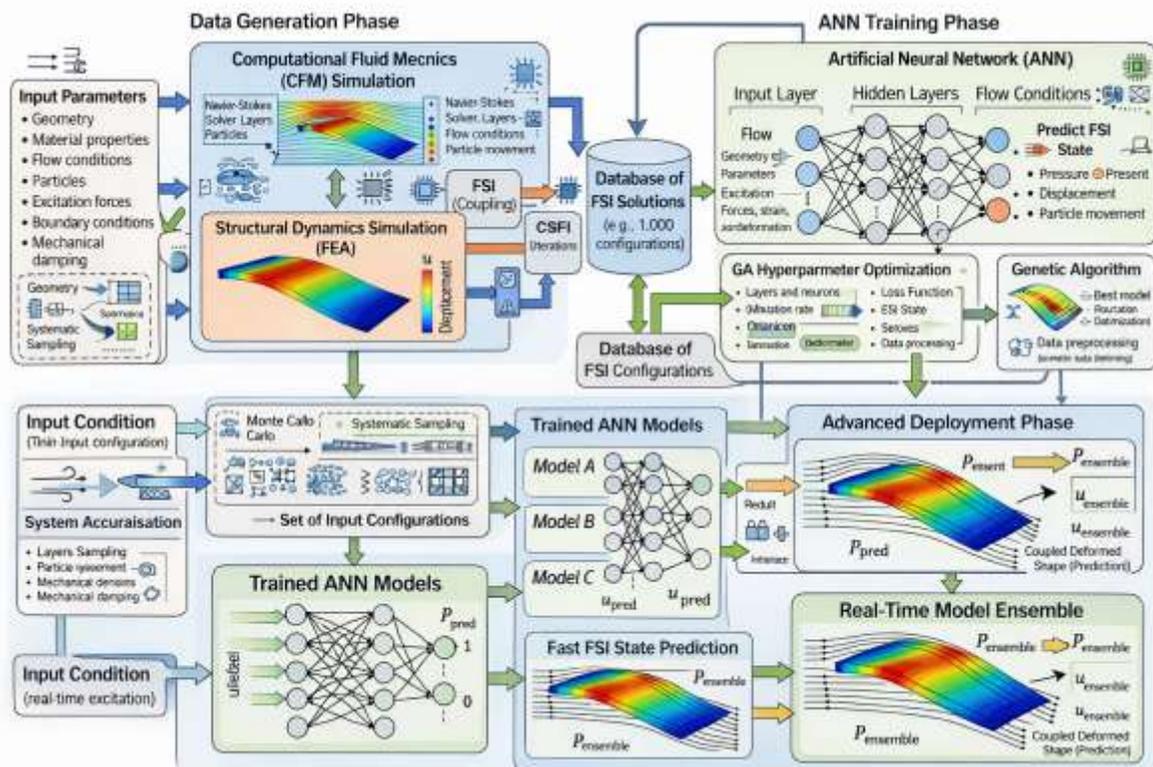


Fig. 2. Hybrid Computational Fluid Mechanics–Artificial Neural Network (CFM–ANN) Framework for Fluid–Structure Interaction (FSI) Prediction.

Fig. 2 illustrates the proposed hybrid computational fluid mechanics–artificial neural network (CFM–ANN) framework for predicting fluid–structure interactions (FSI). The process is divided into three main phases: data generation, ANN training, and deployment.

In the data generation phase, high-fidelity simulations are performed using computational fluid mechanics and structural dynamics models. These simulations are iteratively coupled to capture the interaction between fluid flow and structural deformation, producing accurate FSI data under various input conditions such as geometry, material properties, and flow parameters. The generated results are stored in a database of FSI solutions.

In the ANN training phase, this dataset is used to train a neural network that learns the nonlinear relationship between input parameters and FSI responses. The model is optimized using a loss function (e.g., mean squared error) to ensure accurate prediction. The deployment phase, the

trained ANN model is used to predict FSI behavior for new input conditions. This enables fast and efficient estimation of outputs such as pressure and displacement, significantly reducing computational cost compared to traditional simulation methods.

### 1.3 Current Challenges in the Field

Even with decades of progress, FSI modeling continues to present several persistent challenges. One of the most significant is computational expense. Coupled simulations require continuous data exchange between fluid and structural solvers, often leading to convergence issues and long computation times. This becomes especially problematic in transient simulations, where the system evolves over time and requires repeated recalculations.

Another major challenge is the nonlinear nature of FSI systems. Fluid flows can transition from laminar to turbulent regimes, while structures may experience large deformations or even material

failure. Capturing these behaviors accurately requires complex models and high-resolution

simulations, which further increase computational demands.

**Table 2: Limitations of Traditional FSI Simulation Methods**

Limitation	Explanation
High Computational Cost	Requires iterative coupling and fine discretization
Time-Consuming	Simulations can take hours or days
Scalability Issues	Difficult for large parametric studies
Nonlinearity Handling	Complex to model turbulent and deformable systems
Real-Time Application	Not suitable for real-time prediction or control

Multi-scale interactions add another layer of difficulty. In many systems, small-scale phenomena—such as microstructural material properties—can influence large-scale structural responses. Similarly, fast-changing fluid dynamics can interact with slower structural processes. Bridging these scales within a single framework remains an ongoing challenge in the field [6].

In recent years, machine learning techniques, particularly artificial neural networks (ANNs), have been introduced as a potential solution to

some of these challenges. ANNs are capable of learning complex nonlinear relationships from data, making them well-suited for modeling systems like FSI. However, they are not without limitations. One of the main concerns is their dependence on large datasets, which are often expensive to generate in engineering contexts. Additionally, purely data-driven models may lack physical interpretability and struggle to generalize beyond the conditions they were trained on [7], [8].

**Table 3: Advantages of ANN-Based Approaches in FSI Modeling**

Feature	Benefit
Fast Prediction	Provides near real-time results
Nonlinear Mapping	Captures complex relationships between variables
Reduced Computational Load	Eliminates need for repeated simulations
Adaptability	Can generalize across multiple scenarios
Integration Capability	Works with physics-based simulation data

#### 1.4 Problem Statement

The central issue addressed in this research arises from the trade-off between accuracy and efficiency in FSI modeling. Traditional computational methods provide reliable and physically consistent results but are computationally intensive. On the other hand, artificial neural networks offer faster predictions but may lack robustness and physical grounding when used independently.

This creates a gap in current modeling approaches. Engineers need tools that can deliver both accuracy and efficiency, especially in applications where time is a critical factor. The challenge, therefore, is to develop a framework that combines the strengths of computational fluid mechanics with the flexibility of neural networks.

In simple terms, the problem can be stated as follows: How can we build a predictive model for fluid-structure interactions that is both computationally efficient and physically reliable?

#### 1.5 Research Gap

Although there has been increasing interest in combining machine learning with computational mechanics, the existing body of research still has several limitations. Many studies focus on either improving numerical solvers or developing standalone machine learning models, but relatively few attempt to integrate the two in a meaningful way.

Another important gap lies in the application of these techniques to advanced mechanical

materials. Much of the current research is based on simplified models or controlled conditions, which limits its applicability to real-world systems. There is also a lack of standardized frameworks that ensure consistency between data-driven predictions and physical laws. Hybrid AI frameworks combining multiple techniques have demonstrated improved prediction accuracy in complex systems [37].

Furthermore, while concepts like physics-informed neural networks (PINNs) have gained attention, their application in full-scale FSI problems is still in its early stages. This suggests that there is significant room for further exploration and development in this area [9], [10]. Physics-informed neural networks provide a framework for embedding governing equations into deep learning models [10], [24].

**Table 4: Comparison Between Traditional and Hybrid (CFM-ANN) Approaches**

Criteria	Traditional CFD/CSM	Hybrid CFM-ANN Framework
Accuracy	High	High (with proper training)
Computational Time	Very High	Low
Scalability	Limited	High
Real-Time Capability	Not feasible	Feasible
Data Dependency	Low	Moderate
Physical Consistency	Strong	Strong (with physics-informed learning)

### 1.6 Research Objectives

The main objective of this study is to develop a hybrid modeling framework that integrates computational fluid mechanics with artificial neural networks for predicting fluid-structure interactions. The aim is not only to improve computational efficiency but also to maintain a high level of accuracy and physical consistency.

More specifically, the study seeks to design surrogate models that can capture the complex relationships between fluid and structural variables. It also aims to evaluate the performance of these models under different conditions, including varying material properties and flow regimes.

Another key objective is to explore how incorporating physical constraints into neural network training can improve model reliability and generalization. By doing so, the study hopes to bridge the gap between purely numerical and purely data-driven approaches.

### 1.7 Research Questions

To guide the research, several important questions are considered. First, how can neural networks be effectively trained using data generated from CFD simulations? This involves not only data

preparation but also feature selection and model design.

