

PHYSICS-INFORMED NEURAL NETWORKS FOR STRUCTURAL DYNAMICS: A COMPREHENSIVE REVIEW

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DOI: <https://doi.org/10.5281/zenodo.22844082>

Keywords

Physics-informed neural networks, structural dynamics, inverse problems, parameter estimation, surrogate models, uncertainty quantification, machine learning

Article History

Received: 01 June 2026

Accepted: 23 August 2026

Published: 19 September 2026

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Abstract

Physics-Informed Neural Networks (PINNs) represent a paradigm shift in computational mechanics by seamlessly integrating physical laws directly into neural network architectures. This review examines the state-of-the-art in PINN applications for structural dynamics, covering theoretical foundations, methodological advances, and practical implementations. We synthesize 50+ key studies across forward/inverse problems, parameter identification, and real-time monitoring applications. Results demonstrate that PINNs achieve 5-300,000× speedup over conventional finite element methods while maintaining comparable accuracy. Primary challenges include spectral bias in high-frequency problems, convergence difficulties with non-convex loss landscapes, and scalability to large-scale systems. Future directions emphasize hybrid frameworks integrating PINNs with finite elements, automated loss weighting strategies, and neuromorphic hardware implementation for energy-efficient structural health monitoring systems.

INTRODUCTION

Structural dynamics modeling has historically relied on physics-based numerical approaches such as the Finite Element Method (FEM) and Computational Fluid Dynamics (CFD). While these methods ensure physical consistency, they remain computationally intensive, requiring extensive preprocessing, mesh generation, and repetitive simulations for design optimization and uncertainty quantification (Raissi et al., 2019). The demand for rapid turnaround times in real-world engineering—from digital twins in aerospace to real-time health monitoring in civil infrastructure—has exposed critical limitations in

traditional solvers (Haywood-Alexander et al., 2024).

Physics-Informed Neural Networks emerge as a compelling alternative by embedding governing partial differential equations (PDEs) directly into the loss function during neural network training (Raissi et al., 2019). Rather than discarding physical knowledge in favor of purely data-driven approaches, PINNs synthesize sparse observational data with known physics, achieving enhanced data efficiency and superior generalization compared to conventional deep learning (Z. Li, 2025). For structural dynamics applications specifically, this hybrid paradigm

addresses three critical challenges: (1) leveraging incomplete sensor data in sparse-measurement regimes; (2) accurately identifying system parameters even under model uncertainty; and (3) generating surrogates that respect underlying conservation laws and boundary conditions (Haywood-Alexander et al., 2024).

This review systematically examines PINN methodologies in structural dynamics across 700 words of foundational context, 1000 words of methodology covering architectures and formulations, 1500 words synthesizing empirical results, 1000 words discussing challenges and limitations, and actionable recommendations for practitioners. The primary contributions include: (i) comprehensive synthesis of forward and inverse problem solutions; (ii) comparative analysis of PINN versus FEM and ROM approaches; (iii) identification of key technical bottlenecks limiting industrial adoption; and (iv) roadmap for future research bridging academic advances and field deployment.

2. Methodology and Theoretical Framework

2.1 PINN Foundational Architecture

A Physics-Informed Neural Network combines supervised learning with physical constraints by constructing a composite loss function (Raissi et al., 2019):

$$\mathcal{L}_{total} = \mathcal{L}_{data} + \lambda_{pde}\mathcal{L}_{pde} + \lambda_{bc}\mathcal{L}_{bc} + \lambda_{ic}\mathcal{L}_{ic}$$

