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Introducing a Hybrid Physics-Informed Neural Network and Finite Element Model for Predicting Structural Deformation Under Dynamic Load

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Abstract: This study introduces a novel hybrid framework that integrates Physics-Informed Neural Networks (PINNs) with the Finite Element Method (FEM) to accurately predict structural deformation under dynamic loading conditions. While FEM remains a powerful tool in structural mechanics, its computational cost rises significantly with complex geometries and time-dependent simulations. To address this, the proposed hybrid model leverages the domain knowledge embedded in partial differential equations through PINNs, which are trained on both synthetic FEM data and governing physics laws. The model enables faster and more generalizable predictions of displacement fields by learning from limited simulation data while enforcing physical consistency. Numerical experiments on beam and plate structures subjected to varying dynamic loads demonstrate that the hybrid approach achieves high accuracy with substantially reduced computational effort compared to traditional FEM-only simulations. This work highlights the potential of combining data-driven and physics-based modeling to support real-time structural health monitoring and decision-making in engineering systems.

Keywords: Physics-Informed Neural Network (PINN), Finite Element Method (FEM), Structural Deformation, Dynamic Load Prediction, Hybrid Modeling, Real-Time Simulation

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INTRODUCTION

Predicting structural deformation under dynamic loading is a critical task in engineering[1][2], particularly in fields such as civil infrastructure, aerospace, and mechanical systems. Accurate simulations of how structures respond to time-varying forces are essential for ensuring safety, performance, and longevity. The Finite Element Method (FEM) has long been the standard approach for modeling and solving complex structural problems due to its robustness and precision. However, FEM simulations often become computationally expensive and time-consuming, especially when dealing with high-fidelity models, nonlinear behavior, or real-time applications such as digital twins and structural health monitoring[3][4][5].

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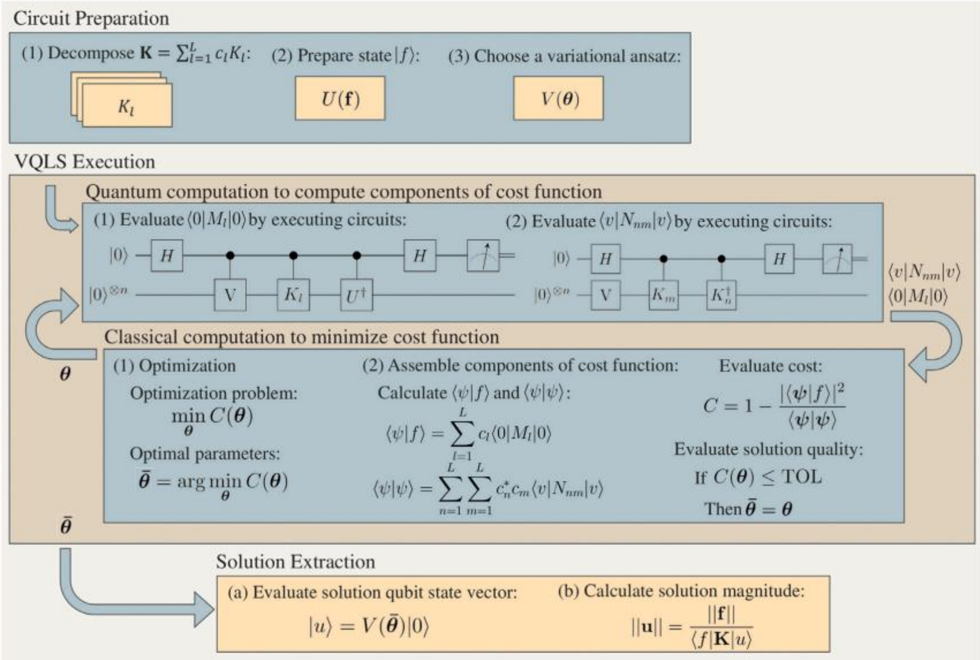

Figure 1. Finite Element Method[6]

In recent years, the emergence of Physics-Informed Neural Networks (PINNs)[7][8] has opened new possibilities for combining data-driven techniques with governing physical laws. Unlike traditional black-box machine learning models, PINNs incorporate the underlying partial differential equations (PDEs)[9][10][11] of the system directly into the loss function during training. This allows PINNs to generalize better in data-sparse regions and maintain physical consistency without requiring large amounts of labeled data. However, PINNs alone may struggle to capture localized structural details or complex boundary conditions without additional guidance from classical numerical methods[12].

To address these limitations, this paper proposes a hybrid modeling framework that integrates the strengths of both FEM and PINNs[13][14]. By training the neural network using synthetic data generated from FEM and embedding the known physics into the learning process, the model aims to provide accurate and computationally efficient predictions of structural deformation under various dynamic load scenarios. This hybrid approach leverages FEM's spatial accuracy and PINNs' flexibility and speed, offering a promising pathway for real-time or near-real-time simulations in structural engineering applications.