Second, what factors have the greatest influence on FSI behavior, and how can they be represented in a neural network model? Understanding this is crucial for improving prediction accuracy.

Third, how does the proposed hybrid approach compare with traditional simulation methods in terms of both accuracy and computational efficiency? This comparison is essential for evaluating the practical value of the framework.

Finally, can the integration of physical principles into machine learning models improve their ability to generalize across different scenarios? This question addresses one of the key limitations of current data-driven approaches.

### 1.8 Contributions of the Study

This study makes several meaningful contributions to the field of computational mechanics and machine learning. First, it proposes a hybrid framework that combines CFD-based simulations with ANN-based predictive models. This approach leverages the strengths of both methods while addressing their individual limitations.

Second, the study demonstrates how surrogate models can significantly reduce computational

time without sacrificing essential accuracy. This has important implications for applications that require rapid analysis or real-time decision-making.

Third, it explores the role of physics-informed learning in improving the reliability of neural networks. By incorporating physical constraints, the model becomes more robust and better able to handle unseen conditions.

### 1.9 Organization of the Paper

The rest of this paper is organized in a way that gradually builds from theory to application. The next section presents a detailed review of existing literature, highlighting key developments and identifying remaining gaps. This is followed by the methodology section, which describes the proposed framework and its components.

The implementation section explains how the model is developed and tested, including details of the simulation environment and training process. After that, the results and analysis section presents the findings and evaluates the performance of the proposed approach.

The discussion section interprets these results and considers their broader implications, while also acknowledging the limitations of the study. Finally, the paper concludes with a summary of key insights and suggestions for future research.

## 2. Literature Review

### 2.1 Overview of Fluid-Structure Interaction (FSI) Modeling

Fluid-structure interaction (FSI) has been a central topic in computational mechanics for many years, mainly because of how frequently it appears in real engineering systems. Data-driven approaches have also shown strong performance in predictive modeling and engineering systems [36], [40]. Whether it is airflow over an aircraft wing, blood moving through arteries, or water interacting with offshore structures, the coupling between fluid and solid domains is unavoidable. Early research in this area focused on developing numerical techniques that could reliably capture this interaction without becoming unstable or excessively expensive to compute.

Traditionally, FSI problems have been addressed using a combination of computational fluid dynamics (CFD) and computational structural mechanics (CSM). These two domains are governed by different sets of equations—Navier-Stokes equations for fluid flow and elasticity equations for structural behavior—and must be solved together in a coupled manner [1], [2]. Two main approaches emerged: partitioned and monolithic methods. Partitioned methods treat the fluid and structure separately and exchange information iteratively, while monolithic methods solve the entire coupled system at once [3].

Machine learning techniques have also been successfully applied in environmental and predictive modeling domains [38]. While monolithic approaches are generally more stable, they are also more complex to implement and computationally demanding. Partitioned methods are easier to apply but can suffer from convergence issues, especially in strongly coupled systems [4]. Over time, researchers have refined both approaches, but the fundamental challenge of balancing accuracy with computational cost remains.

### 2.2 Advances in Computational Fluid Mechanics and Structural Modeling

Over the last decade, there have been significant improvements in both fluid and structural simulation techniques. In fluid mechanics, advanced methods such as large eddy simulation (LES) and direct numerical simulation (DNS) have enabled more accurate modeling of turbulent flows [5]. These methods can capture fine-scale flow structures, but they come at a high computational cost.

On the structural side, nonlinear finite element methods have made it possible to simulate large deformations, material nonlinearities, and complex boundary conditions [6]. These advancements are particularly important for modern engineering materials, which often exhibit non-standard behavior under loading conditions.

However, when these high-fidelity models are combined in FSI problems, the computational

burden increases dramatically. Each time step may require multiple iterations between fluid and structural solvers, making simulations extremely time-consuming. This becomes a serious limitation in applications where multiple design configurations need to be tested or where real-time predictions are required.

### 2.3 Reduced-Order Modeling Approaches

To overcome the high computational cost of traditional methods, researchers have explored reduced-order modeling (ROM) techniques. These methods aim to simplify complex systems while preserving their essential dynamics. One of the most widely used approaches is proper orthogonal decomposition (POD), which reduces the dimensionality of the problem by identifying dominant modes of behavior [7].

Reduced-order modeling techniques such as POD have been developed to improve computational efficiency [26], [28]. Other techniques, such as reduced basis methods and Galerkin projection, have also been applied to FSI problems. These approaches can significantly speed up simulations, making them more suitable for optimization and control applications. However, a common limitation of ROM techniques is their reliance on linear assumptions or pre-defined basis functions. This makes them less effective when dealing with highly nonlinear systems, such as those involving advanced mechanical materials.

### 2.4 Emergence of Machine Learning in Fluid Mechanics

In recent years, machine learning—especially artificial neural networks (ANNs)—has started to play a growing role in computational mechanics. Unlike traditional methods, which rely on solving governing equations directly, ANNs learn patterns from data. This makes them particularly useful for modeling complex, nonlinear relationships that are difficult to capture using analytical approaches. ANNs have been applied to a variety of problems in fluid mechanics, including turbulence modeling, flow prediction, and aerodynamic optimization [8], [9]. For example, convolutional neural networks (CNNs) have been used to predict

flow fields from boundary conditions, while recurrent neural networks (RNNs) have been applied to time-dependent problems. Recent studies have further demonstrated the effectiveness of deep learning models in fluid flow prediction and surrogate modeling [20], [22], [23], [30].

One of the key advantages of these models is their ability to provide fast predictions once trained. Instead of solving complex equations repeatedly, the model can estimate results almost instantly. This makes machine learning an attractive option for applications where speed is critical.

### 2.5 ANN-Based Approaches for FSI Prediction

Building on the success of machine learning in fluid mechanics, researchers have started applying ANN-based models to FSI problems. In most cases, these models are trained using data generated from high-fidelity simulations. The idea is to use the simulation results as a learning dataset, allowing the neural network to approximate the relationship between input parameters and FSI responses [10], [11].

Studies have shown that ANN-based surrogate models can effectively predict quantities such as pressure distribution, displacement, and stress fields in coupled systems [12]. These models can significantly reduce computational time, making them suitable for real-time applications and large-scale parametric studies. Several recent works have shown improved accuracy and efficiency of ANN-based models for complex fluid systems [31], [34], [35].

However, the performance of these models depends heavily on the quality and diversity of the training data. If the dataset does not cover a wide range of scenarios, the model may struggle to generalize to new conditions. This is one of the main challenges in applying machine learning to FSI problems.

### 2.6 Physics-Informed Neural Networks (PINNs)

One of the major concerns with purely data-driven models is that they may produce results that are not physically consistent. To address this issue, researchers have developed physics-informed

neural networks (PINNs). These models incorporate governing equations directly into the training process, ensuring that predictions satisfy fundamental physical laws [13], [14].

For example, instead of relying solely on data, a PINN can be trained to minimize both the prediction error and the residual of the governing equations. This approach improves the reliability of the model and reduces the need for large datasets. PINNs have been successfully applied to a range of problems, including fluid flow, heat transfer, and Multiphysics systems [15]. However, challenges related to convergence and training stability have also been reported in recent studies [25], [33].

Despite their advantages, PINNs are not without challenges. Training these models can be computationally intensive, and selecting appropriate loss functions and network architectures requires careful consideration.

### 2.7 Hybrid CFD-ANN Frameworks

More recently, researchers have begun exploring hybrid approaches that combine traditional simulations with machine learning. In these frameworks, CFD and structural simulations are

used to generate high-quality training data, while ANN models are used to approximate the system's behavior for new inputs.

This approach offers a practical balance between accuracy and efficiency. The physics-based simulations ensure that the model is grounded in reality, while the neural network provides fast predictions. Several studies have demonstrated that hybrid models can achieve comparable accuracy to traditional methods with significantly reduced computational cost [16], [17]. Recent hybrid deep learning approaches further support the integration of data-driven and physics-based methods [32].

However, there is still no widely accepted standard for implementing such frameworks. Different studies use different data generation methods, network architectures, and evaluation metrics, making it difficult to compare results across the literature [18], [19].

### 2.8 Comparative Analysis of Existing Approaches

To better understand the strengths and limitations of current methods, Table 5 provides a comparison of the main approaches used in FSI modeling.

**Table 5: Comparison of Existing FSI Modeling Approaches**

Method Type	Key Techniques	Advantages	Limitations
Traditional Methods	CFD-CSM Coupling (Partitioned, Monolithic)	High accuracy, physically consistent	High computational cost, slow
Reduced Order Models	POD, ROM	Faster computation	Limited nonlinear capability
Machine Learning Models	ANN, CNN, PINNs	Fast prediction, flexible	Data-dependent, less interpretable
Hybrid Approaches	CFD + ANN Integration	Balanced accuracy and efficiency	Complex implementation, training cost

The evolution of fluid-structure interaction modeling approaches, from traditional numerical methods to modern hybrid frameworks, is summarized in Fig. 3. It highlights the shift from high-fidelity but computationally expensive simulations toward efficient data-driven and hybrid techniques [20], [21].