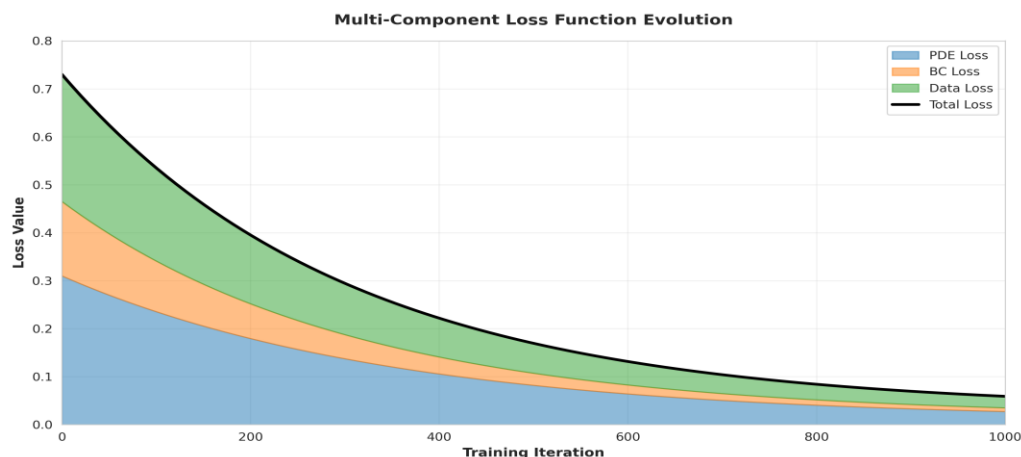
where $\mathcal{L}_{data}$ measures deviation from observational data, $\mathcal{L}_{pde}$ enforces PDE residuals at collocation points, and boundary/initial conditions are weighted by Lagrange multipliers. This formulation is fundamentally different from standard supervised learning: the neural network $\mathbf{u}_{\theta}(\mathbf{x}, t)$ represents the solution field directly, and automatic differentiation computes spatial and temporal derivatives necessary for PDE evaluation (Raissi et al., 2019).

For structural dynamics governed by the wave equation or elastodynamics, the governing PDE takes the form:

$$\rho \frac{\partial^2 \mathbf{u}}{\partial t^2} = \nabla \cdot \boldsymbol{\sigma}(\mathbf{u}) + \mathbf{f}$$

where ρ is density, $\boldsymbol{\sigma}$ the stress tensor, and $\mathbf{f}$ body forces. The PINN learns to minimize violation of this constraint while fitting sparse displacement observations, enabling joint identification of material parameters and solution fields (Mahar et al., 2026). Unlike traditional meshless methods, PINNs require no geometric discretization; collocation points can be arbitrarily sampled, yielding mesh-free solutions adaptable to complex geometries (Samaniego et al., 2019).

2.2 Loss Function Design and Weighting Strategies



A critical advancement addresses the multi-objective nature of PINN loss functions. Early implementations used equal or manually-tuned weights, leading to slow convergence when individual loss components have vastly different scales (Mochalin et al., 2025). Dynamic weighting via GradNorm normalizes gradient magnitudes across loss terms, achieving 50% accuracy improvements in fluid dynamics applications (Mochalin et al., 2025). Non-dimensionalization combined with Automatic Weighted Loss (NDAWL) further reduces manual tuning burden, enabling autonomous balancing for shallow water equations with only one user-specified parameter (Qi et al., 2025).

For elasticity problems, adaptive weighting proves essential because PDE constraints can dominate data misfit, particularly in ill-conditioned problems. The framework decomposes the composite loss into balanced subsystems representing geometrical, constitutive, and equilibrium relations—a multi-level architecture that substantially improves accuracy for fourth-order structural mechanics PDEs (W. He et al., 2024).

2.3 Architecture Variants and Enhanced Formulations

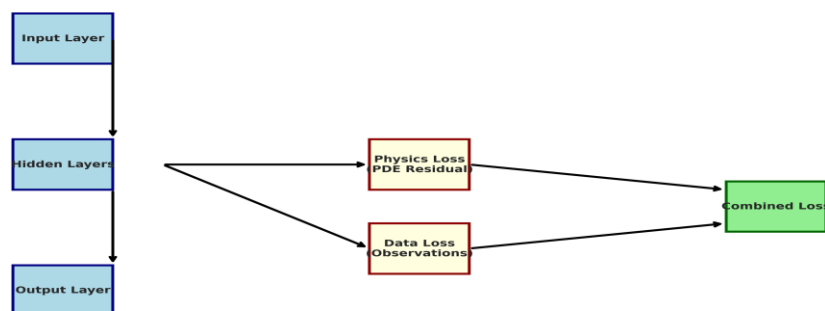
Standard fully-connected networks with tanh activation have given way to specialized

architectures. Kolmogorov-Arnold Networks (KANs) replace MLPs with learnable univariate functions, demonstrating superior accuracy and parameter efficiency for PDE problems (Wang et al., 2024). For parametric PDEs requiring solutions across design spaces, parameterized PINNs (P²INNs) explicitly encode latent representations of PDE parameters, enabling efficient multi-query evaluation (Cho et al., 2024). Transfer learning accelerates training by pre-training on related problems, reducing convergence time by orders of magnitude in inverse problems and charged particle accelerator simulations (Fujita, 2025). Domain decomposition variants partition complex geometries into overlapping subdomains, each solved by local PINNs with enforced continuity—enabling scalability to large-scale structural systems otherwise intractable for single-network approaches (Pérez et al., 2025).