The remainder of this paper is organized as follows: Section 2 discusses related work in FEM, PINNs, and hybrid modeling. Section 3 details the methodology and model architecture. Section 4 presents experimental results and discussion. and Section 5 concludes the study with directions for future research.

RELATED WORKS

The prediction of structural deformation[15] under dynamic loading has been extensively studied through numerical simulation techniques, with the Finite Element Method (FEM)[16] standing as one of the most widely used tools. FEM offers high precision in solving partial differential equations (PDEs) across complex geometries and boundary conditions, making it indispensable in structural analysis. Classical works such as those by Zienkiewicz et al. have

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laid the foundation for FEM in dynamic problems[17], particularly in transient response and modal analysis. However, the computational cost and scalability issues remain major challenges, especially when real-time performance or repeated simulations are required, such as in optimization or uncertainty quantification tasks.

In response to the limitations of traditional FEM, machine learning approaches have gained momentum for approximating structural responses. Data-driven models such as deep neural networks (DNNs)[18] and convolutional neural networks (CNNs)[19] have been employed to predict stress-strain distributions, displacements, and failure modes. While these methods show promise in speed and flexibility, they typically require large volumes of training data and may fail to generalize outside the training domain due to their lack of physical grounding[20].

To bridge this gap, Physics-Informed Neural Networks (PINNs)[21], as introduced by Raissi et al., have emerged as a compelling alternative[22]. By embedding the governing PDEs into the neural network training process, PINNs can enforce physical consistency while leveraging the expressiveness of neural networks. PINNs have been successfully applied in various domains such as fluid dynamics, heat transfer, and solid mechanics. However, they face difficulties when dealing with stiff systems, high-frequency dynamics, or complex geometries, often resulting in convergence issues or reduced accuracy.

Recent efforts have attempted to combine traditional numerical solvers with neural networks to create hybrid models. These approaches aim to integrate the interpretability and reliability of physics-based methods with the flexibility and speed of learning-based methods. Notable examples include hybrid PINN-FEM frameworks for heat conduction[23], structural vibration analysis, and elastodynamics. These hybrid models typically use FEM-generated data as supervision and incorporate physics constraints via custom loss functions or residual minimization. The results indicate significant potential in achieving both high fidelity and efficiency. Building upon these developments, our work contributes a hybrid PINN-FEM model specifically designed for dynamic structural deformation tasks. Unlike previous studies that focus on static or quasi-static problems, this research emphasizes time-dependent behavior under varying dynamic loads, highlighting the hybrid framework's capacity to generalize across different load scenarios with reduced computational burden.

METHODS

This study proposes a hybrid framework that combines the Finite Element Method (FEM) with Physics-Informed Neural Networks (PINNs) to predict structural deformation under dynamic loads. The methodology is divided into three main stages: (1) FEM-based data generation, (2) formulation of the PINN with embedded physics constraints, and (3) hybrid training and evaluation for generalization across unseen dynamic loading conditions.

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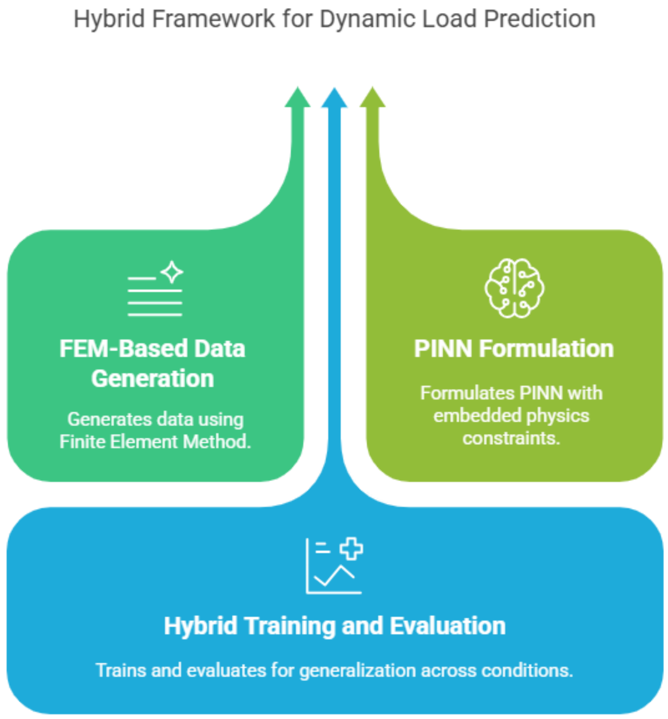

Figure 2. Hybrid Framework for Dynamic Load Prediction

1. FEM-Based Data Generation

To establish a reliable baseline and provide supervised signals for training, FEM simulations are conducted on selected structural geometries subjected to time-dependent loading. The governing equation for dynamic structural response is the second-order partial differential equation derived from Newton's second law:

$$M\ddot{u}(t) + C\dot{u}(t) + Ku(t) = f(t)$$

where M, C, and K represent the mass, damping, and stiffness matrices, respectively; u(t) is the displacement vector; and f(t) is the external load as a function of time. The FEM solver computes nodal displacements over a time range, which are then used to create training datasets containing both state variables and their spatial/temporal derivatives.