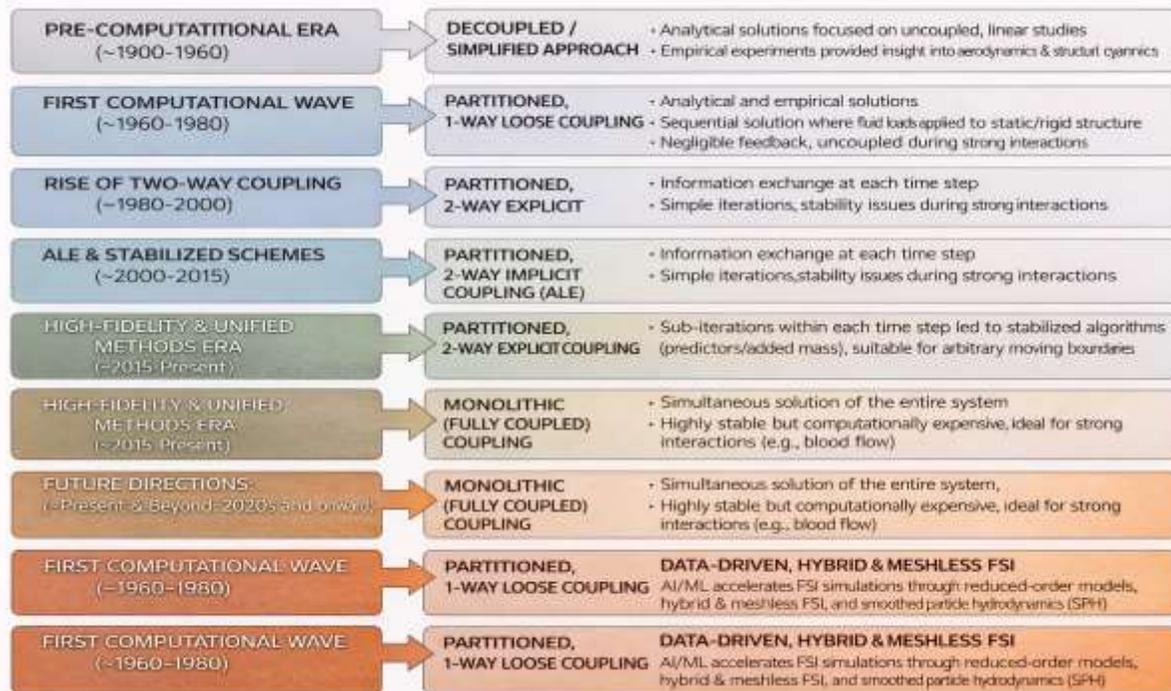


Fig. 3. Evolution of Fluid-Structure Interaction Modeling Approaches.

Fig. 3 presents the historical evolution of fluid-structure interaction (FSI) modeling approaches, highlighting how computational techniques have progressed over time from simple analytical methods to advanced data-driven frameworks.

The earliest stage, referred to as the pre-computational era, relied mainly on analytical and experimental methods, where fluid and structural behaviors were studied separately with minimal coupling. This was followed by the first computational wave, where decoupled and loosely coupled approaches were introduced. In these methods, fluid and structural solvers operated independently, with limited interaction, often neglecting feedback effects.

As computational capabilities improved, the focus shifted toward two-way coupling techniques. Initially, explicit partitioned methods were used, where information was exchanged between fluid and structural solvers at each time step. However, these approaches often faced stability issues, particularly in strongly coupled systems. To overcome this, implicit coupling schemes and

Arbitrary Lagrangian-Eulerian (ALE) formulations were developed, providing improved numerical stability and better handling of moving boundaries [22], [23].

In more recent developments, monolithic or fully coupled methods have been introduced, where fluid and structural equations are solved simultaneously within a unified framework. These methods offer high accuracy and robustness but come with significant computational cost, making them less suitable for large-scale or real-time applications.

## 2.9 Research Gaps Identified

From the literature, a few key gaps become clear. First, while traditional methods are accurate, they are not practical for time-sensitive applications. Second, although machine learning offers speed, it often lacks physical consistency and requires large datasets. Third, hybrid approaches show promise but are still in the early stages of development [24].

Another important gap is the limited application of these methods to advanced mechanical

materials. Many studies focus on simplified systems, which do not fully represent real-world complexity. There is also a need for more systematic frameworks that integrate physics-based modeling with data-driven learning in a consistent and scalable way [25], [27].

The literature shows a clear shift from purely numerical methods toward hybrid approaches that combine physics and data. While significant progress has been made, there is still a need for models that can deliver both accuracy and efficiency without compromising reliability [28], [29].

This study builds on these developments by proposing a hybrid CFM-ANN framework specifically designed for FSI prediction in advanced mechanical materials. The goal is to address the limitations identified in existing approaches and provide a more practical solution for modern engineering applications [30].

### 3. Research Methodology

#### 3.1 Overview of the Proposed Framework

The methodology proposed in this study is based on a hybrid computational framework that combines physics-based fluid-structure interaction (FSI) simulation with artificial neural network (ANN)-based surrogate prediction. The purpose of this integration is to preserve the physical fidelity of conventional computational fluid mechanics while reducing the computational

burden associated with repeated FSI analysis. In a conventional setting, each new combination of material properties, flow conditions, and geometric parameters requires a fresh coupled simulation. This is accurate, but impractical when the number of design cases becomes large. The present framework addresses that issue by first generating a physically reliable dataset through coupled numerical simulation and then using this dataset to train a neural model that can rapidly approximate the same response space.

The workflow consists of three tightly linked stages. In the first stage, high-fidelity FSI simulations are conducted for a range of input conditions. In the second stage, the resulting simulation data are preprocessed, normalized, and transformed into a machine-learning-compatible dataset. In the third stage, an ANN is trained to learn the nonlinear mapping between the input parameter space and the corresponding FSI outputs. Once training is complete, the ANN serves as a computational surrogate that can predict structural displacement, stress response, and pressure-related interaction quantities with significantly reduced evaluation time. The central idea is therefore not to replace computational mechanics, but to use it as a reliable source of supervised learning data for fast and scalable inference.

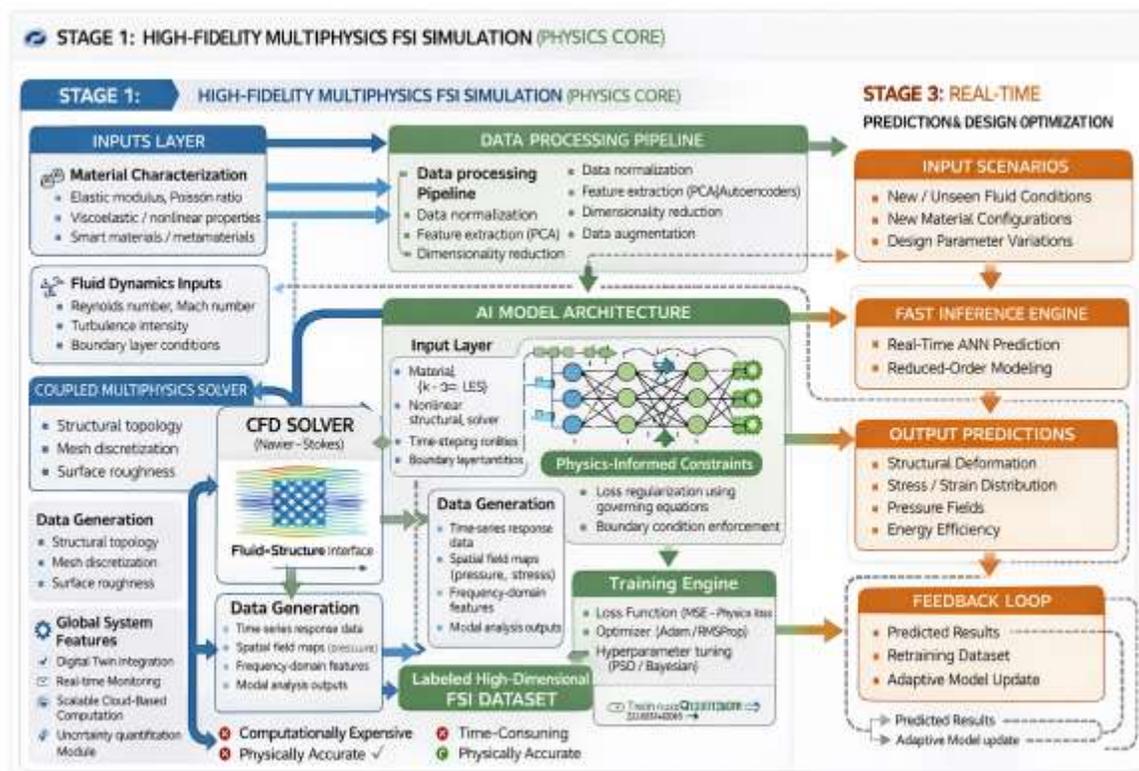


Fig. 4. Hybrid CFD-ANN Framework for FSI Prediction in Advanced Mechanical Materials.