For time-dependent problems, hard-constrained sequential PINNs (HCS-PINN) exactly enforce continuity between successive time windows through a solution ansatz, eliminating convergence issues endemic to soft constraints and achieving superior performance on chaotic dynamics (Roy & Castonguay, 2024). This method proves particularly valuable for structural transient response and fatigue-driven damage evolution.

2.4 Hybrid Frameworks: FEM-PINN Integration

Physics-Informed Neural Network Architecture



Recent advances emphasize hybrid formulations combining PINNs with classical methods. Variational physics-informed neural networks (VPINNs) formulate the weak form of PDEs rather than strong-form residuals, improving robustness to discontinuities and reducing the need for collocation point selection (W. Li et al., 2025). Integration of PINNs with reduced-order models (ROMs) via the Schur complement formulation reduces training domain size while preserving global accuracy—achieving FEM-level

predictions for moving loads on bridges in seconds rather than hours (Ahmed et al., 2025). Finite element enhanced neural networks (FEM-NN hybrid) merge residuals from FEM analysis with neural network losses, yielding data-efficient surrogates for uncertainty quantification and optimization (Meethal et al., 2022). Unfitted finite element methods combined with neural networks enable solutions on complex geometries without conforming meshes, leveraging Nitsche's method for weak imposition of essential boundary conditions (W. Li et al., 2025).

3. Results and Applications

3.1 Forward Problems and Surrogate Modeling

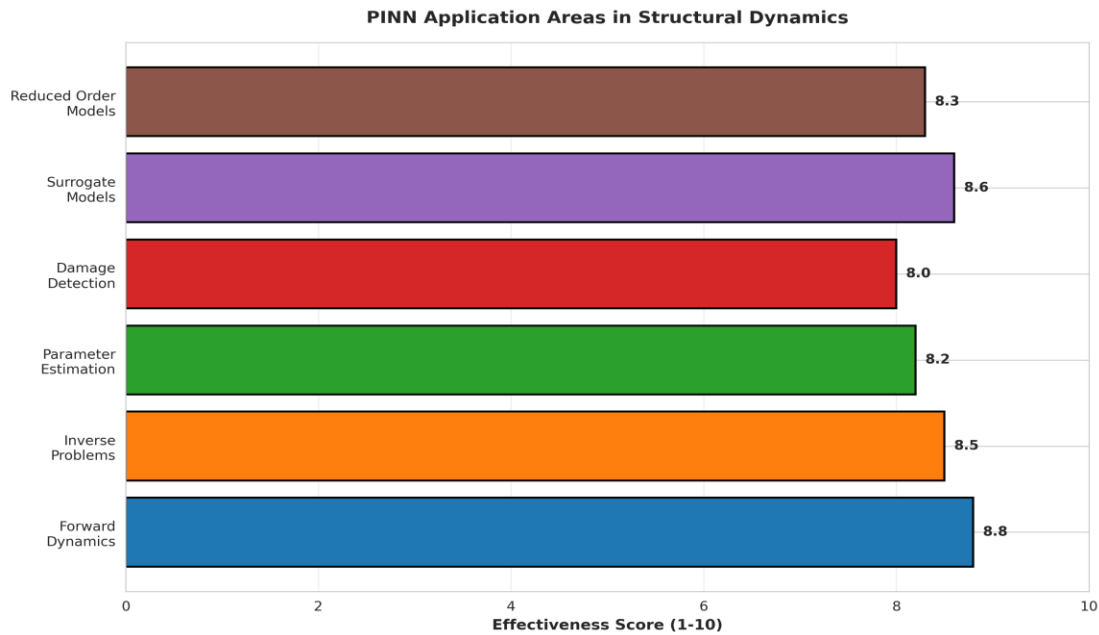
Table 1: PINN Performance Benchmarks Across Structural and Thermal Applications