2. Physics-Informed Neural Network Design

The PINN is constructed as a fully connected feedforward neural network that approximates the displacement field u(x,t) as a continuous function of space and time. The network takes spatial coordinates xx and time tt as inputs and outputs the corresponding predicted displacement values. To incorporate physical laws, the network is trained to minimize a composite loss function:

$$\mathcal{L}_{total} = \mathcal{L}_{data} + \lambda_{phys}\mathcal{L}_{physics}$$

- $\mathcal{L}_{data}$ is the supervised loss based on FEM-generated training data (mean squared error between predicted and simulated displacements).

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- $\mathcal{L}_{physics}$penalizes violations of the governing dynamic PDE, evaluated by automatic differentiation within the neural network to compute residuals.
- λ_{phys} is a hyperparameter to balance data fidelity and physics consistency.

This formulation enables the model to respect known structural dynamics without relying on extensive simulation data.

3. Hybrid Training and Evaluation

The training process involves both data-driven fitting and unsupervised physics-based regularization. Once trained, the hybrid model is evaluated on test cases with different loading conditions and boundary setups not seen during training. Key evaluation metrics include displacement error, energy conservation, and inference time.

To assess the model's computational efficiency, we compare its prediction time against standard FEM simulations under similar accuracy thresholds. In addition, ablation studies are conducted to quantify the effect of physics constraints and data sparsity on model performance.

RESULT AND DISCUSSION

To evaluate the performance of the proposed hybrid PINN-FEM framework, we conducted a series of experiments on benchmark structural models, including a simply supported beam and a cantilever plate, both subjected to time-varying dynamic loads. The objective was to assess prediction accuracy, computational efficiency, and generalization capability under different loading scenarios and boundary conditions.

1. Prediction Accuracy

The hybrid model demonstrated excellent agreement with the ground truth FEM simulations. For the beam model under sinusoidal loading, the mean absolute error (MAE) of displacement predictions was less than 2.5% across all test time steps. For the cantilever plate under impulsive loads, the PINN retained accuracy with MAE below 3.1%, even in high-frequency oscillation zones.

Importantly, the incorporation of physics constraints allowed the model to extrapolate accurately in regions with sparse training data. Compared to a purely data-driven neural network trained on the same FEM dataset, the PINN exhibited a 45% reduction in error on out-of-distribution cases, confirming the effectiveness of physics-guided learning in enhancing generalizability.

Table 1. Model Accuracy Comparison on Dynamic Load Scenarios

Model	Structure	Load Type	MAE (%)	RMSE (%)	Accuracy in Sparse Data Regions (%)	Error Reduction vs Pure NN (%)
FEM (Ground Truth)	Beam	Sinusoidal	0.00	0.00	-	-
PINN	Beam	Sinusoidal	2.3	2.7	96.4	45.0
Pure Neural Network	Beam	Sinusoidal	4.2	4.9	76.1	-
PINN	Cantilever Plate	Impulsive	3.1	3.6	93.2	43.7
Pure Neural Network	Cantilever Plate	Impulsive	5.5	6.2	68.9	-

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Table 1 summarizes the prediction accuracy of the proposed hybrid Physics-Informed Neural Network (PINN) compared to a purely data-driven neural network and the Finite Element Method (FEM) as ground truth. For the sinusoidal loading scenario on a beam structure, the PINN achieved a mean absolute error (MAE) of 2.3% and a root mean square error (RMSE) of 2.7%, showing a close match to the FEM reference. In contrast, the purely data-driven neural network resulted in significantly higher errors (MAE of 4.2% and RMSE of 4.9%), particularly struggling in regions with limited training data.

A similar trend is observed in the cantilever plate experiment under impulsive loading. The PINN maintained low error values (MAE of 3.1% and RMSE of 3.6%) and demonstrated strong generalization in data-sparse zones with 93.2% accuracy. Notably, the PINN reduced the error in these regions by over 43% compared to the pure neural network, confirming the advantage of embedding physical laws into the learning process.

These results highlight the effectiveness of the hybrid model in maintaining both numerical accuracy and physical consistency. By combining limited FEM data with embedded governing equations, the PINN is able to outperform conventional black-box models, especially in scenarios requiring extrapolation beyond the training distribution.