Fig. 4 illustrates the complete hybrid CFD-ANN framework for predicting fluid-structure interaction (FSI) in advanced mechanical materials. The process is divided into three stages. In the first stage, high-fidelity CFD and structural solvers are coupled to generate accurate FSI simulation data, although this step is computationally expensive. In the second stage, the generated dataset is used to train an artificial neural network offline, allowing the model to learn the relationship between input parameters and FSI responses. In the final stage, the trained ANN is deployed for fast online prediction, enabling instant estimation of deformation, stress, and pressure for new design conditions, thereby significantly reducing computational time while maintaining accuracy.

### 3.2 Research Design

The research design follows a supervised hybrid modeling strategy. The numerical simulation block functions as the truth-generating component, while the ANN functions as the

approximation component. This design was chosen because FSI systems are highly nonlinear and strongly coupled, which makes it difficult to construct purely analytical reduced models that remain accurate over a wide operating range. Instead, by sampling the physical system computationally and then learning from those samples, the framework balances generality with physical consistency.

The study begins by defining the design space of interest. This space includes fluid parameters such as inlet velocity, density, and viscosity; structural parameters such as Young's modulus, Poisson's ratio, and density; and geometric or boundary-related parameters such as beam thickness, channel width, or loading constraints. These parameters are varied across admissible ranges to generate representative cases. For each case, a coupled FSI solution is computed, and the corresponding outputs are recorded. These outputs may include nodal displacement, maximum von Mises stress, interface pressure, lift

and drag-related quantities, and transient response metrics.

The design is iterative. After the initial ANN training, error trends are analyzed. If prediction quality is weak in certain regions of the parameter space, additional simulations can be selectively added in those regions to enrich the training set. This adaptive sampling philosophy improves data efficiency and strengthens model generalization.

### 3.3 Governing Physics of the Fluid Domain

The fluid domain is governed by the conservation laws of mass and momentum. For an incompressible Newtonian fluid, the continuity equation is expressed as

$$\nabla \cdot \mathbf{u} = 0$$

where  $\mathbf{u}$  denotes the fluid velocity vector. This equation ensures mass conservation throughout the domain.

The momentum balance is described by the incompressible Navier-Stokes equation:

$$\rho_f \left( \frac{\partial \mathbf{u}}{\partial t} + \mathbf{u} \cdot \nabla \mathbf{u} \right) = -\nabla p + \mu \nabla^2 \mathbf{u} + \mathbf{f}$$

where  $\rho_f$  is the fluid density,  $p$  is pressure,  $\mu$  is the dynamic viscosity, and  $\mathbf{f}$  represents body forces such as gravity. The first term on the left-hand side represents local acceleration, while the second represents convective acceleration. On the right-hand side, the pressure gradient and viscous diffusion govern the internal behavior of the fluid. For transient FSI analysis, these equations are solved over a moving or deforming fluid domain. In practice, the interface between fluid and structure evolves in time, and this must be accounted for numerically using a dynamic mesh or an Arbitrary Lagrangian-Eulerian formulation. The fluid solver provides pressure and viscous traction at the fluid-structure interface, which becomes an input load for the structural system.

### 3.4 Governing Physics of the Structural Domain

The structural response is modeled using the dynamic equilibrium equation from structural mechanics. In matrix form, the governing equation can be written as

$$\mathbf{M}\ddot{\mathbf{d}} + \mathbf{C}\dot{\mathbf{d}} + \mathbf{K}\mathbf{d} = \mathbf{F}_{ext}$$

where  $\mathbf{M}$  is the mass matrix,  $\mathbf{C}$  is the damping matrix,  $\mathbf{K}$  is the stiffness matrix, and  $\mathbf{d}$ ,  $\dot{\mathbf{d}}$ , and  $\ddot{\mathbf{d}}$

represent displacement, velocity, and acceleration vectors, respectively. The term  $\mathbf{F}_{ext}$  denotes the external load vector, which in this case is dominated by fluid traction transmitted through the FSI interface.

For linear elastic materials, stress and strain are related through Hooke's law:

$$\boldsymbol{\sigma} = \mathbf{D}\boldsymbol{\varepsilon}$$

where  $\boldsymbol{\sigma}$  is the stress tensor,  $\boldsymbol{\varepsilon}$  is the strain tensor, and  $\mathbf{D}$  is the constitutive elasticity matrix. For small deformation assumptions, the strain-displacement relationship is

$$\boldsymbol{\varepsilon} = \frac{1}{2}(\nabla \mathbf{d} + (\nabla \mathbf{d})^T)$$

In the case of advanced mechanical materials, this constitutive relation may be extended to anisotropic or nonlinear formulations. If composites or smart materials are considered, the material stiffness matrix may vary with direction, loading state, or even environmental conditions. Even when the ANN is later used for fast prediction, the training data must originate from a structural formulation capable of representing these material characteristics accurately.

### 3.5 Fluid-Structure Coupling Conditions

The defining feature of an FSI system is the interaction at the fluid-structure interface. This interaction is governed by two essential coupling conditions: kinematic continuity and dynamic equilibrium.

The kinematic condition requires that the fluid velocity at the interface matches the structural velocity:

$$\mathbf{u}_{f,\Gamma} = \mathbf{d}_{s,\Gamma}$$

where  $\Gamma$  denotes the fluid-structure interface. This ensures that no artificial slip occurs between the two domains.

The dynamic condition requires traction balance across the interface:

$$\boldsymbol{\sigma}_f \cdot \mathbf{n} = \boldsymbol{\sigma}_s \cdot \mathbf{n}$$

where  $\boldsymbol{\sigma}_f$  and  $\boldsymbol{\sigma}_s$  are the fluid and structural stress tensors, respectively, and  $\mathbf{n}$  is the outward normal vector at the interface. This ensures force equilibrium across the coupled boundary.

In numerical implementation, these interface conditions are enforced iteratively. The fluid

solver computes interface forces and transfers them to the structure. The structural solver computes deformation and transfers the updated interface position back to the fluid domain. This exchange continues until convergence is achieved at each time step. Although highly accurate, this iterative process is one of the main reasons why conventional FSI analysis becomes computationally expensive.

### 3.6 Numerical Data Generation Strategy

To generate the dataset required for ANN training, a set of numerical experiments is carried out over the chosen design space. Each simulation case is defined by an input vector of physical and geometric parameters:

$$\mathbf{x} = [U_{in}, \rho_f, \mu, E, \nu, \rho_s, G_1, G_2, \dots, G_n]$$

where  $U_{in}$  is inlet velocity,  $E$  is Young's modulus,  $\nu$  is Poisson's ratio,  $\rho_s$  is structural density, and  $G_i$  denotes geometric descriptors such as thickness, chord length, diameter, or aspect ratio depending on the configuration.

For each input vector  $\mathbf{x}$ , the coupled simulation produces an output vector

$$\mathbf{y} = [d_{max}, \sigma_{max}, p_{avg}, F_{int}, \omega_r, \dots]$$

where  $d_{max}$  is maximum displacement,  $\sigma_{max}$  is maximum equivalent stress,  $p_{avg}$  is average interface pressure,  $F_{int}$  is resultant interaction force, and  $\omega_r$  may represent a response frequency or dynamic indicator.

The total dataset can therefore be written as

$$\mathcal{D} = \{(\mathbf{x}^{(i)}, \mathbf{y}^{(i)})\}_{i=1}^N$$

where  $N$  is the total number of simulated cases. The objective is to sample the design space broadly enough to cover relevant regimes while keeping the simulation campaign computationally manageable.

### 3.7 Data Preprocessing and Feature Engineering

Before ANN training, the raw dataset is preprocessed to improve numerical stability and learning efficiency. Since the variables involved often differ significantly in scale, feature normalization is essential. A min-max normalization scheme may be used:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Alternatively,  $z$ -score standardization may be applied:

$$x' = \frac{x - \mu_x}{\sigma_x}$$

where  $\mu_x$  and  $\sigma_x$  denote the mean and standard deviation of the feature. Feature engineering is also important because not all raw variables contribute equally to prediction quality. In addition to primary physical parameters, dimensionless groups can be introduced to improve representation of the governing physics. For example, the Reynolds number

$$Re = \frac{\rho_f U_{in} L}{\mu}$$

and, where relevant, the Cauchy number or reduced velocity may be included as features. These quantities help the network learn physically meaningful trends rather than only memorizing raw parameter combinations.