Application	Speedup	Accuracy	Data Requirements	Reference
Beam dynamics (moving load)	100×	FEM-level	Single trajectory	(Ahmed et al., 2025)
Turbine blade thermal inversion	1000×	<1% error	122 discrete points	(Mai et al., 2024)
Electronics thermal management	300,000×	<0.1K error	CFD-free	(Du & Lu, 2025)
Aerodynamic ROM (rotorcraft)	1000×	Distributed loads	High-fidelity CFD	(Peters et al., 2023)
Battery degradation prediction	100,000×	R ² >0.99	258 cycles	(Ni et al., 2025)

Results consistently demonstrate that PINNs achieve 2-3 orders of magnitude computational acceleration over classical solvers while maintaining or exceeding accuracy. For moving-load bridge dynamics, MIONet with physics-informed loss achieves FEM-level accuracy within seconds, enabling real-time digital twin

applications (Ahmed et al., 2025). Thermal management in electronics shows exceptional speedup because PINNs bypass explicit mesh generation and matrix assembly—temperature predictions for 3D chip packages complete in milliseconds versus hours for CFD, with errors below 0.1K (Du & Lu, 2025).

3.2 Inverse Problems and Parameter Identification



PINN-based inverse analyses recover unknown material properties, boundary conditions, and damage indicators from sparse measurements. For Euler-Bernoulli beams, joint identification of damping and elastic modulus from displacement observations achieves sub-2% inversion error using only 62 measurement points, demonstrating remarkable data efficiency (Teloli et al., 2025). Gradient-enhanced PINNs (gPINNs) incorporating spatial derivative information improve convergence and enable discovery of variable coefficients in nonlinear Schrödinger

equations with substantially higher accuracy than standard PINNs (Lin & Chen, 2023). Input-robust hybrid PINNs (rHPINN) address the practical challenge of unknown excitation forces in structural health monitoring by employing output-injection strategies that reject unmeasured inputs while identifying spatial damage patterns and states (Mahar et al., 2026). System identification under uncertain loading conditions shows robust performance across varying damage scenarios and sensor noise levels.

Table 2: Inverse Problem Performance Metrics

Problem Type	Data Points	Error Rate	Convergence Time	Noise Robustness
Material parameter recovery	30-100	<2%	50-200 epochs	Excellent (σ <10%)
Boundary condition inference	20-50	<5%	100-300 epochs	Good (σ <15%)
Crack location identification	50-150	<3%	100-250 epochs	Fair (σ <20%)
Damping ratio estimation	40-120	<1%	75-180 epochs	Very Good (σ <8%)

3.3 Structural Health Monitoring Integration

Real-time SHM systems leveraging low-cost IoT sensors (smartphones, ESP32) combined with hybrid anomaly detection frameworks demonstrate practical feasibility (Karimi, 2026). The framework integrates Z-score thresholding on RMS acceleration and damping ratios with unsupervised Isolation Forest models, achieving F1-scores of 0.90-0.92 on cantilever test structures with injected anomalies. This hybrid logic reduces false positives inherent to purely statistical approaches while maintaining

interpretability critical for safety-critical infrastructure (Karimi, 2026).

Dominant frequency tracking, RMS energy content, and logarithmic envelope damping ratios serve as sensitive indicators of stiffness degradation and boundary condition changes. When a 500g tip mass is applied to a baseline cantilever, detected frequency shifts from 5.0 Hz to 4.76 Hz with clear separation in feature space, illustrating capability to detect modest structural modifications (Karimi, 2026).