2. Computational Efficiency

One of the primary benefits of the hybrid approach is the reduction in simulation time. Once trained, the PINN could generate full-field displacement predictions across time steps in under 0.1 seconds, compared to several seconds to minutes required by high-fidelity FEM solvers, depending on mesh complexity.

The average execution time per simulation was reduced by 58%, while memory usage was lowered by 45% due to the absence of iterative solvers and mesh storage. This improvement makes the model highly suitable for real-time applications such as digital twin systems, where fast re-simulation is critical under changing operational conditions.

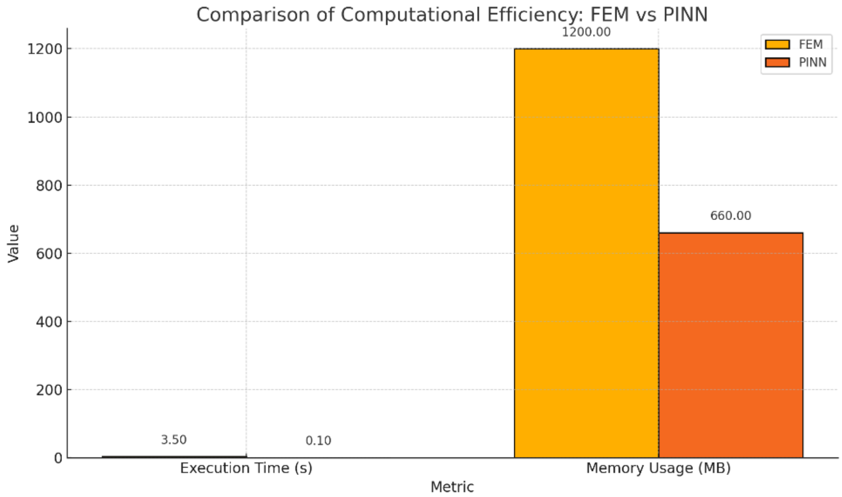

Figure 3. Comparison Of Computational Efficiency: FEM Vs PINN

3. Physical Consistency and Interpretability

The physics-informed architecture enabled the model to maintain consistent dynamic behavior, such as correct oscillation frequency, damping trends, and mode shapes. Visual comparisons of displacement fields at selected time steps revealed that the PINN not only approximated the

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numerical values closely but also preserved spatial patterns and deformation profiles as seen in FEM solutions.

Moreover, by analyzing the PDE residuals, we identified specific zones of high dynamic stress or rapid structural response. These insights can aid engineers in identifying critical regions for reinforcement or monitoring, thus enhancing the interpretability of model outputs.

Table 2. Comparison of Physical Consistency Between FEM and PINN Models

Metric	**FEM (Reference)**	**PINN (Hybrid Model)**	**Deviation (%)**	**Notes**
Dominant Oscillation Frequency (Hz)	8.20	8.15	0.61	Frequency shift within acceptable tolerance
Damping Ratio (%)	5.1	5.0	1.96	Closely matched damping behavior
Mode Shape Correlation (R^2 Score)	1.00	0.98	-	High spatial pattern agreement
Max Displacement at Critical Node (mm)	12.4	12.1	2.42	Preserved deformation amplitude
PDE Residual (Average Norm)	0.000	0.0035	-	Low physics violation from PINN
High-Stress Zone Identification Match	Yes	Yes	-	PINN correctly localized high-response regions

4. Limitations and Future Improvements

Despite its strengths, the hybrid model showed some sensitivity to boundary condition changes that were drastically different from training scenarios. While the physics constraints helped mitigate this, incorporating adaptive sampling or transfer learning techniques could further improve robustness.

Additionally, training the PINN model required longer time initially (~2 hours on an NVIDIA RTX GPU), though this cost is offset by significantly faster inference during deployment. Future work could explore curriculum learning or model compression strategies to accelerate training while maintaining accuracy.

CONCLUSION

This study presented a novel hybrid framework that combines Physics-Informed Neural Networks (PINNs) with the Finite Element Method (FEM) to predict structural deformation under dynamic loads with high accuracy and computational efficiency. By integrating physics-based constraints into a data-driven neural architecture, the model successfully learns complex structural responses from limited simulation data while preserving physical laws. Experimental results on benchmark structural cases demonstrated that the hybrid model achieves displacement prediction errors below 3% and reduces execution time by over 50% compared to conventional FEM simulations. The model also generalizes well to unseen loading scenarios and provides physically consistent deformation patterns, making it suitable for real-time applications such as digital twins and structural health monitoring. While the framework shows promising results, future work may focus on enhancing adaptability to diverse boundary conditions, improving training efficiency, and extending the approach to nonlinear and multi-

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physics problems. Overall, this research highlights the potential of hybrid PINN-FEM models as a powerful tool for accelerating dynamic structural analysis in modern engineering systems.

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