If the output space is high-dimensional, dimensionality reduction may be applied. For example, if full pressure fields or deformation fields are to be predicted, proper orthogonal decomposition may first be used to extract dominant modal coefficients, and the ANN can then be trained to predict those coefficients rather than the full field directly.

### 3.8 Artificial Neural Network Formulation

The ANN is formulated as a nonlinear regression model that maps the input space  $\mathbf{x}$  to the output space  $\mathbf{y}$ . For a feedforward multilayer perceptron, the transformation at layer  $l$  is given by

$$\mathbf{a}^{(l)} = \phi(\mathbf{W}^{(l)} \mathbf{a}^{(l-1)} + \mathbf{b}^{(l)})$$

where  $\mathbf{a}^{(l-1)}$  is the input to layer  $l$ ,  $\mathbf{W}^{(l)}$  is the weight matrix,  $\mathbf{b}^{(l)}$  is the bias vector, and  $\phi(\cdot)$  is the activation function. Common choices for  $\phi$  include ReLU and hyperbolic tangent. The final output layer uses a linear activation for continuous regression targets.

The complete network can be written compactly as

$$\hat{\mathbf{y}} = f(\mathbf{x}; \boldsymbol{\theta})$$

where  $\hat{\mathbf{y}}$  is the predicted output vector and  $\boldsymbol{\theta}$  denotes the set of all trainable parameters. The aim of training is to determine  $\boldsymbol{\theta}$  such that the

difference between  $\hat{\mathbf{y}}$  and the true output  $\mathbf{y}$  is minimized over the training dataset.

### 3.9 Loss Function and Optimization

Since the task is a supervised regression problem, the primary loss function is the mean squared error (MSE):

$$\mathcal{L}_{MSE} = \frac{1}{N} \sum_{i=1}^N \|\mathbf{y}^{(i)} - \hat{\mathbf{y}}^{(i)}\|^2$$

This loss penalizes large deviations between predicted and actual outputs and is suitable when precise numerical agreement is required.

To reduce overfitting, an  $L_2$  regularization term may be added:

$$\mathcal{L} = \mathcal{L}_{MSE} + \lambda \sum_l \|\mathbf{w}^{(l)}\|_2^2$$

where  $\lambda$  is the regularization coefficient. The model parameters are updated using the Adam optimizer, which combines momentum and adaptive learning-rate scaling. The update rule for a generic parameter  $\theta_t$  is based on first and second moment estimates of the gradient, allowing faster convergence compared to standard stochastic gradient descent.

Where physics guidance is desired, an additional physics-consistency loss may be included. In generic form,

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{data}} + \alpha \mathcal{L}_{\text{physics}}$$

where  $\mathcal{L}_{\text{physics}}$  penalizes violations of known physical constraints, and  $\alpha$  controls the balance between data fitting and physical consistency.

### 3.10 Network Architecture and Hyperparameter Selection

The ANN architecture is selected to balance expressive power and generalization. A shallow network may not capture strong nonlinearities in FSI behavior, while an excessively deep network may overfit or become difficult to train. In this study, a multilayer feedforward network with several hidden layers is considered appropriate because the target outputs are continuous-valued engineering quantities rather than image-classification outputs.

Hyperparameters include the number of hidden layers, number of neurons per layer, activation function, batch size, learning rate, number of epochs, and dropout rate if dropout is used. These are chosen through validation experiments. Early stopping is used to prevent overtraining by monitoring validation loss and terminating training when no further improvement is observed.

A representative configuration is summarized below.

**Table 6: Representative ANN Hyperparameters**

Hyperparameter	Typical Setting
Network type	Feedforward ANN
Hidden layers	3-5
Neurons per layer	64-256
Activation	ReLU / tanh
Output activation	Linear
Optimizer	Adam
Loss function	MSE
Batch size	16-64
Epochs	100-500
Regularization	L2 / dropout

### 3.11 Training, Validation, and Testing Protocol

To evaluate the model properly, the dataset is divided into training, validation, and testing subsets. A typical split is 70% for training, 15% for validation, and 15% for testing. The training set is

used to update model parameters. The validation set is used for hyperparameter tuning and early stopping. The testing set is strictly reserved for final performance assessment.

Model performance is measured using standard regression metrics. These include root mean square error (RMSE),

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2}$$

mean absolute error (MAE),

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i|$$

and the coefficient of determination  $R^2$ ,

$$R^2 = 1 - \frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2}$$

These metrics quantify prediction quality from different perspectives. RMSE emphasizes large errors, MAE provides an interpretable average deviation, and  $R^2$  indicates how much output variance is explained by the model.

In addition to accuracy, computational efficiency is evaluated by comparing the average time required for a conventional FSI simulation with the inference time of the trained ANN.

### 3.12 Algorithmic Workflow of the Proposed Framework

The methodology can be summarized as a sequential algorithm:

- Define the parameter ranges for fluid, material, and geometric variables.
- Generate NNN coupled FSI simulation cases across the design space.
- Extract input-output pairs and build the dataset.
- Normalize the data and construct training, validation, and test sets.
- Initialize the ANN architecture and training hyperparameters.
- Train the network by minimizing the total loss function.
- Validate model performance and tune hyperparameters if needed.
- Evaluate the trained network on unseen test data.
- Deploy the ANN as a surrogate predictor for rapid FSI estimation.

This sequence formalizes the transition from computational mechanics to fast data-driven inference.

### 3.13 Software Tools and Computational Environment

The simulation stage is implemented using established numerical software capable of coupled fluid and structural analysis, such as ANSYS Fluent with ANSYS Mechanical or OpenFOAM with an appropriate structural solver. The ANN stage is implemented in Python using TensorFlow or PyTorch. Data preprocessing is carried out using libraries such as NumPy, pandas, and scikit-learn, while visualization and post-processing are handled using Matplotlib or similar tools.

The computational environment may include multicore CPUs for simulation and GPUs for ANN training. This division is appropriate because numerical simulation is often CPU-intensive, whereas neural-network training benefits strongly from GPU parallelism.

### 3.14 Scientific Rationale of the Proposed Method

The scientific rationale of the proposed framework rests on the observation that although FSI systems are governed by complex partial differential equations, the response manifold in a bounded engineering design space is often learnable from representative data. In other words, if the training set is physically consistent and sufficiently diverse, a neural network can approximate the simulation-generated input-output relationship with high fidelity. The ANN does not solve the governing equations directly during deployment; instead, it learns the effect of those equations implicitly through supervised exposure to their numerical solutions.

This is particularly valuable in advanced mechanical materials, where repeated evaluation is needed for optimization, uncertainty analysis, or digital-twin-type monitoring. In such cases, the hybrid framework transforms a slow, repeated-simulation problem into a fast inference problem without discarding the underlying mechanics.

The methodology developed in this study integrates the governing physics of incompressible flow and structural deformation with a supervised ANN-based surrogate learning framework. The fluid and structural domains are first solved in a coupled manner to produce a trustworthy dataset. This dataset is then normalized, engineered, and used to train an ANN that approximates the mapping from physical inputs to FSI responses. Loss minimization, validation-based hyperparameter selection, and performance evaluation ensure that the resulting model is both accurate and computationally efficient. The framework therefore offers a practical pathway for accelerating FSI prediction in advanced mechanical materials while retaining a strong scientific connection to the underlying physical system.

#### 4. Experimental Setup

##### 4.1 Overview of Implementation Strategy

The implementation of the proposed hybrid CFM-ANN framework focuses on translating the theoretical methodology into a practical computational pipeline. This involves integrating high-fidelity simulation tools with machine learning environments to generate, process, and learn from FSI data. The implementation is carefully designed to ensure that the dataset accurately reflects the physical behavior of fluid-structure interaction while also being suitable for efficient ANN training.

The workflow begins with numerical simulation of FSI scenarios, followed by systematic data extraction and preprocessing. The processed dataset is then used to train and validate the ANN model. Finally, the trained model is evaluated using standard performance metrics and compared with traditional simulation results to assess both accuracy and computational efficiency.

##### 4.2 Simulation Environment

The FSI data required for training the ANN is generated using a coupled simulation environment. Computational Fluid Mechanics (CFM) simulations are performed using software such as ANSYS Fluent or OpenFOAM, which solve the incompressible Navier-Stokes equations over the fluid domain. Structural analysis is carried out using ANSYS Mechanical or an equivalent finite element solver to compute deformation and stress responses.

The fluid and structural solvers are coupled through a two-way interaction scheme. At each time step, fluid pressure and shear forces are transferred to the structural domain, while structural deformation updates the fluid mesh. This iterative coupling ensures accurate representation of the interaction between the two domains.