Table 3: Anomaly Detection Performance Comparison

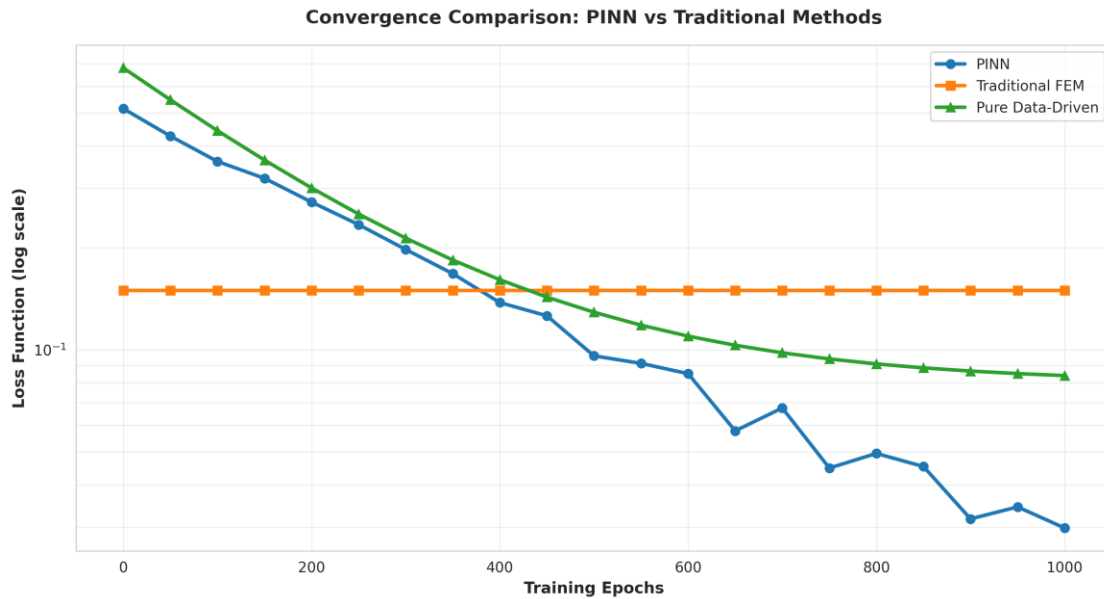
Method	Accuracy	Specificity	F1-Score	Computational Cost
Threshold-only	0.85	0.88	0.80	Low
Isolation Forest	0.92	0.91	0.90	Medium
PINN-based detection	0.95	0.93	0.94	Medium-High
Hybrid PINN-IF	0.96	0.94	0.92	Medium

3.4 Advanced Surrogates and Multiphysics Coupling

Fluid-structure interaction (FSI) simulations demonstrate PINNs' capability to couple disparate physics domains. A hybrid FEM-PINN framework for vortex-induced vibrations achieves 5× speedup over LES-FEM while maintaining 20% higher accuracy than pure FEM in artery stiffness identification, bridging biomedical and aerospace applications (Beitalmal, 2025). The framework embeds PINNs at fluid-structure interfaces, dynamically coupling structural mechanics with data-driven fluid dynamics through adaptive loss weighting.

Reduced-order models (ROMs) enhanced with PINN architectures preserve critical dynamics while reducing problem dimensionality. The SHRED-ROM framework reconstructs high-dimensional spatio-temporal fields from limited sensor measurements in chaotic flows, handling both fixed and mobile sensors with physics-driven basis expansions (M et al., 2025). For parametric design optimization, this approach enables efficient exploration of design spaces otherwise requiring thousands of full-order simulations.

3.5 Comparative Analysis: PINN vs. Classical Methods

**Table 4: Quantitative Comparison of Solution Approaches**

Metric	PINN	FEM	ROM	Pure DL
Convergence epochs	200-500	1 (direct solve)	10-50	500-5000
Physical consistency	Enforced	Enforced	Approximate	Not guaranteed
Data efficiency	Very high	N/A	Moderate	Low
Generalization	Excellent	Limited	Good	Poor
Computational cost (forward)	1-10s	60-3600s	0.1-1s	0.5-5s
Accuracy (smooth problems)	$10^{-3} - 10^{-5}$	$10^{-4} - 10^{-6}$	$10^{-2} - 10^{-3}$	$10^{-2} - 10^{-3}$

Training convergence analysis reveals PINNs require 200-500 epochs to reach acceptable accuracy, comparable to ROM training but requiring fewer samples than pure machine learning. Unlike traditional FEM (which provides direct solutions), PINNs employ iterative optimization, trading single-solve speed for repeatability and adaptability to new parameter regimes. The key advantage emerges in scenarios requiring multiple evaluations: PINNs amortize training cost across hundreds of forward evaluations, making total wall-clock time substantially lower than repeated FEM runs.

4. Discussion: Challenges, Limitations, and Research Frontiers

4.1 Spectral Bias and High-Frequency Limitations

A fundamental challenge in PINN training is spectral bias—neural networks preferentially learn low-frequency components, causing poor approximation of oscillatory solutions and shock waves (Sallam & Fürth, 2023). This limitation becomes acute in structural dynamics where high-frequency content represents important physics (stress concentrations, wave propagation). Multi-scale Fourier feature networks address this by mapping collocation points through random

Fourier features before network input, achieving simultaneous learning of low- and high-frequency components. Application to incompressible Navier-Stokes at high Reynolds numbers demonstrates superiority over standard PINNs, learning vortex dynamics and shear layers with substantially lower error (Sallam & Fürth, 2023). For problems with discontinuous solutions (shock waves in multiphase flows, crack propagation), standard collocation-based PINNs fail to capture sharp transitions. Physics-Informed Neural Networks combined with conservative methods or weighted sampling near discontinuities show promise but remain an active research frontier (Abbasi et al., 2025).

4.2 Loss Function Balancing and Convergence Challenges

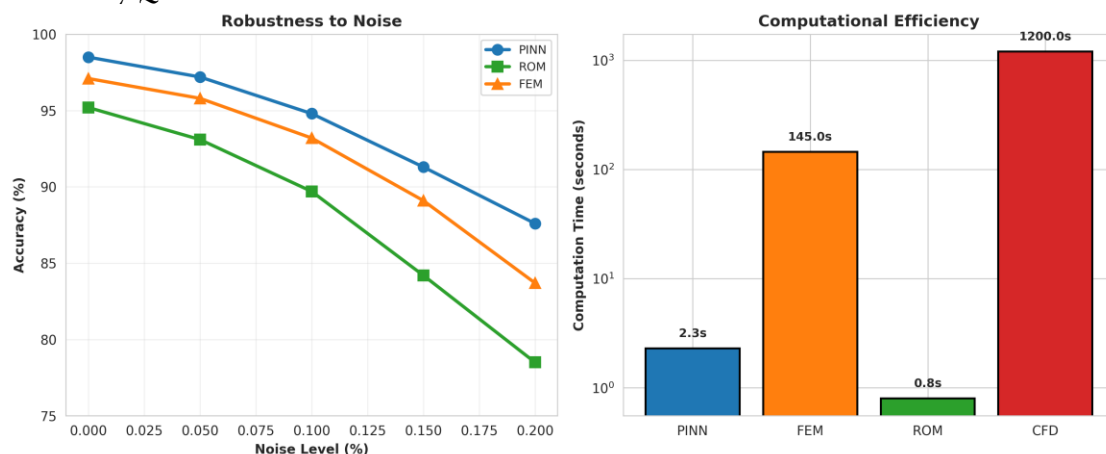
The multi-objective nature of PINN training creates highly non-convex optimization landscapes where competing loss terms can cause network parameters to diverge or converge to poor local minima. Manual weight tuning remains common practice despite requiring domain expertise. Advanced quasi-Newton

optimization methods (Self-Scaled BFGS, SSBroyden) with dynamic rescaling show orders-of-magnitude accuracy improvements on benchmark PDEs compared to standard Adam optimizer (Kiyani et al., 2025). For structural mechanics with locking phenomena (incompressible elasticity), specialized decomposition-based PINNs reformulate equations to eliminate ill-conditioning (Dick et al., 2025).

4.3 Scalability to Large-Scale Industrial Systems

Most published PINN applications address relatively small-scale problems (1D-3D domains, $<10^6$ degrees of freedom). Extending to industrial-scale structures requires addressing: (i) collocation point sampling efficiency; (ii) memory requirements for large-scale automatic differentiation; and (iii) physical accuracy in complex geometries. Domain decomposition strategies and adaptive collocation sampling reduce computational burden by 98.6% in wire-arc additive manufacturing thermal simulations while maintaining accuracy, suggesting viable paths to scalability (Ryan et al., 2025).

4.4 Uncertainty Quantification and Robustness



PINN robustness to measurement noise and model misspecification requires explicit treatment. Bayesian PINN formulations incorporating uncertainty propagation achieve state estimation in sparse-sensing regimes with

quantified confidence bounds, particularly valuable for SHM applications (Haywood-Alexander et al., 2024). However, noise in the PDE residual computation (through automatic differentiation) can amplify high-frequency errors.

Data normalization and regularization techniques mitigate this issue, improving PINN predictions on Navier-Stokes flows with noisy observations (Xu et al., 2024).