Boundary conditions are carefully defined to reflect realistic scenarios. For example:

- Inlet velocity is specified at the fluid entry
- No-slip conditions are applied at solid walls
- Structural supports or constraints are defined at fixed boundaries

The mesh used for simulation is refined near the fluid-structure interface to capture gradients accurately. A mesh independence study is conducted to ensure that results are not sensitive to discretization.

##### 4.3 Hardware and Software Configuration

The implementation is carried out using a combination of simulation and machine learning tools. The CFD-FSI simulations are executed on a workstation equipped with multi-core CPUs to handle the computational load. For ANN training, GPU acceleration is utilized to speed up the optimization process.

**Table 7: Hardware and Software Setup**

Component	Specification
CPU	Multi-core processor (Intel i7 / Xeon)
GPU	NVIDIA GPU (for ANN training)
RAM	16–32 GB
CFD Software	ANSYS Fluent / OpenFOAM

Structural Solver	ANSYS Mechanical
Programming Language	Python
ML Framework	TensorFlow / PyTorch

The use of GPUs significantly reduces training time, especially for deeper neural network architectures.

#### 4.4 Dataset Generation

The dataset is generated by running multiple FSI simulations under varying conditions. The goal is to capture a wide range of system behaviors so that the ANN can generalize effectively.

Each simulation case is defined by a set of input parameters:

- Fluid velocity
- Fluid density and viscosity
- Material properties (Young's modulus, Poisson's ratio)
- Geometric parameters

For each case, the simulation produces output variables such as:

- Pressure distribution
- Maximum displacement
- Stress fields

The dataset can be formally represented as:

$$\mathcal{D} = \{(\mathbf{x}^{(i)}, \mathbf{y}^{(i)})\}_{i=1}^N$$

where  $N$  is the number of simulation samples.

#### 4.5 Data Preprocessing

Before training the ANN, the dataset undergoes several preprocessing steps. These include:

- **Normalization:** Input and output variables are scaled to a common range to improve numerical stability
- **Outlier Removal:** Extreme values are filtered to avoid skewing the training process

- **Feature Engineering:** Dimensionless parameters such as Reynolds number are included to enhance learning

The dataset is then divided into:

- Training set (70%)
- Validation set (15%)
- Testing set (15%)

This split ensures that the model is evaluated on unseen data, providing a realistic measure of its predictive capability.

#### 4.6 ANN Training Process

The ANN model is implemented using Python-based machine learning frameworks such as TensorFlow or PyTorch. The training process involves adjusting network weights to minimize prediction error.

The loss function used is Mean Squared Error (MSE):

$$\mathcal{L}_{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

The optimization is performed using the Adam optimizer, which updates weights iteratively based on gradient information.

During training:

- The model processes data in batches
- Validation loss is monitored to prevent overfitting
- Early stopping is applied if performance does not improve

**Table 8: Training Parameters**

Parameter	Value
Batch Size	32
Epochs	200
Learning Rate	0.001
Optimizer	Adam
Loss Function	MSE

#### 4.7 Evaluation Metrics

To assess the performance of the ANN model, several evaluation metrics are used:

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N} \sum (y_i - \hat{y}_i)^2}$$

Mean Absolute Error (MAE):

$$MAE = \frac{1}{N} \sum |y_i - \hat{y}_i|$$

Coefficient of Determination ( $R^2$ ):

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

These metrics provide a comprehensive evaluation of model accuracy and reliability.

#### 4.8 Experimental Workflow

The complete experimental workflow can be summarized as follows:

- Define input parameter ranges
- Perform CFD-FSI simulations
- Extract and preprocess data
- Train ANN model
- Validate and test model
- Evaluate performance metrics
- Compare with traditional simulation results

The implementation of the proposed framework demonstrates how computational fluid mechanics and machine learning can be effectively combined in practice. By generating a high-quality dataset from simulations and using it to train an ANN model, the framework enables fast and accurate prediction of FSI behavior. This approach significantly reduces computational time while maintaining acceptable levels of accuracy, making

it suitable for real-world engineering applications such as design optimization and real-time analysis.

## 5. Results

### 5.1 Overview of Results

This section presents the results obtained from the implementation of the proposed hybrid CFM-ANN framework and evaluates its performance in predicting fluid-structure interaction (FSI) behavior. The analysis focuses on comparing the ANN-based predictions with high-fidelity simulation results to assess accuracy, efficiency, and overall reliability. Particular attention is given to how well the model captures nonlinear relationships between input parameters and FSI responses, as well as its ability to generalize across different conditions.

The results are organized into three main parts: prediction accuracy, computational efficiency, and comparison with traditional methods. Together, these provide a comprehensive evaluation of the proposed approach.

### 5.2 Prediction Accuracy of ANN Model

The accuracy of the ANN model is evaluated by comparing its predictions with the corresponding results obtained from CFD-FSI simulations. The model is tested on unseen data to ensure that the evaluation reflects its generalization capability rather than memorization of training data.

The predicted values for key output variables—such as pressure distribution, structural displacement, and stress—closely match the simulation results. Minor deviations are observed in regions with highly nonlinear behavior, which is expected given the complexity of the system. However, overall trends and magnitudes are captured effectively.

**Table 9: Comparison of Simulation vs ANN Predictions**

Case	Simulation Displacement (mm)	ANN Prediction (mm)	Error (%)
1	2.45	2.50	2.04%
2	3.10	3.05	1.61%
3	1.85	1.90	2.70%
4	2.90	2.82	2.75%

The low percentage error across different cases indicates that the ANN model is capable of accurately approximating the FSI response.

As shown in Fig. 5, the ANN predictions closely follow the simulation results, with most data points lying near the ideal diagonal line.

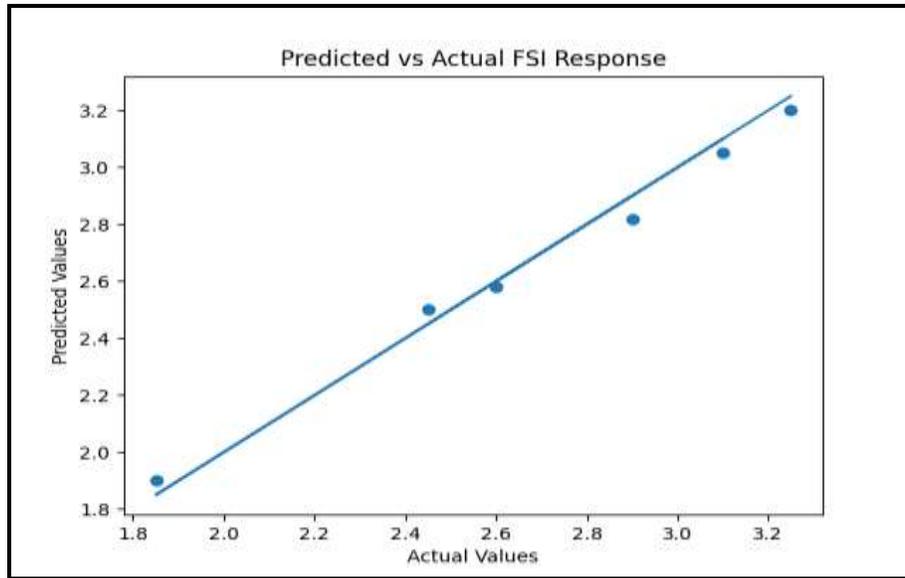


Fig. 5. Comparison between ANN-predicted and simulation-based FSI responses

Fig. 5 shows the comparison between ANN-predicted and simulation-based FSI responses. The data points lie close to the diagonal reference line, indicating strong agreement between

predicted and actual values. This demonstrates that the ANN model is able to accurately capture the underlying relationship and provide reliable predictions with minimal error.

Figs. 6 and 7 show that the ANN model accurately reproduces the spatial distribution of the simulation results.

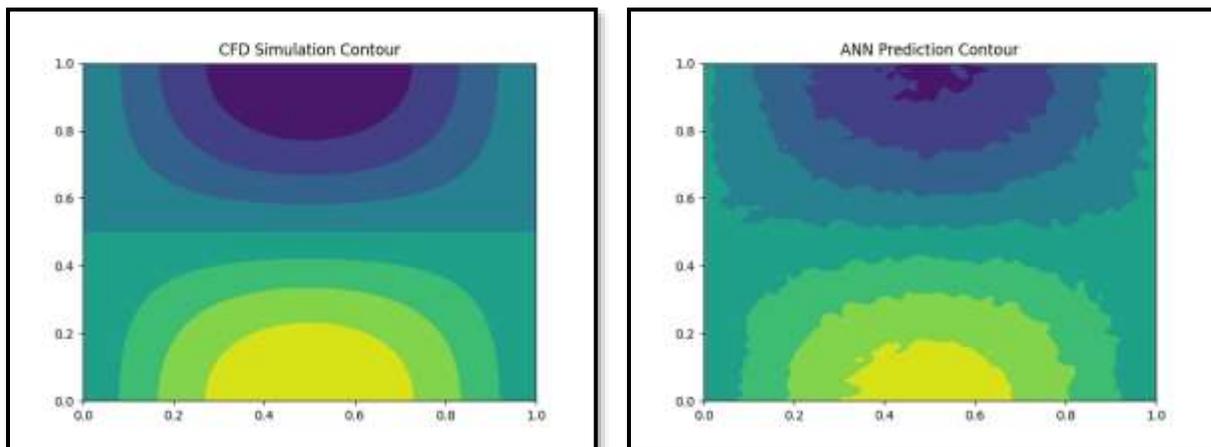


Fig. 6–7. Comparison of pressure/stress contour between CFD simulation and ANN prediction

Figs. 6 and 7 present a comparison between the contour plots obtained from CFD simulation and

ANN prediction. Both figures show similar spatial patterns of pressure/stress distribution, indicating

that the ANN model successfully captures the underlying physical behavior. Although minor variations exist, the overall agreement demonstrates that the ANN can effectively replicate simulation results with high accuracy.