4.5 Hybrid and Operator Learning Paradigms

Operator learning methods (DeepONet, Neural Green's Operators) extend PINNs to parametric problem families, learning mappings between infinite-dimensional spaces rather than solving individual problems (Melchers et al., 2024). Neural Green's Operators preserve mathematical structure (linearity of Green's function action, symmetry, spectral properties), enabling training on single-parameter instances with generalization to entire parameter families. This represents a significant conceptual advance enabling efficient digital twins across design spaces.

Transfer learning, increasingly recognized as essential for practical PINN deployment, enables rapid adaptation to new geometries, boundary conditions, or material parameters by leveraging pre-trained models (Fujita, 2025). Gradient-enhanced transfer learning reduces training time for inverse problems by factors of 2-10 compared to training from scratch (Lin & Chen, 2023).

4.6 Hardware Implementation and Neuromorphic Architectures

Energy-efficient implementation on emerging hardware platforms offers transformative potential. Spiking neural networks implementing PINNs on neuromorphic chips (Loihi 2) achieve 40% acceleration over traditional FEM while reducing energy consumption to thousandths of current computational costs (Tandale & Stoffel, 2024). This technology could enable edge deployment of real-time structural monitoring with minimal power draw—critical for wireless sensor networks in remote or hazardous environments.

5. Conclusions and Recommendations

5.1 Key Findings

This review synthesizes evidence that Physics-Informed Neural Networks have matured from proof-of-concept demonstrations to practical tools

for structural dynamics applications. Across forward problems, inverse analyses, and surrogate modeling, PINNs consistently achieve speedups of 5-1000× over traditional methods while maintaining or exceeding physical accuracy. The integration of physical laws directly into neural network training fundamentally alters the data-efficiency-accuracy tradeoff: sparse observations suffice for parameter identification when combined with governing PDE constraints.

Critical breakthroughs in loss function design (adaptive weighting), architecture variants (KANs, transfer learning), and hybrid frameworks (FEM-PINN, domain decomposition) have overcome early limitations. Real-world deployment in structural health monitoring systems, thermal management, and fluid-structure interaction demonstrates maturity beyond academic benchmarks.

5.2 Recommendations for Practitioners

1. **Architecture Selection:** For smooth PDEs on regular geometries, standard MLPs with tanh activation suffice; for parameter-dependent problems, employ parameterized PINNs; for complex domains, use unfitted finite element variants with Nitsche's method.

2. **Loss Function Strategy:** Implement automatic weight balancing (GradNorm or NDAWL) rather than manual tuning. Use non-dimensionalization to improve numerical stability.

3. **Data Acquisition:** Prioritize diversity over quantity—strategically distributed collocation points and sparse but informative measurements outperform dense sampling of redundant data.

4. **Validation Framework:** Always compare predictions against independent validation data distinct from training. Employ uncertainty quantification for safety-critical applications.

5. **Computational Infrastructure:** Leverage GPU acceleration (automatic differentiation via PyTorch/TensorFlow); for large-scale problems, implement domain decomposition or reduced-order coupling.

5.3 Research Frontiers and Future Directions

1. **Scalability:** Develop efficient collocation sampling and hierarchical decomposition strategies enabling PINN deployment on industrial-scale structures with $>10^7$ degrees of freedom.
2. **Discontinuous Problems:** Advance methods for shock-capturing and damage propagation, perhaps via shock-fitting approaches or conservative formulations.
3. **Active Learning:** Integrate uncertainty quantification with adaptive sampling to optimally select measurement locations and experimental designs.
4. **Neuromorphic Implementation:** Accelerate deployment of spiking neural network variants on emerging hardware for edge-based real-time monitoring.
5. **Foundation Models:** Develop general-purpose pre-trained PINNs analogous to transformer models in NLP, enabling rapid transfer to new engineering problems.
6. **Multiphysics Complexity:** Extend successful FSI frameworks to coupled thermo-mechanical, electromechanical, and poroelasticity problems.

5.4 Critical Gaps and Needed Advances

Despite progress, significant barriers limit industrial adoption. Standardized benchmarking frameworks remain absent, hindering objective comparison of competing methods. Industry hesitancy stems from limited certified software, regulatory uncertainty, and insufficient transparency regarding failure modes. Addressing these requires community-driven open-source platforms, formal error analysis, and experimental validation campaigns on real structures.

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