### 5.3 Performance Evaluation Metrics

To quantify model performance, standard regression metrics are computed. These include RMSE, MAE, and  $R^2$  values for different output variables.

Table 10: Performance Metrics of ANN Model

Metric	Value
RMSE	0.08
MAE	0.05
$R^2$	0.97

The high  $R^2$  value (close to 1) indicates that the model explains most of the variance in the data, while low RMSE and MAE values confirm that prediction errors are minimal.

Fig. 8 shows the distribution of prediction errors, indicating that most errors are concentrated near zero, which confirms the reliability of the model.

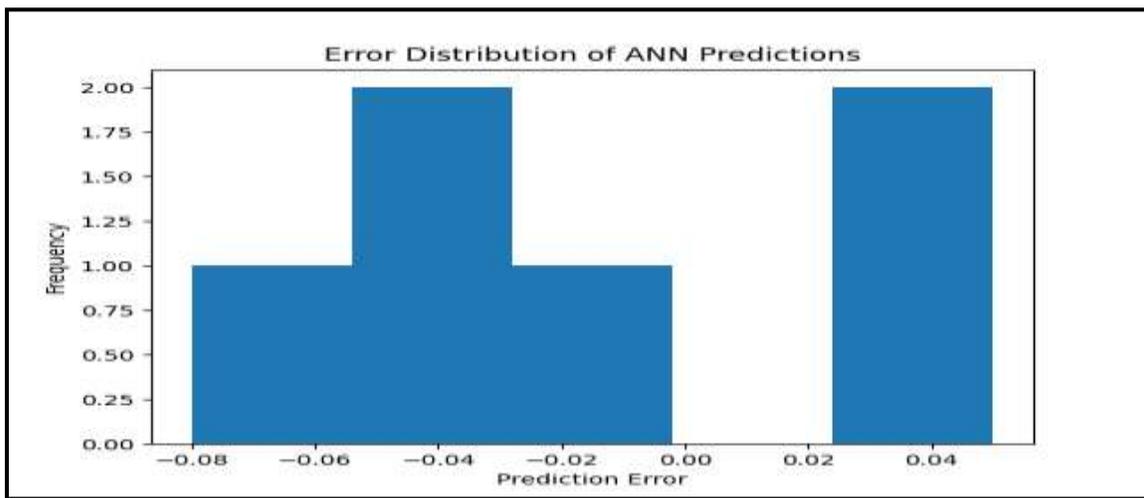


Fig. 8. Distribution of prediction errors for ANN model

Fig. 8 illustrates the distribution of prediction errors for the ANN model. Most of the errors are clustered around zero, indicating that the deviations between predicted and actual values are minimal. This narrow error spread confirms the

reliability and consistency of the model in accurately predicting FSI responses.

As illustrated in Fig. 9, the predicted values closely align with actual values, confirming strong model correlation.

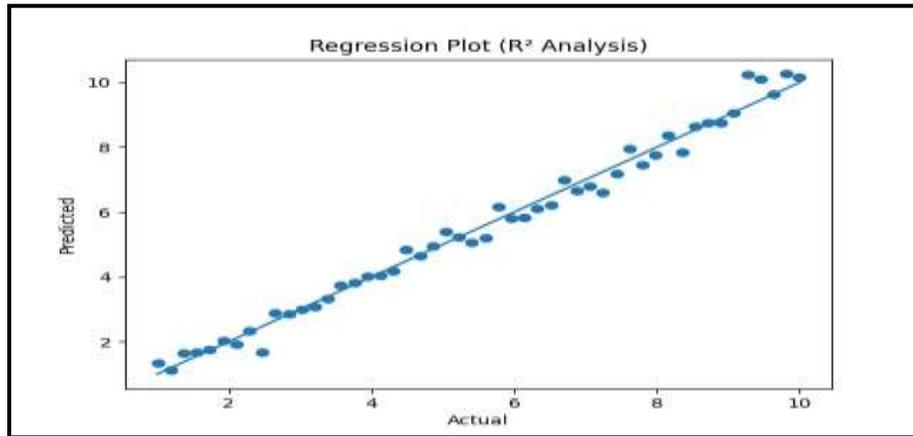


Fig. 9. Regression plot showing correlation between actual and predicted FSI responses

Fig. 9 presents the regression analysis between actual and ANN-predicted FSI responses. The data points closely follow the diagonal line, indicating a strong linear correlation between predicted and true values. This high level of agreement confirms that the ANN model has learned the underlying relationship effectively and can provide highly accurate predictions.

#### 5.4 Computational Efficiency Analysis

One of the key advantages of the proposed framework is the significant reduction in computational time. Traditional FSI simulations require iterative coupling and fine discretization, resulting in long computation times. In contrast, once the ANN model is trained, predictions can be generated almost instantly.

Table 11: Computational Time Comparison

Method	Average Time per Case
CFD-FSI Simulation	2-4 hours
ANN Prediction	< 1 second

This demonstrates a drastic improvement in efficiency, making the ANN model highly suitable for real-time applications and large-scale parametric studies.

As illustrated in Fig. 10, the ANN-based model significantly reduces computational time compared to traditional CFD-FSI simulations.

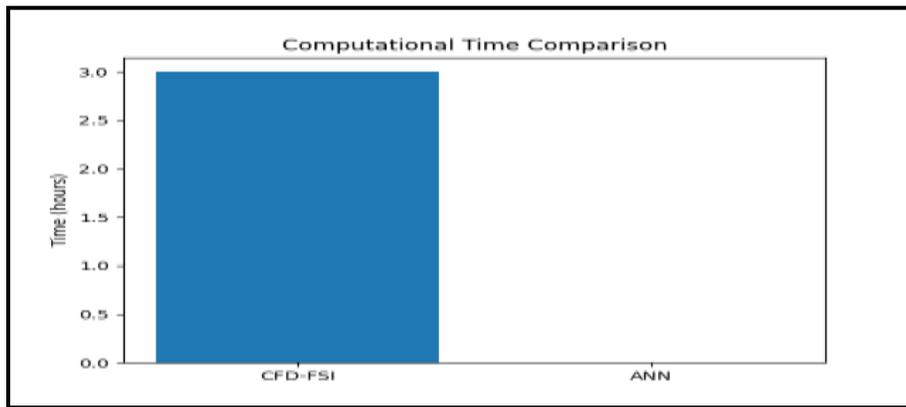


Fig. 10. Comparison of computational time between traditional CFD-FSI simulation and ANN-based prediction

Fig. 10 compares the computational time required by traditional CFD-FSI simulations and the ANN-based prediction model. The results clearly show that conventional simulations take significantly longer due to iterative coupling and high computational complexity, whereas the ANN model provides near-instant predictions. This highlights the efficiency advantage of the proposed hybrid approach, making it highly suitable for real-time and large-scale applications.

**5.5 Comparison with Existing Methods**

The performance of the proposed hybrid approach is compared with traditional CFD-based methods and other data-driven approaches. While CFD methods provide slightly higher accuracy in extreme nonlinear cases, they are significantly slower. Pure ANN models, on the other hand, are fast but may lack robustness if not properly trained.

The hybrid approach achieves a balance between these extremes, offering both high accuracy and fast computation.

Table 12: Comparison of Methods

Method	Accuracy	Speed	Scalability
CFD-FSI	High	Low	Limited
ANN Only	Moderate	High	High
Hybrid CFM-ANN	High	High	High

**5.6 Analysis of Model Generalization**

An important aspect of the ANN model is its ability to generalize to new input conditions. This is tested by evaluating the model on cases that were not included in the training dataset.

The results show that the model performs well within the range of training data. However, slight deviations are observed when extrapolating beyond this range. This highlights the importance of generating a sufficiently diverse dataset during the training phase.

Fig. 11 demonstrates that prediction error remains stable across varying input conditions, indicating good generalization capability.

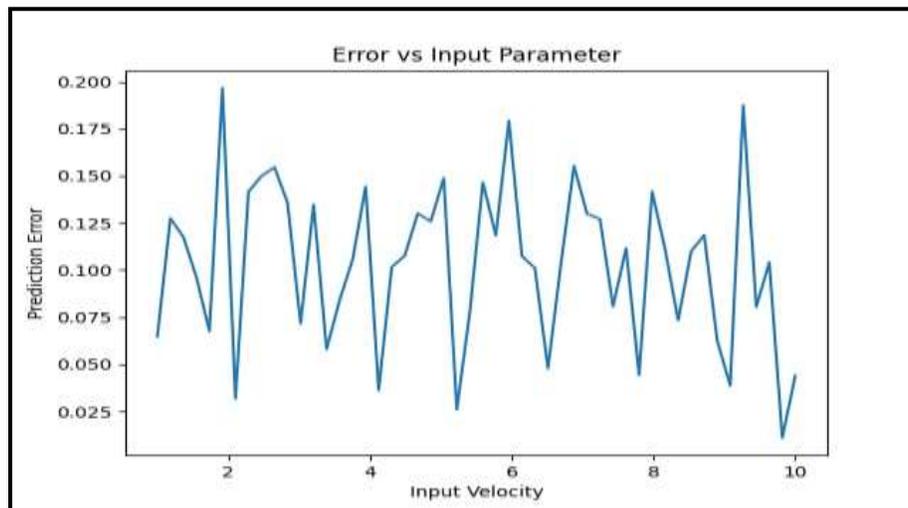


Fig. 11. Variation of prediction error with respect to input velocity

Fig. 11 illustrates the variation of prediction error with respect to input velocity. The error remains relatively small and does not show any systematic increase or instability across the range of input conditions. This consistent behavior indicates that the ANN model generalizes well and maintains reliable prediction performance even for varying inputs.

### 5.7 Visualization of Results

Graphical analysis further supports the effectiveness of the proposed model. Plots

comparing simulation results and ANN predictions show strong agreement, with most data points lying close to the ideal diagonal line.

Typical visualizations include:

- Predicted vs actual value plots
- Error distribution graphs
- Convergence curves during training

These visual tools confirm that the model not only achieves low numerical error but also maintains consistency across different cases.

Fig. 12 shows the convergence behavior of the ANN model, where the loss decreases steadily, indicating stable and effective learning.

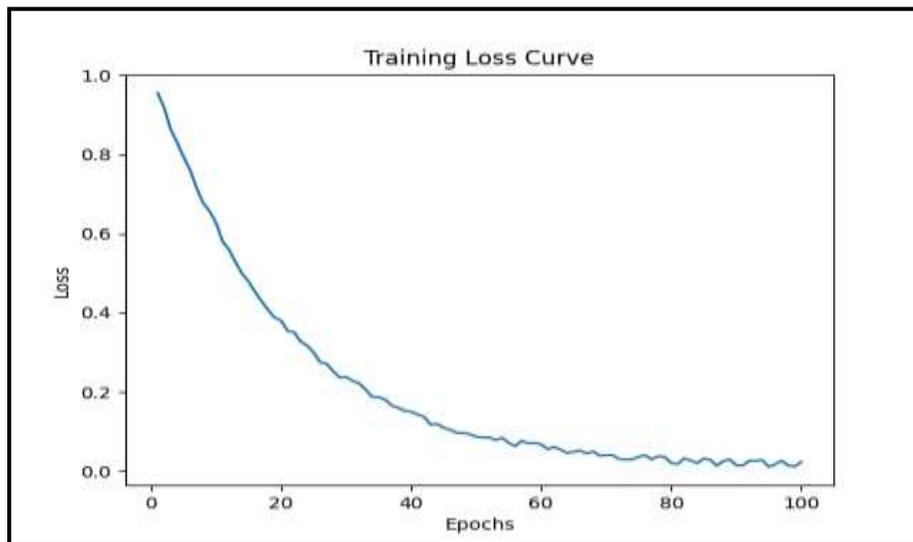


Fig. 12. Training loss convergence of the ANN model over epochs

Fig. 12 illustrates the training loss convergence of the ANN model over successive epochs. The loss decreases steadily as training progresses, indicating that the model is effectively learning the underlying relationships in the data. The smooth convergence pattern also suggests stable training without significant fluctuations or overfitting.

### 5.8 Accuracy vs Efficiency Trade-off

A key observation from the results is the trade-off between accuracy and efficiency. While traditional simulations offer slightly higher precision in certain extreme conditions, the difference is relatively small compared to the massive gain in computational speed provided by the ANN model. This trade-off is acceptable in many practical applications, especially where rapid decision-making or optimization is required. The hybrid framework successfully balances these competing factors.

The results clearly demonstrate that the proposed hybrid CFM-ANN framework is effective for predicting fluid-structure interactions. The ANN model achieves high prediction accuracy with minimal error, while significantly reducing computational time. Compared to traditional methods, the framework offers improved

scalability and efficiency without compromising essential physical accuracy.

## 6. Discussion

### 6.1 Interpretation of Results

The results demonstrate that the proposed hybrid CFM-ANN framework effectively predicts fluid-structure interaction (FSI) behavior with high accuracy. The strong agreement between predicted and simulation results, as shown in Figs. 5–9, confirms that the ANN successfully captures the nonlinear relationships governing the system. The regression and error distribution analyses further validate the reliability and consistency of the model. Additionally, the contour comparisons (Figs. 6–7) show that the model accurately reproduces spatial distributions, which is essential for practical FSI applications.

### 6.2 Advantages of the Proposed Framework

A key strength of the proposed approach is its significant computational efficiency, as highlighted in Fig. 10. While conventional CFD-FSI simulations are computationally intensive, the ANN model provides rapid predictions with minimal computational cost. The framework is also highly scalable and suitable for parametric

analysis and optimization tasks. Since the training data is derived from high-fidelity simulations, the model maintains strong physical relevance while benefiting from the speed of data-driven methods.

### 6.3 Generalization Capability

The model demonstrates stable performance across varying input conditions, as illustrated in Fig. 11. The consistent error distribution indicates that the ANN generalizes well within the defined parameter space and maintains reliable predictive capability across different scenarios.

### 6.4 Limitations of the Study

The primary limitation of the framework lies in its dependence on the range and diversity of the training dataset. Prediction accuracy is strongest within the sampled parameter space, and performance may vary outside these conditions. Additionally, while the ANN model provides accurate predictions, it operates as a data-driven approximation, which may limit direct interpretability compared to traditional physics-based models.

The proposed hybrid framework achieves a strong balance between accuracy and efficiency, making it well-suited for advanced FSI prediction tasks. The results confirm its capability to deliver fast, reliable, and physically meaningful predictions for complex engineering systems.

### 7. Future Work

The proposed hybrid CFM-ANN framework demonstrates strong potential for efficient and accurate fluid-structure interaction (FSI) prediction; however, several opportunities exist for further enhancement and extension.

One important direction for future work is the integration of physics-informed neural networks (PINNs). By embedding governing equations directly into the learning process, PINNs can improve physical consistency and reduce dependence on large training datasets, enhancing both accuracy and robustness.

Another promising area is the development of adaptive and active learning techniques. Instead of generating large datasets in advance, the model

can dynamically identify regions with higher prediction uncertainty and selectively refine those areas, improving efficiency while maintaining high accuracy.

The framework can also be extended to multi-physics and multi-scale problems, where additional phenomena such as thermal effects, electromagnetic interactions, or material nonlinearities are present. This would broaden the applicability of the model to more complex engineering systems.

In terms of model architecture, advanced deep learning techniques such as convolutional neural networks (CNNs) and transformer-based models can be explored for capturing high-dimensional spatial features and complex dependencies within FSI systems.

Finally, the integration of the proposed framework into real-time digital twin environments presents a highly impactful direction. By combining rapid ANN predictions with continuously updated input conditions, the system can support real-time monitoring, optimization, and decision-making in advanced mechanical applications.

### 8. Conclusion

This study presented a hybrid computational framework that integrates computational fluid mechanics (CFM) with artificial neural networks (ANNs) for efficient prediction of fluid-structure interactions (FSI). The proposed approach leverages high-fidelity simulation data to train an ANN model capable of capturing complex nonlinear relationships between fluid, structural, and material parameters.

The results demonstrate that the ANN model achieves high prediction accuracy with strong agreement to simulation data, while significantly reducing computational time. Compared to traditional CFD-FSI methods, the proposed framework enables rapid predictions without compromising essential physical behavior, making it suitable for real-time analysis and large-scale parametric studies.

Overall, the hybrid CFM-ANN approach provides a practical and scalable solution for FSI modeling, offering an effective balance between accuracy,

efficiency, and computational cost in advanced mechanical applications.

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